Vol. 8, No. 4, August 2026

Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

Extending the Technology Acceptance Model with Perceived Immersive Learning for VR Usage in Higher Education

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Received:
February 25, 2026
Revised:
June 3, 2026
Accepted:
July 22, 2026
Published:
August 22, 2026

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DOI:
10.63158/journalisi.v8i4.1696

Abstract. This study examines the adoption of Virtual Reality (VR)-based learning in Indonesian higher education by extending the Technology Acceptance Model (TAM) through Perceived Immersive Learning (PIL). The study investigates how perceived usefulness, perceived ease of use, PIL, behavioral intention, and self-reported usage behavior are related. A quantitative approach using Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to data collected from 180 university students with experience using VR-based immersive learning technologies. The measurement and structural models were analyzed using SmartPLS 4. Results show that perceived ease of use significantly influences perceived usefulness and PIL, while perceived usefulness also has a significant positive effect on PIL. In addition, PIL significantly affects behavioral intention, which subsequently influences self-reported VR usage behavior. The model explains 58.6% of the variance in behavioral intention (R^2 = 0.586), indicating substantial explanatory power. These findings demonstrate that immersive learning experiences play a central role in translating technology perceptions into behavioral intention and subsequent usage behavior. The study contributes to TAM literature by empirically positioning PIL as a mediating construct and offers practical insights for universities seeking to design more engaging, usable, and meaningful VR-based learning environments that can strengthen students' acceptance and sustained engagement with VR.

Keywords: Technology Acceptance Model; Perceived Immersive Learning; Virtual Reality; Behavioral Intention; Higher Education

1. INTRODUCTION

The digital transformation in higher education is driving a shift in learning paradigms from conventional models toward more interactive, personalized, and technology-enhanced learning environments [1]. Advances in digital technology are no longer focused solely on providing access to information but also on creating learning experiences that foster active student engagement and the development of 21st-century skills [2]. Among emerging educational technologies, immersive technologies such as Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) have gained increasing attention because of their ability to provide immersive simulations, three-dimensional visualizations, and contextual learning experiences that closely resemble real-world situations. Systematic reviews indicate that immersive technologies are widely implemented in STEM education because they support the understanding of abstract concepts, enhance spatial visualization, and promote active learning through interaction with virtual environments [3]. Furthermore, immersive technology-based learning has been reported to improve motivation, engagement, and academic performance, although challenges related to device accessibility, user comfort, and technical complexity remain [3], [4].

The Indonesian higher education sector has increasingly emphasized digital transformation through initiatives promoting technology-enhanced learning and educational innovation. The implementation of the Merdeka Belajar-Kampus Merdeka (MBKM) program and various digital transformation policies has encouraged universities to adopt innovative learning technologies, including immersive learning applications [5]. Recent studies also report increasing implementation of VR- and AR-based learning environments in Indonesian higher education, particularly in science, engineering, health, and vocational education programs [5], [6], [7]. Despite this growing interest, empirical evidence explaining how students develop immersive learning perceptions and subsequent self-reported usage behavior toward immersive technologies remains limited within the Indonesian higher education context [6]. Therefore, investigating factors influencing the acceptance and self-reported usage behavior of immersive learning technologies is important for supporting their effective implementation in higher education. Although immersive technologies encompass VR, AR, and MR, the empirical context of this study is limited to learners who have experience with VR-based immersive learning environments. Therefore, VR serves as the primary empirical representation of

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immersive technology adoption examined in this study, while the broader immersive technology literature is used to establish the theoretical context.

One of the key characteristics of immersive technology is its ability to create learning environments that allow students to actively interact within contexts resembling real-world situations. As a result, learning is no longer focused solely on knowledge acquisition but also on how learners perceive, interpret, and evaluate their learning experiences while interacting with technology [1], [6]. These learning perceptions are important because they influence how students assess the quality, value, and effectiveness of immersive learning experiences. Consequently, the effectiveness of immersive technology depends not only on technological capabilities but also on the cognitive and affective processes that occur during learning activities [1], [2], [6].

Although previous studies have demonstrated that immersive technology can improve learning perceptions and learning outcomes, most research has focused primarily on comparing technologies or evaluating learning effectiveness [6], [7]. Prior studies have also suggested that immersion can enhance learning effectiveness, yet the mechanisms through which learners develop perceptions of immersive learning and how these perceptions influence self-reported usage behavior remain insufficiently understood [6], [8]. Furthermore, research on VR-based training has shown that immersive experiences may serve as mechanisms linking learning perceptions and outcomes [7], [9]. These findings indicate that the relationship between technology characteristics and learning outcomes is not necessarily direct but may be shaped by learners' perceptions during immersive learning experiences. Consequently, a gap remains in understanding how technology acceptance perceptions are transformed into meaningful learning experiences and subsequent self-reported usage behavior.

The Technology Acceptance Model (TAM) has consistently identified perceived usefulness and perceived ease of use as important determinants of technology acceptance and behavioral intention [5], [12]. However, TAM primarily explains users' cognitive evaluations of technology and provides limited insight into how these evaluations are transformed into meaningful learning perceptions within immersive learning environments [12], [13]. Although prior studies have confirmed strong relationships among perceived usefulness, perceived ease of use, and behavioral intention across various contexts [14], [15], the formation of learning-related perceptions remains insufficiently explained. This limitation suggests the need for additional mechanisms that can explain how technology acceptance perceptions are translated into learning experiences within immersive educational settings [16].

In this study, Perceived Immersive Learning (PIL) is defined as learners' overall evaluation of the extent to which VR-based immersive learning environments facilitate meaningful learning experiences, cognitive engagement, and perceived learning outcomes. PIL reflects a higher-order learning perception that integrates learners' assessments of the educational value generated through immersive learning experiences [19]. Unlike related constructs such as presence, immersion, engagement, flow, and perceived learning, which represent specific experiential dimensions of immersive environments, PIL represents an overall evaluative judgment regarding the quality and educational effectiveness of immersive learning experiences. Accordingly, PIL is positioned as a holistic learning perception that captures how learners interpret and evaluate the contribution of immersive experiences to meaningful learning processes and outcomes.

This study therefore positions PIL as a mediating construct that explains how technology acceptance perceptions are transformed into behavioral intention and self-reported usage behavior. This approach addresses the limitations of TAM in explaining experiential learning processes within immersive learning environments [21], [22]. Accordingly, the classical TAM paths from perceived usefulness and perceived ease of use directly to behavioral intention are not included in the proposed model. Unlike the classical TAM framework in which perceived usefulness and perceived ease of use directly predict behavioral intention [23], the proposed model posits that PIL fully mediates these relationships. In immersive learning environments, users' intention to adopt technology is not driven merely by utilitarian perceptions but also by the degree to which they perceive the technology as enabling meaningful, engaging, and educationally valuable learning experiences [9], [21], [24]. Consequently, the proposed model theorizes that perceived usefulness and perceived ease of use influence behavioral intention indirectly through PIL, reflecting the central role of immersive learning experiences in shaping technology acceptance [9], [24], [25]. Instead, the study assumes that learners first evaluate their immersive learning experiences through PIL, which subsequently influences their behavioral intention to use VR-based immersive learning technologies.

This extension enables the proposed model to capture both technology acceptance perceptions and experiential learning evaluations within a unified framework.

This study aims to extend the Technology Acceptance Model (TAM) by positioning Perceived Immersive Learning (PIL) as a mediating mechanism that explains how technology acceptance perceptions are transformed into behavioral intention and self-reported usage behavior within immersive learning environments. By focusing on learners' experiences with VR-based immersive learning technologies in Indonesian higher education, this study contributes to a deeper understanding of the experiential processes underlying immersive technology adoption.

