

The acceptance model for camera simulators as a learning media for Indonesian vocational student

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ABSTRACT

This study investigates the acceptance of camera simulator technology as a learning media by Indonesian vocational high school (VHS) students and examines the relationships among influencing factors. It proposes an acceptance model integrating the technology acceptance model (TAM) 3 and the unified theory of acceptance and use of technology (UTAUT). Ten factors impacting technology acceptance were identified, resulting in the formulation of 15 hypotheses regarding inter-construct relationships. In this empirical study, a quantitative approach was employed, distributing questionnaires to 200 students at Public Vocational High School 10 in Bandung, specializing in broadcasting and filmmaking programs. After analyzing 145 valid responses, the study progressed in two stages: the measurement model and the structural model. The evaluation of the measurement model confirmed the validity of all indicators and constructs, ensuring compliance with the established standards. In the structural model evaluation, one construct (computer anxiety) and four inter-construct relationships were excluded. This research enhances our understanding of factors influencing camera simulator technology acceptance among VHS students in Indonesia, shedding light on the complexities of their decision-making process in adopting this educational tool.

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1. INTRODUCTION

During the fourth industrial revolution (IR4.0), various technology-based innovations emerged, disrupting numerous aspects of human life, particularly in manufacturing and industry [1], [2]. The demand for worker competencies continues to evolve in response to the challenges and competition in the industrial world [3], [4]. Workers must possess high-level technical skills, advanced cognitive abilities, and effective interpersonal skills to compete successfully in the IR4.0 era [5]. This situation poses a challenge for the education sector, particularly higher education institutions and vocational schools, in providing graduates who meet the criteria demanded by the industry.

In Indonesia, educational institutions providing vocational education operate at both the high school and college levels. Specifically, at the high school level, these institutions are known as vocational high schools (VHS). In the last five years, the annual enrollment of students in VHS has reached 5 million

annually, distributed across approximately 14,000 vocational schools [6]. However, the issue of low-quality vocational education persists in Indonesia. Based on statistics provided by the Central Statistics Agency, the open unemployment rate among VHS graduates remained high, consistently ranking at the top from 2020 to 2022, reaching 13.55% in 2020 and 9.42% in 2022 [7]. The challenges facing vocational education are multifaceted, including concerns regarding the accessibility of facilities and infrastructure [8]. Among the expertise programs offered within VHS are broadcasting and filmmaking, where cameras serve as essential learning tools. In this context, the shortage of physical cameras impedes students' ability to engage in independent and unrestricted practice. Addressing this challenge, an innovative information technology-based product, the camera simulator application, has emerged, with its acceptance playing a pivotal role in predicting its success as a supportive learning tool [9]–[11].

Within the context of technology acceptance models in education, as elucidated by multiple systematic reviews conducted within the educational domain, two models emerge as the most frequently utilized: the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) [9], [12]–[14]. Both models possess their respective merits and limitations, necessitating careful consideration in their application. Integrating both TAM models (extended and its derivatives) with the UTAUT model is a response aimed at addressing the limitations of both models [15]. The research objectives of this study are as: i) to identify various factors influencing the acceptance of the camera simulator by vocational students based on TAM 3 and UTAUT model; and ii) to build and analyze an acceptance model based on the relationships between these influencing factors. To achieve the research objectives, this study employs empirical research with a quantitative research method and analyzes the collected data using multivariate analysis methods. This research represents one of the first studies to integrate the TAM and UTAUT models to assess the acceptance of vocational high education students in using simulator technology as learning media in Indonesia.

2. PROPOSED MODEL

2.1. References model

An effective solution to afford students cost-effective and versatile learning opportunities is the utilization of digital camera simulators. A camera simulator is an interactive virtual camera that replicates the functions and components of actual complex cameras [16]. By utilizing a camera simulator, users are practically given the chance to experiment with various settings anytime and anywhere, thereby enhancing their ability to predict settings when conducting real shoots [17]. This study used the CameraSim Pro version that provides a 3D game application accessible offline for simulating photo capture with various types of lenses, modes, and settings similar to an actual camera.

