Analyzing VR-SL Models in Physical Education: a study of Indonesian educational institutions based on the e-readiness model

Analizando Modelos VR-SL en Educación Física: un estudio de instituciones educativas indonesias basado en el modelo de preparación electrónica

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Abstract

Background: Virtual Reality (VR) technology is reshaping educational paradigms, particularly when integrated with Seamless Learning (SL) approaches that transcend temporal and spatial boundaries. However, VR adoption in physical education in Indonesia remains constrained by varying levels of technological readiness and conceptual understanding.
Objective: This study aims to examine the readiness to adopt VR-SL models and its influence on technology usage, intention and behavior. It further investigates the moderating role of digital maturity within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework.
Method: A cross-sectional quantitative survey was conducted with 422 respondents, comprising lecturers, elementary, middle, and high school physical education teachers, and university students across East Java. Data were analyzed using Structural Equation Modeling, integrating the Technology Readiness Index (TRI) and UTAUT constructs.
Results: Findings reveal that motivators (innovation capacity and optimism) significantly and positively affect usage intention and behavior, mediated by Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. In contrast, several inhibitors (discomfort and insecurity) showed no significant effect, suggesting that strong UTAUT factors can neutralize resistance to technology. Digital maturity significantly moderates the relationship between UTAUT constructs and usage outcomes, amplifying adoption intention and behaviour among digitally mature users.
Conclusion: Adoption readiness of VR-SL models is characterized by high enthusiasm but varied conceptual understanding and access constraints. Digital maturity emerges as a critical factor that strengthens adoption while mitigating technological barriers, emphasizing its strategic importance in educational technology implementation.

Keywords

E-Readiness; Physical Education; Seamless Learning (SL); UTAUT; Virtual Reality (VR).

Resumen

Antecedentes: La Realidad Virtual está transformando los paradigmas educativos, especialmente al integrarse con el aprendizaje continuo e integrado (*seamless learning*) que trasciende tiempo y espacio. No obstante, su adopción en educación física en Indonesia se ve limitada por niveles dispares de preparación tecnológica y comprensión conceptual.
Objetivo: Evaluar la preparación para adoptar *seamless learning* basado en RV y su efecto sobre la intención y el comportamiento de uso; además, examinar el papel moderador de la madurez digital en el marco UTAUT.
Método: Encuesta transversal cuantitativa a 422 participantes (docentes universitarios, profesorado de educación física de primaria, secundaria y bachillerato, y estudiantes) de Java Oriental. Los datos se analizaron con Modelación de Ecuaciones Estructurales, integrando el *Technology Readiness Index* y los constructos UTAUT.
Resultados: Los motivadores (innovatividad y optimismo) influyen positiva y significativamente en la intención y el comportamiento de uso, mediado por Expectativa de Desempeño, Expectativa de Esfuerzo, Influencia Social y Condiciones Facilitadoras. Los inhibidores (incomodidad e inseguridad) no mostraron efectos significativos, lo que sugiere que factores robustos de UTAUT pueden neutralizar la resistencia. La madurez digital modera de forma significativa las relaciones entre UTAUT y los resultados de uso, amplificando la adopción entre usuarios más maduros digitalmente.
Conclusión: La preparación para adoptar la RV en *seamless learning* se caracteriza por alto entusiasmo, pero comprensión desigual y restricciones de acceso. La madurez digital es un factor clave que refuerza la adopción y mitiga barreras tecnológicas, con implicaciones estratégicas para su implementación educativa.

Palabras clave

Preparación tecnológica (e-readiness); Educación Física; Aprendizaje continuo e integrado (seamless learning); UTAUT; Realidad Virtual.

Introduction

Digital technology has significantly transformed the educational landscape, particularly through the use of Virtual Reality (VR) to create immersive, interactive, and multisensory learning environments. Previous studies have shown that VR adoption can improve learning outcomes, often surpassing conventional learning methods by enhancing learner engagement and comprehension (Boffi et al., 2023). VR-based technologies, such as GeoVirtex in geography education, provide constructivist, autonomous, and contextual learning experiences (Putra & Khalidy, 2023). However, the effectiveness of VR remains inconsistent due to challenges such as immersion levels, cognitive load, and device usability without adequate pedagogical planning (Berti, 2021; Kuhail et al., 2022; Paskova, 2022).

Readiness is a critical factor for optimally and effectively adopting digital technologies such as VR, yet it remains under-addressed among teachers, students, and institutions (AlGerafi et al., 2023; Kohli et al., 2025). In Indonesia, readiness to adopt VR is still low, as indicated by the country's poor digital readiness index (Statista, 2019). Inadequate infrastructure and lack of capacity building hinder technology adoption (UNESCO, 2024). Effective technology adoption requires technical competence and self-efficacy in education (Radianti et al., 2020).

E-Readiness generally refers to technical, cognitive, pedagogical, and social preparedness to adopt and implement digital technologies (AlGerafi et al., 2023). Both internal and external e-readiness determine the institutionalization of technologies such as VR in higher education systems (Shah Alam et al., 2024).

In physical education, the integration of VR has great potential when combined with Seamless Learning (SL), a model that facilitates continuous learning beyond spatial and temporal boundaries through mobile and digital technologies. VR enables physical activity simulation in safe and realistic environments, while SL ensures learning continuity in flexible and personalized ways. Studies indicate that this combination can enhance motivation, engagement, and learning outcomes (Agustini et al., 2023; Hambrock & De Villiers, 2023). However, cognitive load, technological readiness, and lack of training remain significant barriers. Therefore, it is essential to design VR interventions that are not only technically efficient but also adaptive to learner capacities and aligned with Indonesia's physical education context.

Several previous studies have highlighted VR's effectiveness in improving learning performance in sports and physical education. For instance, VR in martial arts training increased motor learning outcomes by 15% (Pu & Yang, 2022). Similarly, VR in geography education has proven effective for visualizing complex concepts (Putra & Khalidy, 2023). Nevertheless, challenges such as cost, technological maturity, and teacher readiness persist (Li & Li, 2024). Meanwhile, Augmented Reality (AR) has shown positive effects on physical activity and student motivation in sports education, supporting the potential of reality-based technology integration in physical education.