Based on the identified research gap, this study addresses the following research questions:

1) RQ1: How does perceived ease of use influence perceived usefulness in immersive technology-based learning environments?
2) RQ2: How does perceived ease of use influence perceived immersive learning in immersive technology-based learning environments?
3) RQ3: How does perceived usefulness influence perceived immersive learning?
4) RQ4: How does perceived immersive learning influence users' behavioral intention to use immersive technologies?
5) RQ5: How does behavioral intention influence self-reported usage behavior of immersive technology?
6) RQ6: Does perceived usefulness mediate the relationship between perceived ease of use and perceived immersive learning?
7) RQ7: Does perceived immersive learning mediate the relationship between perceived ease of use and behavioral intention?
8) RQ8: Does behavioral intention mediate the relationship between perceived immersive learning and usage behavior of immersive technology?

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was first introduced as a framework explaining how user acceptance of technology is influenced by two primary constructs, namely

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Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which subsequently shape behavioral intentions and usage behavior [11]. Developed from the Theory of Reasoned Action (TRA), TAM was designed to predict information system acceptance and usage in organizational and educational settings [26]. Over time, TAM has become one of the most widely applied models for explaining technology adoption, including the adoption of digital learning technologies in higher education. Previous studies have demonstrated that TAM remains relevant for explaining learners' acceptance of immersive and virtual learning technologies because it systematically captures the relationships among user perceptions, behavioral intentions, and technology usage behavior [27].

In immersive learning environments, TAM provides a useful foundation for understanding how learners evaluate the ease of use and usefulness of VR-based learning technologies. These perceptions influence learners' evaluations of their learning experiences and subsequently affect their intentions to use immersive technologies within educational contexts [27]. However, while TAM effectively explains the relationships among perceived usefulness, perceived ease of use, and behavioral intention, it provides limited explanation of how technology perceptions are transformed into meaningful learning experiences in immersive learning environments [19], [20], [28].

Consistent with recent immersive learning research, this study assumes that learners first evaluate the educational value of immersive experiences before forming behavioral intentions toward technology usage. Therefore, the classical TAM paths from perceived usefulness and perceived ease of use directly to behavioral intention are not included in the proposed model. Instead, these relationships are assumed to operate indirectly through Perceived Immersive Learning (PIL), which serves as the primary evaluative mechanism linking technology perceptions with behavioral intention. Accordingly, TAM is employed as the theoretical foundation of this study, while PIL extends the model by capturing the experiential learning processes that occur during VR-based immersive learning activities.

2.2. Perceived Immersive Learning

In this study, Perceived Immersive Learning (PIL) is operationally defined as learners' overall evaluation of the extent to which VR-based immersive learning environments facilitate meaningful learning experiences, cognitive engagement, and perceived learning outcomes. PIL reflects a unified learning perception that captures learners' assessments of the educational value generated through immersive learning experiences [9], [29].

The concept of immersive learning is influenced by theories of immersion and presence, which suggest that immersive virtual environments can create a strong sense of involvement and psychological presence within digital spaces [30], [31]. From an educational perspective, Constructivist Learning Theory and Experiential Learning Theory further explain that meaningful learning emerges through active interaction, direct experience, and reflective learning processes [32], [33], [34]. Consequently, immersive learning environments are considered capable of fostering deeper learning experiences by simultaneously engaging cognitive, affective, and interactive aspects of learning.

Furthermore, the Cognitive Affective Model of Immersive Learning (CAMIL) argues that immersive learning outcomes are shaped by cognitive, affective, motivational, and presence-related factors that collectively influence learners' perceptions of educational experiences within virtual environments [9]. Previous studies have also demonstrated that immersion, technological interactivity, and learning engagement contribute to conceptual understanding, learning satisfaction, and positive perceptions of immersive learning experiences [35].

Based on these theoretical foundations, Perceived Immersive Learning (PIL) is conceptualized as learners' overall perception of the quality and depth of immersive learning experiences within technology-enhanced learning environments. This perception is associated with several important characteristics of immersive learning, including a sense of presence, active interaction with virtual environments, and the integration of learning experiences into meaningful reflection and understanding. Sense of presence reflects learners' perceptions of involvement and self-presence within immersive environments [11], [36]. Active interaction with immersive environments supports exploration, engagement, and knowledge construction during learning activities [37], [38]. Furthermore, immersive learning experiences facilitate reflective processes that help learners connect virtual experiences with meaningful learning outcomes and deeper understanding [39], [40]. These characteristics provide the theoretical basis for understanding how learners evaluate the quality of immersive learning experiences as reflected in the PIL construct.

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Unlike related constructs such as presence, immersion, engagement, flow, and perceived learning, which represent specific experiential dimensions of immersive environments, PIL represents an overall evaluative judgment regarding the quality and educational effectiveness of immersive learning experiences. Presence reflects the psychological sensation of being located within a virtual environment, immersion represents the degree of involvement in that environment, engagement refers to participation in learning activities, flow reflects a state of deep concentration, and perceived learning focuses on learners' perceptions of learning outcomes. In contrast, PIL captures learners' overall evaluation of how immersive learning experiences contribute to meaningful learning processes and educational outcomes. Therefore, PIL is positioned as an overall learning perception that serves as a conceptual link between technology perceptions and behavioral responses within VR-based learning environments.

Although immersive technologies encompass Virtual Reality (VR), Augmented Reality (AR), Mixed Reality (MR), and metaverse-based environments, the empirical focus of this study is limited to learners who have experience with VR-based immersive learning environments. Therefore, VR serves as the primary empirical context for testing the proposed model, while the broader immersive technology literature is used to establish the theoretical foundation of immersive learning.

2.3. Immersive Virtual Reality (IVR)

Virtual Reality (VR) is defined as a complex media system that includes specific technological configurations for sensory immersion and advanced content presentation methods, capable of simulating or replicating both real and imaginary worlds [41]. Rapid advancements in immersive virtual reality (IVR) technology are revolutionizing educational services, particularly in assisting educators in delivering effective and interactive lessons. The application of VR in higher education demonstrates that its main advantage lies in the possibility for users to gain direct experiences that cannot be obtained in the real world [22], [42].

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Figure 1. Immersive Virtual Reality Applications

In higher education, VR-based immersive learning applications have attracted increasing attention because they enable interactive, contextual, and experience-based learning environments. Immersive virtual reality applications have attracted increasing attention in the field of education and demonstrate the potential to transform traditional learning methods by supporting active and experiential forms of learning [9], [42]. Immersive learning in higher education has been shown to enhance student engagement, motivation, and learning outcomes [9]. Past studies found that the use of VR in science learning improves conceptual understanding, motivation, and learning satisfaction compared to traditional methods [9]. Furthermore, it was confirmed that VR in engineering and design education contributes to increased presence, engagement, and knowledge retention [24]. From an andragogical perspective, VR-based simulations are considered effective in providing contextual experiences that are relevant for adult learners and aligned with the need for flexibility and relevance in learning [43], [44]**.** The findings show that VR immersive technology has great potential to enhance the learning process at the university level.

2.4. Hypotheses Development

The current study aims to examine the factors influencing user behavior in VR-based immersive learning environments from the perspectives of the Technology Acceptance Model (TAM) and Perceived Immersive Learning (PIL). Although immersive technologies

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encompass Virtual Reality (VR), Augmented Reality (AR), Mixed Reality (MR), and metaverse-based environments, the empirical context of this study is limited to VR-based immersive learning. Therefore, the proposed hypotheses are developed and tested based on learners' perceptions and experiences within VR learning environments, while the broader immersive learning literature is used to provide theoretical support.