Nadal *et al.* [18] in their publication discussing the definitions and measurements of technology acceptability, acceptance, and adoption, summarized that researchers often interchangeably use these three terms with varying meanings. In this study, the term “technology acceptance” is defined as the user's willingness to voluntarily or intentionally embrace and utilize technology to support task completion [18]–[20]. Numerous literature reviews have covered various models that describe how users accept or adopt new technology and the factors influencing technology acceptance. These models comprise the Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Theory of Interpersonal Behavior (TIB), Technology Acceptance Model (TAM) and its extensions, Diffusion of Innovations Theory (DOI), and the Unified Theory of Acceptance and Use of Technology (UTAUT) [11], [21]. Among these models, two have gained widespread usage and validation in assessing user behavior toward technology adoption in the education context: TAM and UTAUT [9], [12]–[14], [21].

Technology acceptance models, originally developed by Davis, has been proven effective in predicting user acceptance of information system-based technology. TAM utilizes two main constructs, perceived ease of use (PEOU) and perceived usefulness (PU), to predict user acceptance of new technology. Over the years, TAM has been expanded to include user resources, later termed external control factors. Venkatesh *et al.* [22] extended TAM's focus to factors that support PU, behavioral intention (BI), and moderator variables or factors (experience and voluntariness), resulting in TAM 2. On the other hand, the development of TAM with a focus on factors that support the PEOU factor, proposed by Venkatesh and Bala [23], is known as TAM 3. In another publication, Venkatesh *et al.* [24] identified and summarized key factors from various prior models to measure BI and actual technology usage, consolidating them into four factors: performance expectancy, effort expectancy, social influence, and facilitating conditions (FC). This model is known as UTAUT. In their publication, Venkatesh claimed that UTAUT can enhance prediction efficiency by up to 70% in technology acceptance.

Within the context of vocational education, TAM has been extensively used to evaluate the acceptance among teachers or students towards using learning technologies. Antonietti *et al.* [25] conducted an analysis of teachers' intentions to use digital tools by applying TAM. The results of the data analysis showed that teachers' belief in their digital competence significantly affects PU, PEOU, and BI. Research by Zarafshani *et al.* [26] examined how external factors related to TAM (such as facilitating conditions, available resources, job relevance, self-efficacy, subjective norms, age, and computer anxiety) influence PU, PEOU, BI, and actual usage. Their study, which involved secondary-level vocational agriculture subjects in Iran, revealed that the proposed modifications to TAM's external factors had significant effects, except for the influence of SE on BI, age on PU, and available resources on PU. Yanto *et al.* [27] conducted a study on the use of TAM to evaluate the acceptance of virtual laboratories in enhancing practical power electronics learning at Universitas Negeri Padang. The analysis revealed that all factors within TAM had a significant and positive influence, from independent to dependent factors. Chatterjee *et al.* [28] carried out quantitative research to investigate the moderating roles of peer influence and government support in the successful implementation of technology in vocational education. The study emphasized the moderating variables that could improve the intention of users to adopt technology in vocational education settings.

Zhang *et al.* [29] conducted a study on the application of UTAUT in vocational education, identifying the factors that influence higher vocational students' use of e-learning. The study utilized SEM methodology and found that PU and FC have a significant impact on the acceptance of e-learning systems. In a separate study, Li *et al.* [30] explored the acceptance of mobile learning in China's vocational higher education through UTAUT. The SEM analysis of the data showed that SE significantly affects effort expectancies, performance expectancies, social influence, and FC. Additionally, research by Li *et al.* [31] on the acceptance behavior towards blended learning among students in secondary vocational schools used a modified UTAUT model and revealed that SE and perceived joyfulness have a stronger influence than other factors.