To date, there is limited empirical evidence explicitly examining the integrative impact of VR-SL models in Indonesia's physical education context. Giakoni-Ramírez et al. (2023) found that VR use in physical activities resulted in moderate to high activity levels without significant gender differences. Predescu et al. (2023) reported that the use of VR headsets significantly improved learning outcomes and student satisfaction. However, these findings largely overlook the Indonesian context and local characteristics, such as infrastructure readiness, technological literacy, and educator training needs.

This study stems from the understanding that technology adoption in learning is not solely determined by device availability but is significantly influenced by pedagogical, social, and institutional dimensions. It is suggested that educators' curiosity about VR is more influenced by consistent pedagogical training than by prior use experience. The successful integration of VR-SL models depends heavily on the professional development of teachers and lecturers. Technologies such as Coach's Eye have proven effective in enhancing movement analysis and decision-making in physical education (Zulkifli & Danis, 2022).

On the basis of this model, this study explores the following Research Questions (RQ):

RQ1: To what extent does readiness to adopt VR-SL models technology influence technology use?

RQ2: Does digital maturity moderate the UTAUT model's influence on VR-SL technology use in physical education within Indonesian educational institutions?

Literature Review

E-Readiness In Higher Education for Virtual Reality

In the context of AR/VR, e-readiness refers to the extent to which institutions, educators, and students are prepared to adopt and implement digital technology, encompassing both feasibility and sustainability (AlGerafi et al., 2023). The fundamental framework of e-readiness provides a robust theoretical basis for understanding VR adoption at the individual level in educational settings. Mutula & van Brakel (2006) emphasized four critical dimensions: organizational readiness, ICT readiness, human resources readiness, and external readiness. At the individual level, e-readiness manifests through four key dimensions highly relevant to educational VR adoption: innovation capacity and optimism as "motivators" and discomfort and insecurity as "inhibitors" (Parasuraman, 2000; Blut & Wang, 2019; Kaushik & Agarwal, 2020). The e-readiness framework shapes technology adoption intention and usage through the integration of the Technology Readiness Index (TRI) with the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003). In line with this, Reyes-Mercado et al. (2023) argue that integrating TRI and UTAUT elucidates how individual technological readiness factors predict adoption intention in the educational context.

Unified Theory of Acceptance and Use of Technology (UTAUT)

The UTAUT model remains one of the most comprehensive and widely used theoretical frameworks for understanding individual technology adoption across various settings. UTAUT2, developed by Venkatesh et al. (2012), expands the original UTAUT to create a more inclusive model of consumer technology acceptance behavior. The four primary constructs in UTAUT include Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) (Alkhwaldi, 2024; Guo, 2022; Xue et al., 2024). Gunasinghe et al. (2020) identified five key constructs: PE, EE, FC, Habit (HB), and Hedonic Motivation (HM). However, Wang et al. (2022) and Sitar-Taut & Mican (2021) argue for further development of UTAUT to better explain technology use behavior in higher education.

Seamless Learning Models in Physical Education

Seamless refers to uninterrupted, natural, and immersive VR experiences in which users feel as though they are in real-world environments. This model is characterized by ten fundamental dimensions: formal and informal learning, personal and social aspects, temporal flexibility, ubiquitous access to learning resources, integration of physical and digital spaces, multi-device usage, transitions, knowledge synthesis, self-directed learning, and flexibility (Hiew & Chew, 2016; Looi et al., 2019; Wong & Looi, 2011; Wong et al., 2015). Seamless Learning Models serve as pedagogical frameworks developed based on learners' readiness to integrate technology into learning processes that transcend contextual limitations, such as classrooms, homes, and field settings (Almusawi et al., 2021). The seamless learning scheme includes: (1) individual inquiry using digital technology, (2) shared artifact spaces, (3) collaborative construction, and (4) reflective iteration (Looi et al., 2010). You et al. (2018)emphasized that the seamless learning concept in VR is developed through immersive and VR environments integrated with the Internet of Things (IoT). This approach incorporates formal, informal, and non-formal learning modes, both online and offline, to support learning continuity (Xin et al., 2018). The principles of seamless learning include natural transitions, continuous access, and integrated contexts.

Digital Maturity

Digital maturity refers to an organization's ability to swiftly leverage opportunities offered by new technologies. It encompasses a set of knowledge, skills, abilities, and other characteristics that enable the efficient and successful performance of tasks involving digital media (Guillén-Gámez et al., 2024). Digital maturity also reflects individual capacities and attitudes that support independent, growth-oriented, and responsible technology use, as well as the ability to navigate digital risks and challenges (Laaber et al., 2023). Moreover, digital maturity serves as a predictive model of digital transformation success or failure, focusing not only on an organization's ability to implement new technologies and software but also on human factors, culture, and processes. It represents a holistic approach to digitalization by assessing how prepared an organization is to understand and adapt consistently to evolving customer demands driven by continual change.

Hypothesis Development

Motivators (innovation capacity and optimism) are positively associated with usage intention and usage behavior.

Motivators, which function as enablers of technology adoption, positively influence intention and behavior in learning contexts (Reyes-Mercado et al., 2023). Innovation capacity and optimism contribute to positive perceptions of VR use in education, particularly in terms of perceived usefulness and ease of use (Shah Alam et al., 2024). E-readiness supports flexible and personalized learning (Goh & Abdul-Wahab, 2020; Goh & Blake, 2021), serving as a foundation for integrating VR into educational practice and ensuring consistently high levels of intention and use. E-readiness enables educators to meaningfully and dynamically integrate VR into their teaching (Kohli et al., 2025; Lee & Hwang, 2022; Wu & Lim, 2024; Albishri & Blackmore, 2025).