Perceived Immersive Learning (PIL) is operationally defined as learners' overall evaluation of the extent to which VR-based immersive learning environments facilitate meaningful learning experiences, cognitive engagement, and perceived learning outcomes. Unlike presence, immersion, engagement, flow, and perceived learning, which represent specific experiential dimensions of immersive environments, PIL reflects a higher-order evaluative judgment regarding the overall educational quality and effectiveness of immersive learning experiences. Accordingly, PIL is positioned as a psychological mechanism through which technology perceptions are transformed into behavioral intention within VR-based learning environments.

Furthermore, behavioral intention is viewed as a direct determinant of usage behavior, consistent with the fundamental assumption of TAM that intention is the strongest predictor of self-reported usage behavior [18]. TAM emphasizes the roles of Perceived Ease of Use (PEOU), Perceived Usefulness (PU), and Behavioral Intention (BI) in explaining technology acceptance and usage [18], [23]. Previous studies have demonstrated the applicability of TAM in explaining the adoption of immersive learning technologies in higher education [11], [21], [45]. However, while the original TAM proposes direct relationships between PEOU, PU, and behavioral intention, recent immersive learning studies suggest that learners often evaluate the educational value of immersive experiences before forming intentions to use the technology [9]. Therefore, the classical TAM paths from PEOU and PU directly to BI are not included in the proposed model. Instead, the proposed model theorizes that these effects operate indirectly through Perceived Immersive Learning (PIL), which serves as the primary evaluative mechanism linking technology perceptions with behavioral intention in VR-based learning environments.

Perceived ease of use refers to the degree to which users believe that interacting with a VR learning system requires minimal effort [18], [20], [46]. Ease of use enables smoother interactions with technology, allowing learners to focus more on learning activities rather than technical operations. Such conditions may reduce unnecessary cognitive load and support the development of positive learning experiences. Previous studies consistently demonstrate that systems perceived as easier to use are also perceived as more useful in supporting learning activities [47]. Accordingly, perceived ease of use is expected to positively influence both perceived usefulness and perceived immersive learning. Moreover, when learners perceive VR systems as easy to use, they are more likely to experience meaningful immersive learning experiences, which may subsequently strengthen their intention to use the technology. Therefore, perceived usefulness and perceived immersive learning are expected to function as mediating mechanisms linking ease of use to subsequent learning perceptions and behavioral intention [8], [12], [13].

H1: Perceived ease of use has a positive effect on perceived usefulness.

H2: Perceived ease of use has a positive effect on perceived immersive learning.

H6: Perceived usefulness mediates the influence of perceived ease of use on perceived immersive learning.

H7: Perceived immersive learning mediates the influence of perceived ease of use on behavioral intention.

Perceived usefulness refers to the extent to which individuals believe that using a VR learning system enhances their effectiveness in achieving learning objectives [18]. In educational contexts, perceptions of usefulness extend beyond functional benefits and influence how learners evaluate the quality and value of their learning experiences. Empirical evidence suggests that perceived usefulness is positively associated with learning engagement, perceived learning, enjoyment, and presence within immersive environments [12], [48]. Consequently, learners who perceive VR technology as useful are more likely to develop positive immersive learning perceptions.

H3: Perceived usefulness has a positive effect on perceived immersive learning.

Research has shown that experiential factors such as learning value, engagement, enjoyment, and intrinsic motivation contribute to the formation of behavioral intention toward technology use [49], [50]. These findings suggest that behavioral intention is influenced not only by cognitive evaluations of technology but also by learners' assessments of the experiences gained while interacting with the system. In VR-based learning environments, learners who perceive immersive experiences as meaningful,

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engaging, and educationally valuable are more likely to develop stronger intentions to use the technology. Therefore, perceived immersive learning is expected to positively influence behavioral intention.

H4: Perceived immersive learning has a positive effect on behavioral intention.

Behavioral intention is widely recognized as a direct predictor of usage behavior within TAM and related technology acceptance models [18]. Previous studies consistently indicate that stronger behavioral intentions increase the likelihood of subsequent technology usage behavior [23]. Although usage behavior may also be influenced by factors beyond the scope of the model, behavioral intention remains one of the most robust predictors of technology adoption behavior. Furthermore, learners who perceive immersive learning experiences positively may be more likely to engage in actual technology use through the formation of stronger behavioral intentions. Therefore, behavioral intention is expected to directly influence usage behavior and simultaneously mediate the relationship between perceived immersive learning and usage behavior.

H5: Behavioral intention has a positive effect on Usage Behavior of Immersive Technology.

H8: Behavioral intention mediates the influence of perceived immersive learning on Usage Behavior of Immersive Technology.

3. METHODS

This study employs a quantitative approach to examine the causal relationships among the variables in the proposed research model [51]. A structured survey was used to collect data on the perceptions and self-reported behaviors of university students with prior experience using Virtual Reality (VR) in higher education. The empirical context of this study focuses on VR-based immersive learning, with data collected from voluntary student participants recruited from several public and private higher education institutions in Semarang, Indonesia, between February and March 2026. Respondents were recruited using purposive sampling through an online questionnaire distributed via Google Forms. Purposive sampling was employed to ensure that only participants who had prior experience with VR-based learning were included, thereby providing responses that were relevant to the constructs examined in the proposed research model [52]. Because the questionnaire was distributed through open online channels using purposive

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sampling, the total number of students who received the survey invitation could not be determined. Consequently, a response rate could not be calculated. A total of 180 valid responses meeting the inclusion criteria were retained for analysis.

To ensure that participants possessed sufficient experience to evaluate VR-based learning environments, the inclusion criteria required respondents to (1) be active university students in Semarang, (2) have participated in learning activities using Virtual Reality (VR) as an instructional medium, (3) have experienced VR-based learning in at least two learning sessions, and (4) voluntarily complete the questionnaire. The final sample consisted of 180 students, including 100 students from public universities and 80 students from private universities, representing the fields of Business, Education, Engineering, Medicine, Nursing, and Science. Regarding prior VR experience, 65 respondents (36.11%) had participated in two VR learning sessions, 46 respondents (25.56%) had participated in three sessions, and 69 respondents (38.33%) had participated in more than three sessions. Since the objective of this study was to examine students' perceptions of VR-based learning rather than evaluate a specific hardware platform or software application, respondents were not restricted to particular VR devices or applications. The selection of Semarang as the research location reflects the increasing integration of immersive technologies within Indonesian higher education as part of the broader digital transformation of education.

Prior to participation, all respondents were provided with an informed-consent form explaining the purpose of the study, the voluntary nature of participation, the confidentiality of responses, and their right to withdraw at any time without consequence. Participation was entirely voluntary, and informed consent was obtained from all respondents before they completed the questionnaire. All collected data were anonymized and used solely for academic research purposes. As the study involved a voluntary questionnaire without intervention, collection of personally identifiable information, or sensitive personal data, no formal institutional ethics approval was required under the applicable institutional procedures. Nevertheless, all research procedures were conducted in accordance with generally accepted ethical principles for research involving human participants.

H1: Perceived Ease of Use (PEOU) positively affects Perceived Usefulness (PU).

H2: Perceived Ease of Use (PEOU) positively affects Perceived Immersive Learning (PIL).

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H3: Perceived Usefulness (PU) positively affects Perceived Immersive Learning (PIL).

H4: Perceived Immersive Learning (PIL) positively affects Behavioral Intention (BI).

H5: Behavioral Intention (BI) positively affects Behavioral Usage of Immersive Technology.

H6: Perceived Ease of Use (PEOU) indirectly affects Perceived Immersive Learning (PIL) through Perceived Usefulness (PU) as a mediating variable.

H7: Perceived Ease of Use (PEOU) indirectly affects Behavioral Intention (BI) through Perceived Immersive Learning (PIL).

H8: Perceived Immersive Learning (PIL) indirectly affects Behavioral Usage of Immersive Technology through Behavioral Intention (BI).