The literature review for the grounded model reveals that two prominent models for measuring user behavior in adopting information technology within the education sector are TAM and UTAUT. However, the TAM model is critiqued for its simplicity and limited scope, as it does not adequately account for factors that influence user intentions and behaviors, such as control behaviors by the user and environmental or social influences [15], [32], [33]. Venkatesh and Bala [23] argued for the inclusion of external factors pertinent to the specific technology, its context, and the characteristics of the user. TAM 3 is an advancement over the original TAM, designed to overcome its flaws by incorporating various external factors affecting PU and EPU. Although TAM 3 seeks to address some of the original model's deficiencies, it introduces external factors that might not be relevant in an educational setting. The UTAUT model, too, has been criticized for its explanatory power regarding BI under certain conditions and its effectiveness in acceptance measurement [34]. Buabeng-Andoh and Baah [15] have discussed the inconsistent results of UTAUT applications in education and suggested combining UTAUT with TAM 3 to evaluate teachers' willingness to utilize a learning management system. This study introduces a combined model of UTAUT and TAM 3 to assess vocational education students' acceptance of using a camera simulator, making specific adjustments to both models' constructs to ensure relevance to the research context. This includes modifying several external constructs from both TAM 3 and UTAUT to better suit the research subjects.

2.2. Hypotheses

Each construct within the UTAUT framework has its roots in other models. For instance, the "performance expectancy" construct draws from the "PU" construct in TAM or the "relative advantage" construct in DOI. Similarly, the "effort expectancy" construct is rooted in the "PEOU" construct of TAM, while the "social influence" construct originates from the "SN" of TRA, TAM 2, and TAM 3 [21]. Additionally, the "FC" construct can be traced back to the "perceived behavioral control" construct in TPB and TAM [21], [24].

In this research, the acceptance model for the camera simulator among Indonesian VHS students involved adaptations of constructs from both TAM 3 and UTAUT. The proposed model in this study comprises six independent constructs: FC, SN, output quality (OUT), SE, ANX, and perceived enjoyment (PEJ). Additionally, there are four dependent constructs: PU, PEOU, attitude towards using (ATU), and BI. From the selected constructs, hypotheses were formulated by integrating relationships among these constructs. Table 1 present the hypothesis from the relation between constructs.

2.3. Proposed model

The model proposed in this study is grounded on chosen factors, with the interrelations among these factors depicted in Figure 1. In the proposed model of acceptance, ten factors are integrated, combining TAM 3 and UTAUT. Six constructs within the model are derived from the constructs constituting UTAUT and TAM 3, serving as independent variables. Meanwhile, four dependent variables are PU, PEOU, ATU, and BI. BI is the primary dependent construct of the proposed model.

Table 1. Hypotheses

Constructs	Hypotheses	Statement	References
ANX	H1	ANX exerts a significant and negative influence on PEOU.	Regarding the adoption of e-learning in Indonesia amid the COVID-19 pandemic, ANX significantly influenced the PEOU [35].
SE	H2	SE significantly and positively influences PEOU.	Amid the Covid-19 pandemic, the adoption of e-learning in Indonesia revealed that SE significantly affects the PEOU [35]. Chen's study indicates that SE significantly enhances both PU and PEOU [36].
PEJ	H3a	PEJ exerts a significant and positive influence on PEOU.	In the context of adopting e-learning in Indonesia following the COVID-19 outbreak, PE has a significantly positive effect on both PEOU and PU [35].
	H3b	PEJ exerts a significant and positive influence on PU.	Bagdi and Bulsara's [37] research found that PE significantly affects PEOU and PU regarding digital natives' intentions towards online learning.
OUT	H4	OUT has a significant and positive influence on PU.	Investigating the adoption of online learning among university students in Iran during and after Covid-19 showed that OUT significantly affects both PEOU and PU [38]. In the study by Fathema <i>et al.</i> [39] on the use of learning management systems (LMS) in rural USA for higher education institutions, it was discovered that OUT significantly and positively influences PU.
SN	H5a	SN have a significant and positive influence on PU.	Binyamin <i>et al.</i> [40] analyzed the influence of SN on students' acceptance of LMS in Saudi Arabia, with results showing that the SN construct significantly affects PU. An evaluation of the acceptance of video conferencing to support distance learning during the Covid-19 pandemic impact in Vietnam indicated that SN significantly influences BI [41].
	H5b	SN have a significant and positive influence on BI.	
FC	H6a	FC have a significant and positive impact on PEOU.	Buabeng-Andoh and Baah [15] proposed an integrated model combining UTAUT and TAM to assess pre-service teachers' intentions to use LMS, demonstrating that FC affect UTAUT's effort expectancy or TAM's PEOU. Similarly, an expanded model that merges TAM and UTAUT for evaluating the acceptance of podcasting in a university setting in the USA suggests that FC have an influence on PU and BI [42].
	H6b	FC have a significant and positive impact on PU.	
	H6c	FC have a significant and positive impact on ATU	
PEOU	H7a	PEOU has a significant and positive impact on PU.	Numerous publications that corroborate this statement encompass the adoption of e-learning in Indonesia amidst the Covid-19 pandemic [35], a study on the acceptance of e-portfolios by 242 students in the UK [43], an analysis of LMS usage in higher education institutions in the USA [39], and a research into the factors influencing student behavior towards massive open online courses (MOOCs) adoption in Malaysia [44].
	H7b	PEOU has a significant and positive impact on ATU.	
PU	H8a	PU has a significant positive impact on ATU.	In research focusing on the acceptance of e-learning in Indonesia amid the COVID-19 pandemic, PU was found to significantly influence BI [35]. Similarly, in the case of e-learning acceptance among junior high school teachers in Taiwan, PU had a significant effect on BI [36]. An extended TAM used to examine the adoption of LMS in higher education revealed that PU had a significant impact on both ATU and BI [39].
	H8b	PU has a significant positive impact on BI.	
ATU	H9	ATU has a significant and positive impact on BI.	In the publication by Zobeidi <i>et al.</i> [38] the ATU construct significantly impacts BI. Fathema <i>et al.</i> [39] published results from an evaluation of LMS acceptance among faculty members in higher education, demonstrating that ATU significantly influences BI. In the study conducted by Al-Hajri <i>et al.</i> [45] regarding the adoption of a cloud computing system for higher education in Oman, it was demonstrated that PU significantly influences BI.
BI	-	Main dependent construct	BI acts as a motivating factor affecting specific behaviors, with a stronger intention to engage in a behavior increasing the probability of its execution [15], [46].