The proposed hypothesis is:

Ha1: Motivators (innovation capacity and optimism) are positively associated with usage intention and usage behavior.

In contrast, inhibitors (discomfort and insecurity) are negatively associated with usage intention and usage behavior.

Technology does not always yield positive outcomes and can cause technostress (Lin & Yu, 2025), affecting both students (Asad et al., 2023; Daud, 2025; Sharma & Gupta, 2023) and lecturers (Gabbiadini et al., 2023; Li & Wang, 2021). Reyes-Mercado et al. (2023) highlight that discomfort arising from high technological dependence and insecurity about data security and system reliability negatively influences technology adoption. Pressure to rapidly adapt to new platforms disrupts work-life balance, while continuous communication demands blur boundaries between work and rest. Discomfort reduces flexibility and increases pressure, whereas insecurity involves doubts about personal data safety and the system's reliability in achieving educational outcomes. Both factors reduce perceived benefits and ease of use which are critical conditions for technology adoption (Wu & Lim, 2024).

Proposed hypothesis:

Ha2: Inhibitors (discomfort and insecurity) are negatively associated with usage intention and usage behavior.

Motivators (innovation capacity and optimism) are positively associated with technological usage both directly and indirectly through Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

Individuals with high motivation and optimism tend to believe that technology supports better learning outcomes, even under challenging conditions (Shah Alam et al., 2024). High innovation capacity encourages experimentation and firsthand experience of VR benefits, enhancing users' perception of its importance. Such individuals are less likely to feel alienated by technology and find it easier to adapt to evolving features and platforms. Wu & Lim (2024) found that innovation capacity and optimist strengthen usage intentions and behavior—both directly and through Performance and Effort Expectancy.

Innovative and optimistic individuals are also more likely to be opinion leaders, open to social influence, and receptive to positive recommendations within their communities. Social influence significantly impacts technology usage intentions (Köroğlu, 2024). These individuals additionally trust the support provided by their environment, including technical and technological assistance.

Proposed hypotheses:

Ha3: Motivators (innovativion capacity and optimism) are positively associated with Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

Ha4: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions mediate the influence of Motivators (innovation capacity and optimism) on usage intention and behavior.

In contrast, inhibitors (discomfort and insecurity) are negatively associated with technological usage both directly and through Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions affect technology use across different contexts (Gunasinghe et al., 2020; Guo, 2022; Negm, 2023; Zhang et al., 2023). However, discomfort and insecurity—stemming from poor control, inadequate skills, and distrust in data security, system reliability, and technological capacity—undermine these perceptions. Discomfort increases anxiety, self-isolation, and doubts about technical support and VR's effectiveness, while insecurity breeds mistrust, social resistance, and skepticism about existing infrastructure. These inhibitors reduce PE, EE, SI, and FC, ultimately decreasing VR usage intention and behavior (Blut & Wang, 2020; Reyes-Mercado et al., 2023; Wu & Lim, 2024).

Proposed hypotheses:

Ha5: Inhibitors (discomfort and insecurity) are negatively associated with Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

Ha6: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions mediate the negative influence of Inhibitors (discomfort and insecurity) on usage intention and behavior.

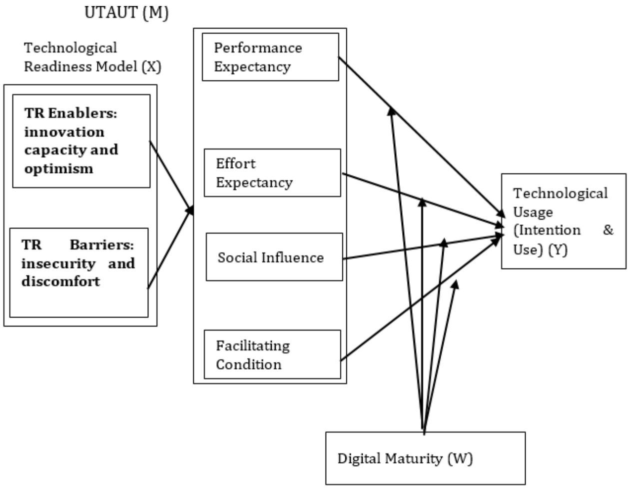
Digital Maturity moderates the influence of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions on usage intention and behavior.

It amplifies the positive effects of educational technology. In environments with technological limitations, learners with high digital maturity demonstrate an enhanced capacity to overcome barriers to technological adoption. Digital maturity minimizes errors and mitigates unaddressed technostress, both of which could negatively impact users' intentions and sustained engagement with technology. Furthermore, it enhances trust in key elements of technology acceptance while reducing a wide range of adoption barriers. Wu & Lim (2024) found that digital capability strengthens both intention and actual usage across various contexts. Users with high digital maturity are generally less sensitive to interface simplicity; they tend to learn quickly, adapt swiftly to new tools, and often resolve technical issues independently. Digital maturity increases the predictive power of the UTAUT framework regarding technological usage (intention and actual use) and modifies the strength of factors such as Performance Expectancy and Effort Expectancy in determining technology use. This is consistent with findings by Gagnero & Huang (2018), who emphasized that navigating and interacting with 3D models in VR environments—without requiring manual conversions, complex technical configurations, or rendering adjustments—demands a high level of digital maturity.

Ha7: Digital Maturity moderates the influence of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions on usage intention and behavior.

Proposed Model:

Figure 1. Proposed Model



Method

Research Paradigm and Design

This study employed a quantitative approach with a cross-sectional survey design, aligned with its research objectives (Creswell & Creswell, 2018). The cross-sectional design, which involves collecting data at a single point in time, was chosen for its efficiency, particularly within the context of physical education (Bryman, 2016).

Population and Sample

The study population included all educators and students involved in physical education subjects or programs in East Java Province, Indonesia. The inclusion criteria were direct users or key stakeholders of VR technology in formal education. The target population comprised: (1) primary school physical education teachers, (2) junior high school physical education teachers, (3) senior high school physical education teachers, (4) university physical education lecturers, and (5) students enrolled in physical education study programs. The sampling technique employed was convenience sampling, a non-probability method that selects respondents based on availability and willingness to participate (Etikan et al., 2016). Although this method has limitations regarding generalization, it was chosen due to practical considerations related to the availability of respondents across various educational institutions in East Java and the efficiency of data collection (Dörnyei, 2007).