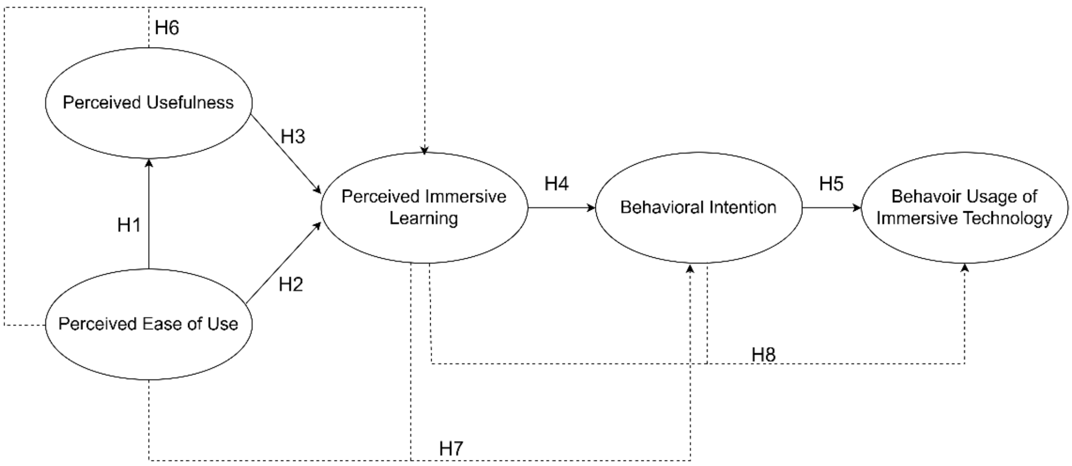

Figure 2. Conceptual Framework

The conceptual framework presented in Figure 2 was developed by integrating the Technology Acceptance Model (TAM) with Perceived Immersive Learning (PIL) to provide a more comprehensive account of VR technology adoption in educational contexts. Unlike the classical TAM, which positions Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as direct antecedents of Behavioral Intention (BI), the proposed model removes these direct paths and instead routes their effects through PIL as the primary mediating mechanism. This modification reflects the theoretical assumption that, in VR-based learning environments, learners evaluate the quality of their immersive learning experiences before forming behavioral intentions toward VR usage. Structurally, the proposed model specifies a sequential process comprising cognitive technology perceptions (PEOU and PU), immersive learning evaluation (PIL), behavioral intention (BI), and self-reported Usage Behavior of Immersive Technology (UBIT). In this study, UBIT was

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operationalized as self-reported usage behavior, reflecting respondents' own assessments of their VR use during learning activities rather than objectively observed usage obtained from system logs or platform analytics. Furthermore, PIL was modeled as a first-order reflective construct measured directly by six indicators. Although the literature identifies several conceptual dimensions of immersive learning, PIL was operationalized as a unidimensional construct to maintain model parsimony and to ensure consistency with the available sample size and measurement indicators.

3.1 Hypotheses Research Procedure and Data Collection

Quantitative data were collected using a structured questionnaire measured on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The measurement instrument was compiled from measurement items reported in multiple previously validated studies corresponding to the constructs examined in this research. Specifically, the Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) items were compiled from established Technology Acceptance Model (TAM) studies, whereas the Perceived Immersive Learning (PIL), Behavioral Intention (BI), and Usage Behavior of Immersive Technology (UBIT) items were compiled from previous studies on immersive learning and technology adoption. Since no single existing instrument comprehensively covered all constructs examined in this study, measurement items were compiled from multiple validated studies and contextually harmonized into a single questionnaire suitable for the present research. Table 1 presents the measurement items and their original sources.

Table 1. Original Sources of Measurement Instruments

No	Construct	Items	Source
1	Perceived Usefulness (PU)	PU1 – PU3	[21], [39], [53]
2	Perceived Ease of Use (PEOU)	PEOU1 – PEOU3	[21], [39]
	Perceived Immersive Learning (PIL)	PIL1 – PIL6	[38], [54], [55]
3	Behavioral Intention (BI)	BI1 – BI3	[38], [39], [53]
4	Usage Behavior of Immersive Technology (UBIT)	UBIT1 – UBIT3	[53]

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To ensure conceptual consistency with the objectives of the present study, the selected questionnaire items were reviewed and contextually modified to reflect the VR-based learning environment investigated in this study. This process primarily involved adjusting terminology and contextual wording (e.g., replacing references to metaverse, learning platforms, or AR with VR-based learning) while preserving the original conceptual meaning of each item. No additional constructs or measurement dimensions were introduced. Similar contextual modification procedures have been reported in previous VR questionnaire adaptation studies [56], [57].

Prior to the main survey, a pilot test was conducted involving 30 respondents who had prior experience using VR-based learning in higher education. The pilot study aimed to evaluate the clarity, comprehensibility, and preliminary psychometric properties of the adapted questionnaire. The pilot-test results indicated acceptable internal consistency reliability based on the Composite Reliability values. As the primary purpose of the pilot study was to assess item clarity and preliminary instrument performance, several items with relatively lower factor loadings were retained because they were theoretically relevant and demonstrated satisfactory psychometric properties in the full-sample measurement model. Therefore, the questionnaire was considered appropriate for use in the main survey. The pilot-test results are presented in Table 2.

Table 2. Pilot Test Result

Construct	Indicator Code	Measurement Item	R Value	CR
Perceived Usefulness (PU)	PU1	The use of VR media is beneficial in the learning process	0.836	0.723
	PU2	The use of VR makes the learning process more effective	0.872	
	PU3	Using VR helps me develop my creative thinking skills.	0.705	
Perceived Ease of Use	PEOU1	Operating the VR system is easy for me	0.921	0.838

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Construct	Indicator Code	Measurement Item	R Value	CR
	PEOU2	Learning how to use the VR system was easy for me	0.759	
	PEOU3	I can customize my VR learning environment to my liking with minimal effort	0.929	
Perceived Immersive Learning (PIL)	PIL1	I feel as if I'm in a VR environment	0.502	0.839
	PIL2	I feel completely immersed in the VR learning environment	0.549	
	PIL3	When using this VR device, I feel completely immersed in the task at hand	0.734	
	PIL4	I understand the VR content presented in a clear and in-depth manner.	0.854	
	PIL5	The content presented using VR really caught my attention.	0.893	
	PIL6	VR content helps me focus despite external distractions	0.875	
Behavioral Intention	BI1	I plan to continue using this VR technology in my studies	0.854	0.848
	BI2	If I could use VR for learning, I'd want to make the most of it	0.903	
	BI3	I will recommend VR to my colleagues	0.891	
Usage Behavior Immersive Technology	UBIT1	I plan to use VR technology more often than other learning technologies	0.892	0.790

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Construct	Indicator Code	Measurement Item	R Value	CR
(UBIT)	UBIT2	Overall, I use this VR device on a regular basis.	0.749	
	UBIT3	I made use of the various Virtual Reality (VR) features available whilst taking part in the learning activities	0.875	

Note: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Immersive Learning (PIL), Behavior Intention (BI), Usage Behavior Immersive Technology (UBIT)

The R Value presented in Table 2 refers to the item validity coefficient obtained during the pilot-test evaluation and was used to assess the validity of each measurement item prior to the main survey. Higher R values indicate stronger item validity. In addition, all constructs achieved Composite Reliability (CR) values above the recommended threshold of 0.70, indicating satisfactory internal consistency. Although PIL1 and PIL2 exhibited relatively lower R values, these indicators were retained because they were theoretically important and demonstrated satisfactory measurement properties in the final measurement model.