3. METHOD

3.1. Determining the subject and sample size

This study targets students enrolled in the VHS broadcasting and film program. The research was conducted in West Java Province, which has the highest number of vocational school students in Indonesia [47]. Public Vocational High School 10 Bandung is one of the schools located in the city of Bandung, West Java Province, Indonesia, offering a broadcasting and film program. The total number of students in the broadcasting and film department in 2023 is 302. To determine the sample size, this research employs the Krejcie and Morgan method, which is suitable for small population sizes and facilitates the calculation of the margin of error to control the precision of sample estimates [48]. With a confidence level of 95% and a margin of error of 6%, the minimum sample size used in this study is 142 students. This study used 145 valid responses from students.

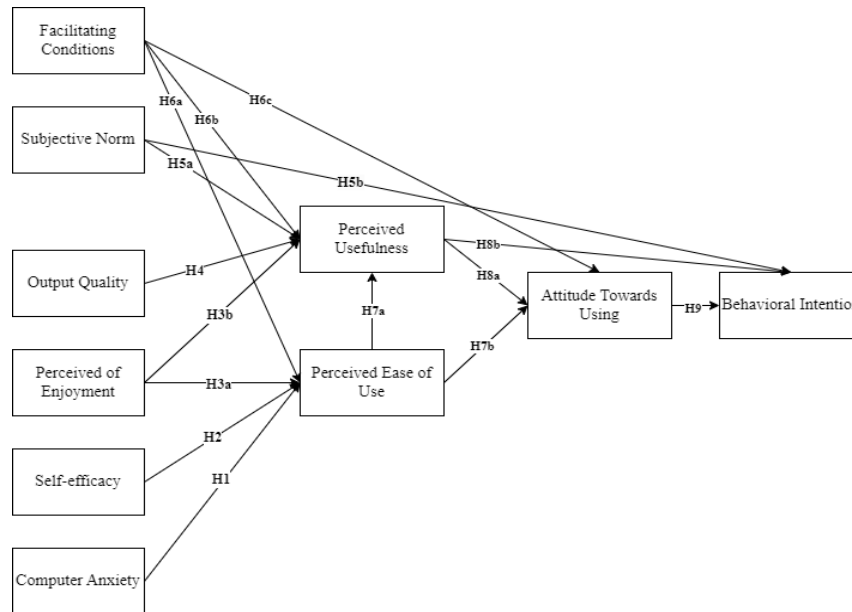


Figure 1. The proposed acceptance model featuring hypotheses derived from integrating TAM 3 and UTAUT