Following Hair et al. (2019), who recommend a minimum of 5–10 respondents per estimated parameter for Structural Equation Modeling (SEM), this study included 487 respondents comprising elementary, junior high, and senior high school teachers, lecturers, and students in physical education. This sample size meets adequacy requirements for SEM analysis and provides sufficient statistical power to detect meaningful effect sizes (Cohen, 1988).

Instruments and Variable Measurements

The research instrument was a structured questionnaire adapted to assess the adoption of VR-SL in physical education, derived from the TRI-UTAUT model proposed by Parasuraman (2000) and further developed by Reyes-Mercado et al. (2023). The instrument had been previously validated, with a minimum Cronbach's alpha of 0.72, considered acceptable for internal consistency (Nunnally & Bernstein, 1994). The instrument’s average variance extracted (AVE) exceeded 0.50, and the lowest composite reliability was 0.887.

Digital Maturity was measured using an instrument adapted from Laaber et al., (2023), which had also been validated. Technological usage was measured following Aideed et al. (2025), comprising three items: (1) “If I adopt VR Seamless Learning technology, I intend to use it in physical education learning.” (2) “If I adopt VR Seamless Learning technology, I expect that I will use it in physical education activities.” (3) “I plan to routinely use VR Seamless Learning technology in physical education learning.”

Data were collected via an online survey using Google Forms, distributed to respondents across various educational institutions in East Java. Questionnaire distribution spanned four weeks, with institutional coordinators facilitating adequate respondent representation. Each participant received an informed consent form explaining the study’s purpose, data collection procedures, and confidentiality guarantees.

Common Method Bias and Ethical Considerations

To minimize common method variance (CMV), which can threaten the validity of results, both procedural and statistical remedies were applied (Podsakoff et al., 2003). Procedurally, negatively worded items were embedded in the questionnaire. Statistically, Harman's single-factor test and the common latent factor method were employed to detect and control for common method bias.

This study received ethical approval from the institutional research ethics committee with a relevant protocol number. Ethical principles adhered to in this study included: (1) obtaining informed consent from all participants, (2) ensuring confidentiality and anonymity of respondent data, (3) voluntary participation, (4) the right to withdraw from the study at any time, and (5) beneficence, ensuring that the study contributes to the development of physical education. Research data were stored on encrypted servers with restricted access, available only to the research team (Israel & Hay, 2006).

Research Data Analysis

Descriptive analysis was conducted to characterize respondents' demographic profiles and variable distributions. Descriptive statistics included the mean, standard deviation, skewness, and kurtosis to assess data normality (Field, 2018). The main analysis employed Structural Equation Modeling (SEM) using the two-step approach recommended by Anderson & Gerbing (1988). The first step involved Confirmatory Factor Analysis (CFA) to assess the measurement model, followed by structural model analysis to evaluate causal relationships among latent constructs. Model evaluation followed goodness-of-fit criteria as outlined by Hair et al. (2019) and was conducted using AMOS 28.0 with the maximum likelihood estimation method.

Results

Sample and Demographic Characteristics

Analysis was conducted on 422 respondents, comprising 43 lecturers, 66 elementary school teachers, 45 junior high school teachers, 68 senior high/vocational school teachers, and 200 students majoring in physical education. The data provided detailed information regarding gender, age, teaching experience in physical education, and the educational level being taught.

Table 1. Demographic Characteristics

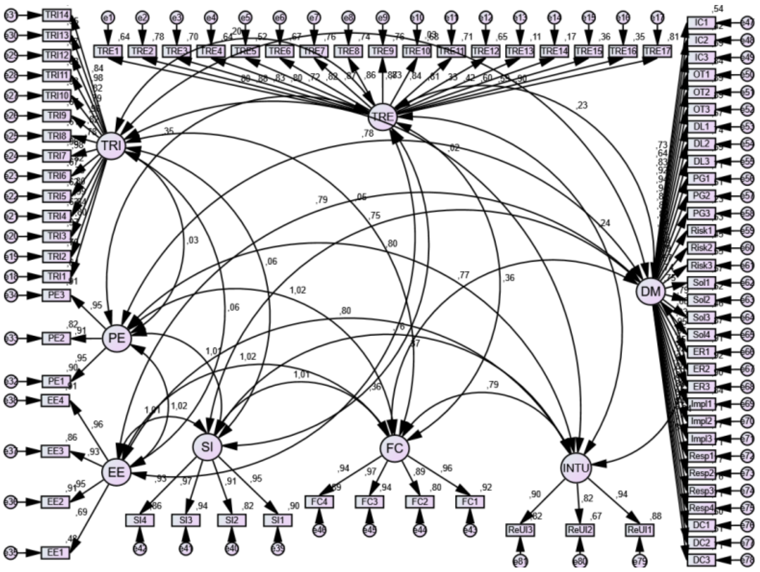
Characteristics	Category	Percentage
Gender	Male	54%
	Female	46%
Age Group	< 30 years	31%
	30–40 years	34%
	41–50 years	35%
Teaching Experience (Lecturers)	Not teaching	47%
	< 5 years	14%
	5–10 years	15%
	11–15 years	13%
	> 15 years	11%
Semester (Students)	1-11	16%
	3 s.d 4	16%
	5 s.d 6	11%
	>6	47%
	Approaching the thesis defense	10%

The results of the study indicate that the majority of respondents were male (54%), slightly higher than female respondents (46%). Most participants were aged 30–50 years. Nearly half (47%) of respondents were students who were not teaching. Among teaching respondents, 29% had less than 10 years of experience, 14% had less than 5 years of experience, 15% had 5–10 years of teaching experience, 13% had 11–15 years of experience, and 11% had more than 15 years of experience. Regarding students, nearly half (47%) were in their final semester (>6) or final/senior year. Overall, the composition of respondents was fairly balanced, with adequate representation across different categories for both teachers and students. Although the sampling was limited by region, the available data were sufficient to test the VR-SL technology adoption readiness model in the physical education context.