The final dataset consisted of 180 valid responses obtained through purposive sampling from university students who had prior experience with Virtual Reality (VR)-based learning. This sample size was considered adequate for Partial Least Squares Structural Equation Modeling (PLS-SEM), which provides stable parameter estimates for moderately complex structural models. Following the commonly recommended guideline of using 10 observations per measurement indicator, the proposed model consisted of 18 measurement indicators. Based on the more conservative criterion of ten observations per indicator (18 × 10), a minimum sample size of 180 respondents was required. Therefore, the final sample of 180 respondents satisfied the recommended sample size requirement for the analysis. In addition, an a priori statistical power analysis was conducted using G*Power 3.1 [52]. Assuming a medium effect size ($f^2 = 0.15$), a significance level of 0.05, statistical power of 0.80, and a maximum of two predictors in the most complex regression equation, the required minimum sample size was 68 respondents. Therefore, the final sample of 180 respondents exceeded both the 10-times rule and the minimum

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sample size recommended by the statistical power analysis, indicating sufficient statistical power for hypothesis testing. The demographic characteristics of the respondents are presented in Tables 3 and 4.

Table 3. Demographic Characteristics Respondents based on Age and Gender

Age (Years)	Participants (N)	%	Gender	Participants (N)	%
< 25	104	57.8	Female	98	54.4
25-30	42	23.3	Male	82	45.6
> 30	34	18.9			
Total	180	100		180	100

Table 4. Demographic Characteristics Respondents based on Grade Study and Field of Study

Grade Study	Participants (N)	%	Field of Study	Participants (N)	%
Postgraduate	50	27.8	Business	13	7.2
Undergraduate	130	72.2	Education	12	6.7
			Engineering	17	9.4
			Medicine	86	47.8
			Nurse	36	20
			Science	16	8.9
Total	180	100	Total	180	100

3.2 Data Analysis Techniques

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the assistance of SmartPLS 4 software. This method was chosen because it is capable of analyzing complex structural models, testing mediating relationships, and emphasizing prediction and theory development. Model evaluation was performed in two stages, namely the measurement model and the structural model. Prior to evaluating the measurement model, Common Method Bias (CMB) was assessed using the full collinearity approach by examining the Variance Inflation Factor (VIF) values. VIF values below 3.3 indicate that common method bias is unlikely to threaten the validity of the results [58].

The measurement model was evaluated using convergent validity (outer loadings > 0.70), discriminant validity (HTMT < 0.90), and construct reliability assessed through composite reliability and Cronbach's alpha (≥ 0.70). The structural model was evaluated based on the coefficient of determination (R^2), while the significance of the hypothesized relationships was assessed using the bootstrapping procedure with a significance criterion of t-statistics > 1.96 and p-values < 0.05. Multicollinearity was evaluated using the Variance Inflation Factor (VIF) [52]. The predictive power of the model was assessed using the PLSpredict procedure as the conventional blindfolding procedure is no longer supported in SmartPLS 4 [59]. Predictive performance was evaluated using Q^2predict, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), obtained through a 10-fold cross-validation procedure with 10 repetitions. The prediction errors were subsequently compared with those of a linear model (LM) benchmark to assess the model's out-of-sample predictive capability.

4. RESULTS AND DISCUSSION

4.1 Common Method Bias Assessment

Because all constructs in this study were measured using a single self-report questionnaire, a common method bias (CMB) assessment was conducted prior to evaluating the measurement and structural models. Following Kock's full collinearity assessment approach, all latent variables were regressed on a common random variable [58]. Figure 3 illustrates the full collinearity assessment model, while Table 5 presents the corresponding full collinearity variance inflation factor (VIF) values.

All full collinearity VIF values ranged from 1.565 to 2.645, which are below the recommended threshold of 3.3, indicating that common method bias is unlikely to threaten the validity of the study [58]. These findings further suggest that neither lateral multicollinearity nor common method bias poses a serious concern. Therefore, the observed relationships among the latent constructs are unlikely to be substantially influenced by common method variance.

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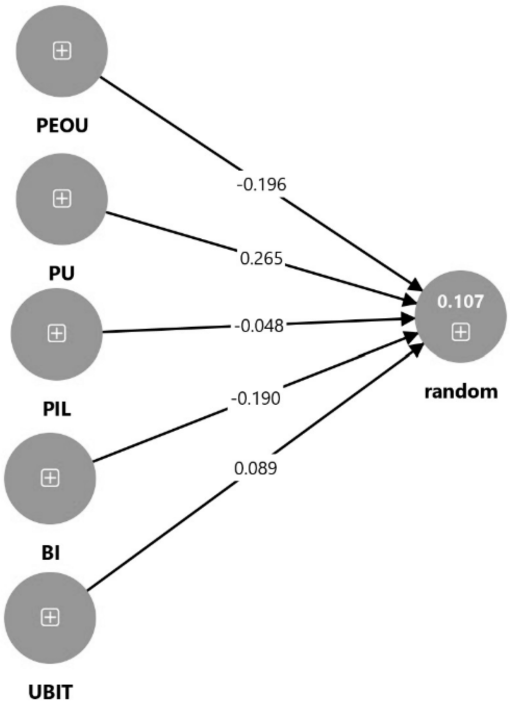

Figure 3. Full Collinearity Assessment Results for Common Method Bias

Table 5. Full Collinearity VIF Results

Construct	Full Collinearity VIF
PU	2.051
PEOU	1.735
PIL	2.645
BI	2.084
UBIT	1.565

4.2 Measurement Model (Outer Model)

The outer model represents the direct relationship between each indicator block and the latent variable. The measurement model (outer model) can be assessed using tests of convergent validity, discriminant validity and composite reliability, as explained below [52].

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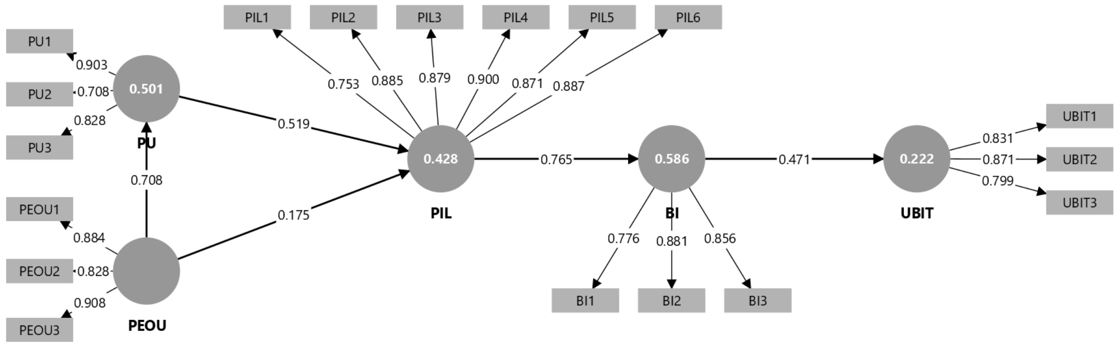

Figure 4. Results of PLS-SEM Analysis

Table 6. Reliability and Convergent Validity Results

	Cronbach's alpha	Rho_a	Composite reliability	AVE
PU	0.748	0.748	0.856	0.667
PEOU	0.845	0.856	0.906	0.764
PIL	0.931	0.936	0.946	0.747
BI	0.789	0.801	0.877	0.704
UBIT	0.789	0.840	0.873	0.696

Note: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Immersive Learning (PIL), Behavior Intention (BI), Usage Behavior Immersive Technology (UBIT); AVE> 0.5; CR > 0.7