Model Testing

Model testing was conducted following the steps of covariance-based Structural Equation Modeling (SEM) as follows:

Figure 2. CFA (Confirmatory Factor Analysis) Model Test Results



CFA Model Testing Results

The results of the Confirmatory Factor Analysis (CFA) indicate that most indicators in the model have factors loading above 0.70, suggesting that they validly represent their respective latent constructs. However, several indicators, such as TRI16 and TRI17, exhibit factor loading below 0.50. Nevertheless, according to Hair et al., loadings above 0.30 are still considered acceptable. The computed Average Variance Extracted (AVE) for key constructs, including Performance Expectancy (PE) and Effort Expectancy (EE), exceeds 0.50, indicating satisfactory convergent validity. Overall, the CFA model demonstrates empirical robustness and conceptual adequacy in measuring the constructs under investigation.

The Structural Model

AVE, Composite Reliability, Discriminant Validity

The assessment of construct validity and reliability was performed using AVE, Composite Reliability (CR), and discriminant validity. The results of the construct testing are presented in Table 2:

Table 2. Average Variance Extracted (AVE), Composite Reliability (CR), and Discriminant Validity.

Variables	Mean	Std	AVE	CR	Discriminant Validity							
					1	2	3	4	5	6	7	8
TREnabler	3.38	0.82	0.592	0.951	0.770							
TRInhibitter	2.79	0.84	0.741	0.980	0,201	0.861						
Performance Expectancy	3.29	0.98	0.879	0.906	0,13	0,00	0.938					
Effort Expectancy	3.27	0.80	0.791	0.903	0,13	0,00	0,10	0.889				
Social Influence	3.22	0.95	0.880	0.934	0,14	0,00	0,14	0,27	0.938			
Facilitating Conditions	3.28	0.99	0.889	0.937	0,13	0,00	0,06	0,18	0,05	0.943		
Digital Maturity	3.43	0.79	0.667	0.976	0,05	0,00	0,61	0,63	0,56	0,60	0.817	
intention and usage	3.51	0.90	0.789	0.859	0,06	0,00	0,64	0,64	0,58	0,62	0,39	0.888

According to Table 2, the descriptive statistics indicate that respondents exhibit moderately positive perceptions across all constructs. Technology Readiness Enablers show a moderate mean value (3.38), whereas Inhibitors report a lower mean score (2.79), reflecting perceived barriers that are present but not dominant. The core UTAUT constructs-(Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)-all fall within the moderate range (3.22–3.29), with standard deviations ranging from 0.80–0.99. This suggests some variability in perceptions, though not to an extreme extent. Digital Maturity demonstrates a slightly higher and more consistent mean values (3.43). Behavioral Intention records the highest mean score (3.51), indicating a relatively strong willingness among respondents to use the technology.

Consistent with the AVE and CR results, all constructs satisfy the criteria for adequate convergent validity and internal reliability. AVE values range from 0.592 to 0.889, while Composite Reliability (CR) values range from 0.859 to 0.980, indicating strong internal consistency. The square roots of the AVE values (presented on the diagonal in bold) exceed the inter-construct correlations, thereby confirming discriminant validity. Moreover, the correlations among constructs do not suggest any multicollinearity issues. Overall, the measurement model is considered both valid and reliable, demonstrating that each construct is empirically distinct and appropriately measured for inclusion in the structural model.

Normality, Linearity, Sampling Adequacy, and Univariate Outlier Assessment

The results of the normality assessment, based on a scatter plot analysis, indicate that the data are approximately normally distributed, as the observed values align closely with the line of equality. This finding is further supported by univariate normality tests, with skewness values below 2 and kurtosis values below 3, which fall within acceptable thresholds. The assumption of linear relationships among variables is also satisfied. The sample size of 383 respondents is adequate for SEM analysis. Univariate outliers was examined using Z-scores, and all valules were within the acceptable range of ±3.29, indicating the absence of extreme observations. Accordingly, Structural Equation Modeling (SEM) was performed using the Maximum Likelihood (ML) estimation method.

Goodness-of-Fit Test Results, Model Evaluation and Model Modification

Table 3. GOF Model test results

Parameters	Recommended Threshold	Stage 1	Respecficication	Conclusion
	Absolute Fit Measures			
p-value (Sig.)	>0.05	0.000	0.000	Moderate Fit
CMIN/df	≤ 2	7.191	2.908	Fit
GFI (Goodness-of-Fit Index)	>0.90	0.651	0.829	Moderate Fit
RMSEA (Root Mean Square Error of Approximation)	≥ 0.08	0.082	0.071	Fit
	Incremental Fit measures			
AGFI (Adjusted Goodness-of-Fit Index)	>0.95	0.690	0.935	Moderate Fit
CFI (Comparative Fit Index)	≥ 0.95	0.781	0.951	Fit
IFI (Incremental Fit Index)	≥ 0.90	0.711	0.908	Fit
RFI (Relative Fit Index)	≥ 0.90	0.839	0.900	Fit
	Parsimonious fit measure			
PNFI (Parsimonious Normed Fit Index)	≥ 0.60	0.619	0.725	Fit
PGFI (Parsimonious Goodness-of-Fit Index)	≥ 0.90	0.485	0.682	Moderate Fit

Source: Data processing (2025)

The analysis results indicate that the initial model did not satisfy several goodness-of-fit criteria, particularly with respect to absolute and incremental fit indices. Based on theoretical considerations and modification indices, model refinements were implemented in accordance with the UTAUT framework and the digital maturity model. This respecification process led to a substantial improvement in overall model fit. The CMIN/df value decreased to 2.908, indicating and acceptable level of model fit. The RMSEA value improved to 0.071, while incremental fit indices--including CFI, IFI, and RFI--met the recommended fit thresholds. Overall, the improved results suggest that the revised model is well aligned with the empirical data.

Hypothesis-Testing Summary Based On Causal Relationships

Table 4. Results of Direct Relationships Between Variables

	path		estimate	C.R.	p-value	Decision
Performance Expectancy	<--	TR Enablers	0.219	4.39	0.00	significant
Effort Expectancy	<--	TR Enablers	0.292	5.97	0.00	significant
Social Influence	<--	TR Enablers	0.258	5.22	0.00	significant
Facilitating Conditions	<--	TR Enablers	0.249	5.023	0.00	significant
Usage Intention and Behavior	<--	TR Enablers	0.053	-0.923	0.356	Not significant
Performance Expectancy	<--	TR Inhibitors	-0.014	-0.28	0.781	Not significant
Effort Expectancy	<--	TR Inhibitors	-0.047	-0.881	0.521	Not significant
Social Influence	<--	TR Inhibitors	-0.042	-0.79	0.431	Not significant
Facilitating Conditions	<--	TR Inhibitors	-0.038	-0.751	0.453	Not significant

Usage Intention and Behavior	<--	TR Inhibitors	-0.044	-0.224	0.662	Not significant
Usage Intention and Behavior	<--	Performance Expectancy	0.424	8.87	0.00	significant
Usage Intention and Behavior	<--	Effort Expectancy	0.292	8.57	0.00	significant
Usage Intention and Behavior	<--	Social Influence	0.381	7.72	0.00	significant
Usage Intention and Behavior	<--	Facilitating Conditions	0.383	7.79	0.00	significant

Note: Source: Authors' data processing (2025). Significance level at $p < 0.05$.

The results of the data analysis indicate that eight hypotheses were supported, while six were rejected, as presented in Table 4. Motivators function as 'initial triggers' that strengthen users' perceptions--namely Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC). However, usage behaviour emerges only after these perceptions are established. In contrast, inhibitors did not significantly impede this process. The UTAUT framework thus remains the primary mechanism linking psychological readiness to technology use behaviour. To assess the robustness and consistency of the proposed model, multi-group analysis and robustness checks were conducted using 5,000 bootstrap resamples.

Mediation Test Result

Table 5. Mediation Test Results

Indirect Path					Estimate	p-value	Decision
Usage Intention and Behavior	<--	Performance Expectancy	<--	TR Enablers	0.102	0.00	significant
Usage Intention and Behavior	<--	Performance Expectancy	<--	TR Inhibitors	-0.063	0.72	Not significant
Usage Intention and Behavior	<--	Effort Expectancy	<--	TR Enablers	0.138	0.00	significant
Usage Intention and Behavior	<--	Effort Expectancy	<--	TR Inhibitors	0.020	0.378	Not significant
Usage Intention and Behavior	<--	Social Influence	<--	TR Enablers	0.108	0.00	significant
Usage Intention and Behavior	<--	Social Influence	<--	TR Inhibitors	0.015	0.656	Not significant
Usage Intention and Behavior		Facilitating Conditions		TR Enablers	0.105	0.00	significant
Usage Intention and Behavior		Facilitating Conditions		TR Inhibitors	0.014	0.656	Not significant

Source: Author's data processing (2025).

The results indicate that the direct effect of TR Enablers on usage intention and behavior was not significant; however, the indirect effects through the mediating variables—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)—were all statistically significant. This finding suggests that the influence of TR Enablers on usage intention and behavior is fully mediated by the four UTAUT constructs. In contrast, neither the direct nor indirect effects of TR Inhibitors on usage intention and behavior were significant. This indicates that TR Inhibitors do not exert a substantial influence on technology adoption, either directly or indirectly through the UTAUT mediators.

Moderation Analysis

Overall, the moderation analysis demonstrates that Digital Maturity significantly moderates the relationships between UTAUT constructs and usage intention and behavior:

Table 6. Moderation Test Results

Interaction between independent variables and Digital Maturity			estimate	C.R.	P-value	Decision
Usage intention and behavior	<--	PE x Digital Maturity	0.186	4.72	0.00	significant
Usage intention and behavior	<--	EE x Digital Maturity	0.199	4.153	0.00	significant
Usage intention and behavior	<--	SI x Digital Maturity	0.170	4.092	0.00	significant
Usage intention and behavior	<--	FC x Digital Maturity	0.174	4.430	0.00	significant

Source: Author's Data Processing (2025)

The moderation test results indicate that digital maturity functions as a positive and significant moderator, strengthening the effects of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) on behavioral intention and usage. The regression slopes vary across levels of digital maturity, with individuals possessing higher digital maturity exhibiting stronger effects of performance expectancy on usage intention. Specifically, individuals with high digital maturity are more responsive to perceptions of ease of use, whereas this influence is relatively weaker among those with lower digital maturity. Digitally mature individuals also tend to be more responsive to social and environmental support when forming their intention to adopt technology. Furthermore, users with higher digital maturity demonstrate greater increases in usage intention when they perceive sufficient facilities and resource support.

The strongest moderating effects were observed on the paths between Effort Expectancy and Facilitating Conditions, suggesting that more digitally mature users are better able to leverage perceptions of ease of use and available support in shaping their intention to use the system. Digital maturity can therefore be considered a key factor in strategies aimed at enhancing digital technology adoption, particularly in contexts with varying levels of technological readiness.