Table 7. Outer Loading Results

Construct	Indicator Code	Measurement Item	Outer Loadings	VIF
Perceived Usefulness (PU)	PU1	The use of VR media is beneficial in the learning process	0.903	1.991
	PU2	The use of VR makes the learning process more effective	0.708	1.317
	PU3	Using VR helps me develop my creative thinking skills.	0.828	1.732
Perceived Ease of Use	PEOU1	Operating the VR system is easy for me	0.884	2.119
	PEOU2	Learning how to use the VR system was easy for me	0.828	1.813

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Construct	Indicator Code	Measurement Item	Outer Loadings	VIF
	PEOU3	I can customize my VR learning environment to my liking with minimal effort	0.908	2.478
Perceived Immersive Learning (PIL)	PIL1	I feel as if I'm in a VR environment	0.753	2.035
	PIL2	I feel completely immersed in the VR learning environment	0.885	3.454
	PIL3	When using this VR device, I feel completely immersed in the task at hand	0.879	3.354
	PIL4	I understand the VR content presented in a clear and in-depth manner.	0.900	3.876
	PIL5	The content presented using VR really caught my attention.	0.871	3.350
	PIL6	VR content helps me focus despite external distractions	0.887	3.547
Behavioral Intention	BI1	I plan to continue using this VR technology in my studies	0.776	1.501
	BI2	If I could use VR for learning, I'd want to make the most of it	0.881	1.982
	BI3	I will recommend VR to my colleagues	0.856	1.737
Usage Behavior of Immersive Technology (UBIT)	UBIT1	I plan to use VR technology more often than other learning technologies	0.831	1.853
	UBIT2	Overall, I use this VR device on a regular basis.	0.871	1.531
	UBIT3	I made use of the various Virtual Reality (VR) features available	0.799	1.696

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Construct	Indicator Code	Measurement Item	Outer Loadings	VIF
		whilst taking part in the learning activities		

Note: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Immersive Learning (PIL), Behavior Intention (BI), Usage Behavior Immersive Technology (UBIT), aitem loading >0.70.

Table 8. Discriminant Validity Assessment (Fornell–Larcker Criterion and HTMT Ratio)

Fornel-Larcker-Criterion					
Construct	BI	UBIT	PEOU	PIL	PU
BI	0.878				
UBIT	0.565	0.832			
PEOU	0.510	0.613	0.874		
PIL	0.962	0.616	0.546	0.868	
PU	0.603	0.709	0.708	0.648	0.817
HTMT Ratio					
Construct Pair	HTMT Value				
BUIT <-> BI	0.560				
PEOU <-> BI	0.484				
PEOU <-> UBIT	0.695				
PIL <-> BI	0.893				
PIL <-> UBIT	0.666				
PIL <-> PEOU	0.603				
PU <-> BI	0.621				
PU <-> BUIT	0.895				
PU <-> PEOU	0.881				
PU <-> PIL	0.752				

The diagonal elements (in bold) are the square roots of the AVE; the non-diagonal elements represent inter-construct correlations. All HTMT values are below 0.9, indicating adequate discriminant validity

Based on the results of the outer model test for each variable, namely Perceived Ease of Use, Perceived Usefulness, Perceived Immersive Learning, Behavioral Intention, and Usage Behavior of Immersive Technology, all variables showed Cronbach's alpha values > 0.7, composite reliability values > 0.7, and discriminant validity values, as measured by AVE, >

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0.5 (see Table 6). These results indicate satisfactory internal consistency among the measurement items. All construct values for Perceived Ease of Use, Perceived Usefulness, Perceived Immersive Learning (PIL), Behavioral Intention, and Usage Behavior of Immersive Technology demonstrated high reliability values, which also indicate strong internal consistency across all indicators within each construct. Therefore, the measurement scales used in this study can be considered reliable and stable for measuring the research constructs.

Based on the outer loading test results, each item showed a strong relationship with its respective construct, indicating adequate indicator reliability across all constructs in this study. Furthermore, all HTMT values were below the recommended threshold of 0.90 (see Table 8) [60]. However, the HTMT value for the relationship between Perceived Immersive Learning (PIL) and Behavioral Intention (BI) was relatively high (0.893), indicating that these constructs are conceptually closely related and should be interpreted with caution. In addition, the Fornell–Larcker assessment showed that the correlation between PIL and BI (0.962) exceeded the square root of the AVE for both constructs (0.868 for PIL and 0.878 for BI), indicating that this construct pair does not fully satisfy the Fornell–Larcker criterion and may not be empirically distinct. Nevertheless, because the HTMT value remained below the recommended threshold of 0.90, both constructs were retained in the proposed model, while the observed overlap is acknowledged as a limitation of the study.

The relatively high correlation between PIL and BI can be theoretically explained by the close conceptual relationship between perceived immersive learning and behavioral intention in the context of VR-based learning. Both constructs were measured using the same self-report questionnaire at a single point in time and referred to the same learning context. Consequently, respondents may have provided highly consistent responses across both constructs, resulting in substantial shared variance. Similar findings have been reported in technology adoption studies, where conceptually related constructs may exhibit high correlations despite representing theoretically distinct concepts [61], [62]. Taken together, these findings suggest that although the two constructs are theoretically distinguishable, their empirical separation in the present study is limited. Therefore, the relationships involving PIL and BI should be interpreted with appropriate caution. Future studies are encouraged to develop more distinctive measurement items,

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employ time-lagged data collection designs, or further examine whether these constructs can be more clearly differentiated in VR-based learning environments.

4.3 Inner Model

The inner model, also known as the structural model, is evaluated based on the R^2 value to measure the model's explanatory power, as well as the significance of the relationships between variables in the study.

Table 9. Hypothesis Testing Results

Hypothesis	Beta Coefficient	St. dev	T Stat	VIF	P Values	Result
			Direct			
H1: PEOU → PU	0.708	0.038	18.831	1.000	< 0.001	Supported
H2: PEOU → PIL	0.175	0.086	2.032	2.004	0.042	Supported
H3: PU → PIL	0.519	0.087	5.938	2.004	< 0.001	Supported
H4: PIL → BI	0.765	0.064	11.960	1.000	< 0.001	Supported
H5: BI → UBIT	0.471	0.054	8.712	1.000	< 0.001	Supported
			Indirect			
H6: PEOU → PU → PIL	0.367	0.067	5.468		< 0.001	Supported
H7: PEOU → PIL → BI	0.134	0.067	2.011		0.044	Supported
H8 : PIL → BI → UBIT	0.360	0.062	5.833		< 0.001	Supported
		R Square				
PU			0.501			
PIL			0.428			
BI			0.586			
UBIT			0.222			

Based on Table 9, the results of the structural model analysis indicate that all hypotheses in this study, namely H1 to H8, are statistically significant and empirically supported. More specifically, H1 (Perceived Ease of Use → Perceived Usefulness) has a value of (β = 0.708; p = <0.001), indicating that perceived ease of use positively influences perceived usefulness. Meanwhile, H2 (Perceived Ease of Use → Perceived Immersive Learning) has a value of (β = 0.175; p = 0.042), indicating that perceived ease of use positively influences perceived immersive learning.

For H3 (Perceived Usefulness → Perceived Immersive Learning), the result shows a value of ($\beta = 0.519$; $p = <0.001$), indicating that perceived usefulness positively affects perceived immersive learning. These findings confirm that perceived usefulness also enhances perceived immersive learning. Furthermore, H4 (Perceived Immersive Learning → Behavioral Intention) has a value of ($\beta = 0.765$; $p = <0.001$), indicating that perceived immersive learning positively influences behavioral intention, which in turn affects H5 (Behavioral Intention → Usage Behavior of Immersive Technology) with a value of ($\beta = 0.471$; $p = <0.001$), indicating that behavioral intention positively influences self-reported usage behavior. Perceived immersive learning becomes relevant because students' cognitive and affective responses toward immersive learning perceptions are assumed to act as a mediating mechanism that bridges technology acceptance factors and actual Usage Behavior of Immersive Technology.