At low levels of digital maturity, increases in perceived benefits may paradoxically reduce intention to use. At moderate levels of digital maturity, this relationship becomes non-significant. However, at high levels of digital maturity, the relationship becomes positive and significant. These findings imply that the benefits of technology can only be effectively translated into actual use when both organizations and individuals possess sufficient digital maturity.

a. Digital maturity (DM) functions not only as a contextual variable but also as a conditional enhancer that significantly alters the direction and strength of the relationship between Performance Expectancy (PE) and Behavioral Intention and Usage (BIU). The Johnson–Neyman test identified a critical threshold: at low to medium levels of DM (16–50%), the effect of PE on BIU is weak or even negative. Users with limited digital maturity are unable to translate performance expectations into actual intentions or usage, regardless of the benefits they perceive. Conversely, at high levels of DM (>84%), the PE × DM interaction exhibits a significant positive change. The relationship between PE and BIU becomes positive and increasingly steep, indicating that as digital capacity increases, users are able to leverage the functional value of technology, directly converting performance expectations into adoption and usage behavior. In this range, the regression slope demonstrates a clear alignment between digital readiness and the strengthening effect of PE on BIU. These findings suggest that PE is not a universal predictor for all user groups; its effect is conditional, depending on the individual's level of digital maturity. DM thus acts as a catalyst, enabling perceived benefits to be transformed into actual behavior.

b. Conditional effect analysis indicates that when digital maturity (DM) is low ($DM = 2.56$), the effect of Effort Expectancy (EE) on Behavioral Intention and Usage (BIU) is significantly negative ($\beta = -0.2602$; $p < 0.001$). This suggests that for individuals with low digital maturity, higher perceived ease of use is associated with lower intention to adopt the technology. At a moderate level of DM ($DM = 3.47$), the effect of EE weakens and becomes insignificant ($\beta = -0.0783$; $p = 0.067$). When DM reaches a high level ($DM = 4.34$), the effect of EE shifts to positive, although it remains statistically insignificant ($\beta = 0.0956$; $p = 0.098$). This pattern demonstrates a gradual transition from a negative to a positive effect as digital maturity increases. According to the Johnson–Neyman test, the effect of EE on BIU is significantly negative at DM values below approximately 3.0. Within the range of $DM \approx 3.0–4.1$, the effect of EE is no longer significant. For DM values above approximately 4.1, the effect of EE becomes positive, though the observed point ($DM = 4.34$) has not yet reached statistical significance. These findings confirm that the influence of Effort Expectancy on technology adoption intention is conditional, depending on the individual's level of digital maturity.

c. The conditional effect analysis revealed changes in both the direction and significance of the influence of Social Influence (SI) across the range of Digital Maturity (DM) values. At low DM levels (16th percentile), SI had a significant negative effect on Behavioral Intention to Use (BIU) ($\beta = -0.2021$; $p < 0.001$). This indicates that for individuals with minimal digital capability, social pressure may generate resistance or additional burden, thereby weakening the intention to use technology. At medium DM levels, the effect of SI became non-significant ($\beta = -0.0484$; $p =$

0.1624), suggesting that social influence is not strong enough to either encourage or hinder usage intention. Conversely, at high DM levels (84th percentile), the effect of SI turned significantly positive ($\beta = 0.0986$; $p = 0.0454$), indicating that individuals with high digital readiness are more responsive to social influence in enhancing their intention to use technology. This pattern is further supported by the Johnson–Neyman technique, which identified the DM range boundaries where the effect of SI on BIU shifts from significantly negative to non-significant and then to significantly positive. Therefore, DM functions as a moderator that substantively alters both the strength and direction of the SI–BIU relationship. Digital readiness is a key factor determining the extent to which individuals internalize social influence in forming technology usage intention. When digital maturity is low, social pressure can have a counterproductive effect; however, at higher levels of digital maturity, social influence effectively serves as a driver of technology adoption and usage.

d. The conditional effect analysis also revealed a qualitative (crossover) interaction between Facilitating Conditions (FC) and BIU, contingent on DM levels. At low DM (2.56), the relationship between FC and BIU was strongly negative ($\beta = -0.2154$; $p < 0.001$). At medium DM (3.47), the relationship weakened considerably and became statistically non-significant ($\beta = -0.0571$; $p = 0.0884$). At high DM (4.34), the relationship reversed direction and became significantly positive ($\beta = 0.0943$; $p = 0.043$). DM thus functions as a strong reversing factor: at high DM levels, the potential negative impact of FC is fully offset and transformed into a positive contribution to BIU. Based on the conditional effect outputs, the Johnson–Neyman test conceptually identifies two transition points: Negative Significance Transition Point: A DM value below the median (between 2.56 and 3.47) where the FC effect ceases to be significantly negative. Positive Significance Transition Point: A DM value above the median (between 3.47 and 4.34) where the FC effect becomes significantly positive. The Johnson–Neyman test further determines the DM value range between these transition points (approximately 3.0–4.0) where the relationship between FC and BIU is statistically indistinguishable from zero (non-significant). This analysis provides precise thresholds for DM levels, indicating when FC can exert a statistically significant influence on BIU, either negatively or positively.

Discussion

The results of the study indicate that readiness to adopt VR varies widely among respondents and develops progressively. Motivators, including innovation capacity and optimism, are positively associated with usage intention and usage behavior. Respondents expressed a high level of enthusiasm and optimism regarding the pedagogical benefits of VR in physical education. However, significant challenges remain in understanding the concept of VR seamless learning in alignment with the context of physical education. Readiness also requires a solid understanding of the conceptual framework of physical education and the compatibility between VR seamless learning technology and the curriculum.

The findings show that readiness significantly influences the intention to use VR Seamless Learning Models in Physical Education. Both students and lecturers with higher readiness demonstrate a stronger intention to adopt VR technology. Readiness considers both feasibility and sustainability (AlGerafi et al., 2023). Furthermore, the study demonstrates that integrating the Technology Readiness Index (TRI) with the Unified Theory of Acceptance and Use of Technology (UTAUT) provides a robust explanation of adoption intention in physical education, improving predictions of both the intensity and actual use of VR seamless learning technology (Reyes-Mercado et al., 2023).