In addition, all mediation effects were also found to be significant. H6 (Perceived Ease of Use → Perceived Usefulness → Perceived Immersive Learning) has a value of ($\beta = 0.367$; $p < 0.001$), indicating that perceived usefulness acts as a mediating variable in the relationship between perceived ease of use and perceived immersive learning. In hypothesis H7 (Perceived Ease of Use → Perceived Immersive Learning → Behavioral Intention), the result shows a value of ($\beta = 0.134$; $p = 0.044$), indicating that perceived immersive learning acts as a mediating variable in the relationship between perceived ease of use and behavioral intention. Furthermore, H8 (Perceived Immersive Learning → Behavioral Intention → Usage Behavior of Immersive Technology) has a value of ($\beta = 0.360$; $p < 0.001$), meaning that behavioral intention acts as a mediating variable in the relationship between perceived immersive learning and Usage Behavior of Immersive Technology.

The results of this study indicate that the endogenous constructs are explained by the exogenous constructs, as reflected in the R^2 values. The R^2 value for Perceived Usefulness (PU) is 0.501, indicating that 50.1% of its variance is explained by Perceived Ease of Use (PEOU). The R^2 value for Perceived Immersive Learning (PIL) is 0.428, the R^2 value for Behavioral Intention (BI) is 0.586, and the R^2 value for Usage Behavior of Immersive Technology (UBIT) is 0.222 (see Figure 4). These findings indicate that the proposed structural model has satisfactory explanatory power and successfully explains the relationships among technology acceptance, perceived immersive learning, behavioral intention, and self-reported usage behavior in the context of VR-based learning.

4.4 Predictive Power Assessment (PLSpredict)

Predictive power was evaluated using the PLSpredict procedure with 10-fold cross-validation and 10 repetitions. This procedure compares the prediction accuracy of the PLS-SEM model with a benchmark linear regression model (LM) at the indicator level to assess the model's out-of-sample predictive performance. Following the recommendations of previous research, predictive power is considered high when the majority of indicators exhibit lower prediction errors (RMSE or MAE) for the PLS-SEM model than for the benchmark LM [59].

Table 10. Construct-Level PLSpredict Results

Construct	Q^2predict	RMSE	MAE
PU	0.492	0.721	0.588
PIL	0.284	0.854	0.687
BI	0.151	0.933	0.735
UBIT	0.196	0.908	0.766

As shown in Table 10, all endogenous constructs produced positive Q^2predict values ranging from 0.151 to 0.492. These results indicate that the proposed model possesses adequate predictive relevance for all endogenous constructs. Among them, Perceived Usefulness (PU) demonstrated the highest predictive relevance, followed by Perceived Immersive Learning (PIL), Usage Behavior of Immersive Technology (UBIT), and Behavioral Intention (BI).

Table 11. Indicator-Level Prediction Errors (PLS-SEM versus Linear Model)

Construct	Indicator	Q^2 Predict	PLS-RMSE	LM-RMSE	PLS-MAE	LM-MAE	PLS < LM (RMSE)
PU	PU 1	0.441	0.705	0.714	0.544	0.549	√
	PU 2	0.265	1.238	1.247	0.922	0.927	√
	PU 3	0.273	0.948	0.952	0.695	0.705	√
PIL	PIL 1	0.062	1.247	1.259	1.001	1.036	√

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Construct	Indicator	Q^2 Predict	PLS-RMSE	LM-RMSE	PLS-MAE	LM-MAE	PLS < LM (RMSE)
	PIL 2	0.237	0.961	0.984	0.772	0.780	✓
	PIL 3	0.253	0.920	0.945	0.713	0.727	✓
	PIL 4	0.259	0.906	0.945	0.696	0.706	✓
	PIL 5	0.198	0.998	1.029	0.789	0.801	✓
	PIL 6	0.257	0.915	0.922	0.705	0.704	✓
	BI 1	0.037	1.248	1.262	1.026	1.049	✓
BI	BI 2	0.140	1.038	1.057	0.836	0.847	✓
	BI 3	0.142	1.017	1.028	0.759	0.773	✓
	UBIT 1	0.101	1.270	1.247	1.019	0.946	✗
UBIT	UBIT 2	0.200	0.943	0.784	0.775	0.606	✗
	UBIT 3	0.086	1.519	1.511	1.285	1.208	✗

Table 11 compares the prediction errors of the PLS-SEM model with those of the benchmark linear model (LM) for each endogenous indicator. Of the fifteen indicators evaluated, twelve indicators (80%) showed lower RMSE values for the PLS-SEM model than for the LM, indicating superior predictive performance. However, all three indicators of the Usage Behavior of Immersive Technology (UBIT) construct exhibited higher RMSE and MAE values than the benchmark model, suggesting that the linear model achieved slightly better prediction accuracy for this construct.

Overall, the findings indicate that the proposed model demonstrates high predictive power. The majority of endogenous indicators were predicted more accurately by the PLS-SEM model than by the benchmark linear model, supporting the model's ability to generalize to out-of-sample observations. Although the UBIT construct showed weaker predictive performance, this limitation was confined to a single endogenous construct, whereas the remaining constructs consistently demonstrated satisfactory predictive performance. Therefore, the proposed model can be considered to possess good out-of-sample predictive capability for explaining self-reported VR usage behavior in higher education.

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4.5 Discussion

The results of the empirical analysis indicate that all direct-effect hypotheses (H1–H5) are statistically significant. These findings demonstrate that the proposed model is capable of explaining the process through which students develop perceptions, intentions, and self-reported usage behavior toward immersive technology within digital learning environments. Conceptually, the findings reinforce the relevance of the Technology Acceptance Model (TAM) in explaining technology acceptance in increasingly complex digital learning contexts, particularly when extended by incorporating Perceived Immersive Learning (PIL) as an additional explanatory construct [18], [21], [45].

The findings show that Perceived Ease of Use significantly influences Perceived Usefulness (H1). This result indicates that the easier immersive technology is perceived to operate, the greater the likelihood that students will perceive the technology as useful for supporting their learning activities. Previous studies have consistently demonstrated that ease of use represents a key determinant in shaping positive evaluations of technology and enhancing perceptions of usefulness [18], [20]. Within immersive learning environments, ease of navigation, interaction with virtual interfaces, and accessibility of technological features may allow students to focus more effectively on learning tasks rather than on overcoming technical difficulties associated with system operation.

In addition, Perceived Ease of Use was found to significantly influence Perceived Immersive Learning (H2). This finding suggests that technology that is easier to operate can facilitate richer, more interactive, and more immersive learning experiences. Prior studies have similarly reported that immersive learning experiences become more effective when technological systems are intuitive and user-friendly [9], [12]. Therefore, ease of use contributes not only to utilitarian evaluations of technology but also to the quality of the learning experience perceived by students [18], [20].

Furthermore, Perceived Usefulness significantly affects Perceived Immersive Learning (H3). This result indicates that the benefits students perceive from immersive technology extend beyond functional or instrumental value and contribute to the development of deeper learning experiences. Previous research has shown that perceptions of usefulness can enhance engagement, learning effectiveness, and the overall quality of immersive technology-supported learning experiences [12], [48]. Consequently, students who perceive immersive technology as beneficial for achieving learning objectives are more likely to experience stronger immersion during learning activities.

The results also indicate that Perceived Immersive Learning significantly influences Behavioral Intention (H4). This finding suggests that students who perceive immersive learning experiences as engaging, meaningful, and cognitively enriching are more likely to develop stronger intentions to use immersive technology in educational settings. Similar findings have been reported in previous studies, which emphasize that immersive learning experiences can increase learner motivation, engagement, and willingness to adopt educational technologies [50]. Nevertheless, given the cross-sectional nature of the present study, these findings should be interpreted as reflecting behavioral intention measured at a single point in time rather than behavioral outcomes observed across multiple time periods.