Motivators were found to have a direct and indirect positive influence on usage intention and behavior through Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Consistent with Reyes-Mercado et al. (2023) and Goh & Blake (2021), motivator factors form a critical foundation for integrating VR into physical education learning practices. However, a positive disposition toward technology does not automatically lead to adoption. Perceptual mechanisms, as explained by UTAUT, underlie the translation of readiness into behavioral intention. The integration of psychological readiness frameworks with UTAUT demonstrates that readiness is a latent predisposition: it shapes how individuals evaluate the benefits and ease of technology rather than immediately driving usage behavior.

Contrary to prior studies reporting negative effects of inhibitors (e.g., discomfort, insecurity) on usage intention and behavior (Lin & Yu, 2025; Asad et al., 2023; Daud, 2025; Sharma & Gupta, 2023), this study found no such negative effect. Adequate levels of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions neutralized the potential negative impact of inhibitors. Inhibitors such as discomfort and insecurity did not significantly influence PE, EE, SI, FC, or usage intention (Ha2 not supported). While these findings diverge from classic TRI predictions, they can be explained by the strong structural influence of UTAUT: when perceptions of benefits, ease of use, social support, and facilities are moderate to high, psychological barriers lose their effect. This suggests that positive perceptions can counteract initial anxiety or doubts about technology. In the Indonesian physical education context, prior positive experiences with digital media may have increased users' resilience to discomfort associated with new technology.

Another key finding is that high digital maturity significantly strengthens both usage intention and behavior. This aligns with Wu & Lim (2024), who emphasized the critical role of digital maturity in technology adoption. Gagnero & Huang (2018) also highlighted that digital maturity enables users to overcome technical adjustments and adapt to technological advancements. Integrating TRI and UTAUT requires consideration of digital maturity, which acts as a moderating variable in the relationship between UTAUT constructs and both intention to use and actual use of VR seamless learning models.

Digital maturity, as described by Guillén-Gámez et al. (2024) and Laaber et al. (2023), evolves over time. Therefore, the interaction between UTAUT constructs and digital maturity provides a conceptual framework for more accurately predicting intention and usage behavior in VR seamless learning implementation. This study demonstrates that VR technology, combined with seamless learning, supports continuous learning in physical education beyond spatial and temporal constraints. Moreover, digital maturity effectively mitigates the negative effects of inhibitors, illustrating that technological barriers can be minimized when users possess sufficient digital capacity. Benefits of technology are realized in behavior only when users have adequate digital maturity. At low levels of digital maturity, perceived benefits may produce negative or insignificant effects, as indicated by Johnson–Neyman results. At high digital maturity, the relationship becomes positive and strong, confirming that digital maturity functions as a conditional amplifier that determines whether technology perceptions translate into actual usage.

This study extends the TRI–UTAUT framework by showing that the relationship between technology perception and intention is conditional, depending on users' digital readiness. Theoretically, this addresses a gap in the literature on VR seamless learning and educational technology by demonstrating that digital maturity is not merely a user trait but a contextual condition for activating UTAUT effects. Practically, this implies that technology adoption strategies should go beyond feature training to include staged development of digital capabilities, including digital literacy, productive digital habits, and supportive environments for technology exploration.

Finally, the study addresses an empirical gap by contextualizing VR adoption in Indonesian physical education, considering local factors such as infrastructure readiness, digital literacy, and the need for professional educator training—factors previously unexplored in this context. The findings provide practical guidance for higher education institutions on critical pre-adoption considerations, including the design of a staged readiness framework that accounts for feasibility and sustainability. This research highlights the importance of conceptual alignment and institutional support and provides holistic, actionable insights to enhance the adoption of VR seamless learning in physical education in Indonesia, considering pedagogical, social, and institutional dimensions.

Conclusions

Readiness to adopt the VR–SL technology model in physical education is characterized by participatory and enthusiastic attitudes; however, it remains limited in terms of conceptual understanding, infrastructure, and technical skills. Adequate training support, provision of devices, and enhancement of digital literacy are required to achieve optimal and sustainable adoption. Respondents demonstrate high enthusiasm but limited comprehension of the VR–SL concept, indicating that technology adoption depends not only on technical readiness but also on pedagogical alignment with the physical education context.

In this regard, Technology Readiness Enabler (TR Enablers) plays a critical role as a driver of technology adoption, whereas Technology Readiness Inhibitor (TR Inhibitors) does not significantly hinder adoption. Inhibiting factors are largely neutralized by constructs within the Unified Theory of Acceptance and Use of Technology (UTAUT), which exert strong influence on usage intention. The integration of the TRI and UTAUT models, further enriched by the inclusion of Digital Maturity as a moderating variable, enhances the understanding of both intention and usage behavior of VR in physical education.

Theoretical and Practical Implications

This study provides several important theoretical and practical contributions. First, it addresses an empirical gap in research on VR adoption in physical education. Second, it proposes an integrative TRI–UTAUT framework, strengthened by the inclusion of Digital Maturity. Third, it offers policy recommendations and training design guidance based on a staged readiness approach that considers both feasibility and sustainability. Finally, the study emphasizes a holistic, contextual, and strategic approach to technology adoption that aligns with the characteristics and challenges of the Indonesian educational environment.

The findings underscore the importance of local context, particularly infrastructure limitations, variations in digital literacy, and the need for professional training—factors that have been largely overlooked in previous studies. These results reinforce the need for interventions aimed at improving digital literacy and capacity as essential prerequisites for translating the performance value of technology into adoption and sustainable use.

Limitations

Future research should adopt more in-depth and diverse approaches to strengthen the current findings. Longitudinal designs are particularly important for understanding the dynamics of VR technology adoption in physical education over time. Such designs can capture transitional processes and challenges that cross-sectional studies may overlook, monitoring changes in users' perceptions and behaviors.

Expanding the research scope to include multiple regions in Indonesia, with diverse geographical, cultural, and infrastructural contexts, would improve the generalization of the findings. Multi-regional studies can provide a more representative picture of readiness and barriers to VR adoption nationwide. Additionally, experimental approaches implementing VR directly in physical education settings can offer stronger empirical evidence regarding the effectiveness of the seamless learning model, enabling direct assessment of technology's impact on learning outcomes and student engagement.

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