Furthermore, Behavioral Intention was found to significantly influence Usage Behavior of Immersive Technology (H5). This finding supports the central assumptions of TAM and the Theory of Planned Behavior, which posit that behavioral intention represents one of the strongest predictor of self-reported technology usage behavior [11]. The findings are also consistent with previous evidence showing that students with stronger intentions to use educational technologies are more likely to report higher levels of technology utilization in learning activities [63]. However, it is important to note that the Usage Behavior construct examined in this study reflects self-reported usage behavior rather than objectively observed system usage.

In addition to the direct effects, this study identified significant indirect effects through multiple mediating mechanisms. These findings suggest that the process through which students accept and use immersive technology is not linear but involves interconnected cognitive and experiential pathways. The results show that Perceived Usefulness mediates the relationship between Perceived Ease of Use and Perceived Immersive Learning (H6). This finding indicates that ease of use contributes to immersive learning experiences not only directly but also indirectly through its influence on students' perceptions of technology usefulness. Such findings are consistent with the TAM framework, which positions Perceived Ease of Use and Perceived Usefulness as fundamental determinants of users' cognitive evaluations of technology [18]. Previous research has similarly demonstrated that ease of use contributes to the formation of positive perceptions of usefulness and technology-related experiences [20].

Furthermore, Perceived Immersive Learning was found to mediate the relationship between Perceived Ease of Use and Behavioral Intention (H7). This result suggests that the influence of ease of use on intention becomes stronger when students experience meaningful and immersive learning interactions. In this context, Perceived Immersive Learning functions as an important explanatory construct linking technological characteristics with students' intentions to use immersive technology. Previous studies have similarly indicated that immersive learning experiences contribute to higher levels of engagement, involvement, and motivation in digital learning environments [9], [12].

The results also demonstrate that Behavioral Intention mediates the relationship between Perceived Immersive Learning and Usage Behavior of Immersive Technology (H8). This finding indicates that immersive learning experiences are more likely to be translated into usage behavior when accompanied by a strong intention to use the technology. Consistent with previous studies and established technology acceptance theories, behavioral intention serves as an intermediary mechanism connecting technology-related perceptions with behavioral outcomes [18]. Within the context of this study, students who perceive stronger immersive learning experiences tend to report higher usage behavior through the development of stronger behavioral intentions.

An important finding of this study is the significant relationship between Perceived Immersive Learning and Behavioral Intention ($\beta = 0.765$, $p < 0.001$). This finding indicates that students' perceptions of immersive learning experiences significantly contribute to their intention to use VR-based learning technologies. However, this relationship should be interpreted with caution because the discriminant validity assessment showed a relatively high HTMT value between PIL and BI (HTMT = 0.893), suggesting a close conceptual relationship between the two constructs. This finding also suggests the possibility of partial construct overlap between Perceived Immersive Learning and Behavioral Intention, although the two constructs remain theoretically distinguishable within the proposed model. Accordingly, the present findings should not be interpreted as definitive evidence of the complete discriminant validity of the PIL construct but rather as preliminary evidence supporting its role within the proposed model. Therefore,

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further studies are needed to examine the distinctiveness of these constructs through additional construct-validation procedures, more diverse educational contexts, and longitudinal research designs [9], [12], [52].

The explanatory power of Behavioral Intention ($R^2 = 0.586$) indicates that the proposed model explains a substantial proportion of variance in students' intentions to use immersive technology. While this finding highlights the relevance of PIL within the extended TAM framework, alternative explanations should also be considered. The high level of explained variance may partially result from common-method bias associated with self-reported survey data, the conceptual closeness between the measured constructs, the use of similarly worded questionnaire items, and the relatively homogeneous characteristics of the respondent group, which consisted of university students from a single national context. Future studies should therefore employ more heterogeneous samples and complementary methodological approaches to verify the robustness of the model.

Furthermore, it is important to clarify that the Usage Behavior of Immersive Technology construct in this study represents self-reported usage behavior rather than objectively observed system usage. Behavioral intention reflects students' motivational readiness or willingness to use immersive technology, whereas self-reported usage behavior represents students' own assessments of how they use the technology during learning activities. Consequently, the findings should be interpreted as reflecting perceived technology utilization tendencies rather than objectively recorded behavioral data obtained from system logs or platform analytics. Accordingly, behavioral intention should not be interpreted as actual technology use, while self-reported usage behavior should also be distinguished from objectively observed usage because it relies on respondents' own perceptions and recollections of their technology use. Future studies are encouraged to combine self-reported measures with objective usage indicators to provide a more comprehensive understanding of immersive technology adoption [11].

Overall, the findings suggest that Perceived Immersive Learning (PIL) plays an important role in explaining how students' perceptions of immersive technology are translated into behavioral intention and self-reported usage behavior within digital learning environments. Within the context of this study, PIL is conceptualized as reflecting learners' overall evaluations of immersive learning experiences, including their perceptions of engagement, interest, and the depth of learning facilitated by immersive technology. By incorporating PIL as a mediating construct within the Technology Acceptance Model, this study provides preliminary evidence that immersive learning experiences may serve as an important explanatory mechanism linking technology perceptions with behavioral intention and usage behavior. However, these findings should be interpreted with caution because the study relied on cross-sectional self-reported data collected from a relatively homogeneous sample of university students in Indonesia. In addition, the use of purposive sampling may limit the representativeness of the sample and restrict the generalizability of the findings to broader student populations and educational contexts. Consequently, the proposed model is intended to explain behavioral intention and self-reported usage behavior within the evaluated educational context at the time of data collection. Further research employing longitudinal designs, objective usage-log data, and more diverse educational settings is needed to further examine the stability, generalizability, and construct validity of the proposed relationships.

5. CONCLUSION

This study extends the Technology Acceptance Model (TAM) by incorporating Perceived Immersive Learning (PIL) as a mediating construct to explain self-reported usage behavior of immersive technology in higher education. Specifically, perceived ease of use significantly influenced perceived usefulness ($\beta = 0.708$, $p < 0.001$) and PIL ($\beta = 0.175$, $p = 0.042$), while perceived usefulness significantly enhanced PIL ($\beta = 0.519$, $p < 0.001$). PIL emerged as a significant predictor of behavioral intention ($\beta = 0.765$, $p < 0.001$), and behavioral intention significantly predicted self-reported usage behavior ($\beta = 0.471$, $p < 0.001$). The proposed model explained 42.8% of the variance in PIL ($R^2 = 0.428$), 58.6% in Behavioral Intention ($R^2 = 0.586$), and 22.2% in self-reported usage behavior ($R^2 = 0.222$), indicating satisfactory explanatory power. The mediation analyses also supported the proposed indirect effects. These findings provide preliminary evidence for the role of PIL in explaining behavioral intention and self-reported usage behavior within the evaluated context of VR-based immersive learning in Indonesian higher education. Conceptually, this study extends TAM by highlighting the explanatory role of PIL beyond traditional cognitive constructs. Practically, higher education institutions should emphasize both

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system usability and meaningful immersive learning experiences. However, the findings should be interpreted with caution because the study relied on cross-sectional self-reported data and purposive sampling, which may limit causal inference, sample representativeness, and generalizability. In addition, the close conceptual relationship between PIL and Behavioral Intention warrants further construct validation. Future studies should employ longitudinal designs, incorporate objective usage-log data, further validate the PIL construct across diverse educational contexts, and examine additional determinants of immersive technology adoption, including learning engagement, flow experience, self-efficacy, and facilitating conditions.

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