3.2. Instrument development and data collection

The development of the questionnaire instrument involved adapting items from TAM 3 [23], and UTAUT [49] to suit the specific context of this study. Question modifications were made to align with the usage of the camera simulator, the characteristics of the participants, educational levels, and the research site. Constructing the instrument drew upon insights from various studies [26], [27], [29], [31], [35]. The questions were structured on a five-point Likert scale, spanning from 'strongly disagree' and 'disagree' to 'neutral,' 'agree,' and 'strongly agree'. These responses were assigned numerical values, with 'strongly disagree' assigned a score of 1, 'disagree' assigned 2, 'neutral' receiving 3, 'agree' set at 4, and 'strongly agree' allotted 5. However, for constructs that have a negative impact, the numerical values are reversed compared to those with a positive impact.

Before distribution to the students, the instrument underwent thorough evaluation and validation by five educators from the vocational program at Public Vocational High School 10 Bandung. Among their responsibilities as validators, they ensured the semantic validity of the instrument, given its use in the Indonesian language. The research instrument was disseminated electronically through group channels within an instant messaging application, utilizing a tailored survey form. The distribution strategy involved dispatching the survey to a sample of 200 students selected at random, subsequent to their participation in practical sessions involving the camera simulator. Before initiating data collection, all students were provided with the opportunity to fully engage with and explore the features of the camera simulator. Data collection took place over a one-week period in August 2023.

3.3. Data analysis

The collected data were analyzed using partial least square (PLS) and statistical analysis techniques employing structural equation modeling (SEM). PLS-SEM is a precise method for evaluating exploratory studies [28], [50]. Moreover, this method does not necessitate multivariate normality [51], supports predictive modeling capability [52], [53], and does not impose restrictions on various types of research samples [51]. SmartPLS was employed in this study for data computation. Data analysis comprised two stages: measurement model and measurement structural model [52]. The measurement model was conducted to evaluate the relationships between latent and observed items, using significant loading, convergent validity (CV), and discriminant validity (DV) as the criteria for assessment. The measurement structural model was conducted to establish the connections between dependent and independent variables or constructs. The analysis of the structural model employed predictive relevance contrast and hypotheses testing methods.

Significant loading is employed to assess the correlation between statements or indicators and their respective constructs. Ideally, significant loading values should be above 0.6, or more precisely, 0.7 or higher [53]. Convergent validity serves to measure the contributions of the constituent instruments or indicators to their respective constructs. CV measurement involves an analysis of item's outer loading, encompassing the evaluation of Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). The

accepted standards for these values are a Cronbach's alpha of above 0.7, a minimum CR of 0.7, and an AVE value of at least 0.5 [54], [55].

The DV is to measure the distinctions between constructs within a model. The measurement of DV utilizes the Fornell-Larcker criterion, cross loadings, and heterotrait-monotrait ratio of correlations (HTMT). The Fornell-Larcker criterion calculation involves taking the square root of the AVE values [54]. Constructs are distinct from one another or discriminately valid if the square root of their AVE value is greater than the correlation with other constructs. In the cross loadings approach, it is expected that the minimum value for a construct should exceed 0.7, and a construct is deemed valid if its own cross-loading value surpasses the cross-loading values of other constructs [56]. In the case of HTMT, constructs are categorized as valid if their HTMT value is less than 0.9 [57]. For structural model analysis purposes, this study calculates the R² value for each construct and verifies that the endogenous constructs have a value greater than 0.1 to ensure an adequately explained variance [58]. Furthermore, to assess hypotheses testing, each relationship between constructs in the proposed model should exhibit a path coefficient greater than 0.2 [59], t-values should exceed 1.96, and p-values should be less than 0.05 [43].

4. RESULTS AND DISCUSSION

4.1. Results

4.1.1. Significant loading

Figure 2. illustrates the significant loading values associated with each instrument relative to its corresponding construct. The significant loadings for all indicators within each construct are above 0.7. The lowest significant loading value is 0.703 for the SN construct with SN1 instrument regarding the influence of the nearest environment on system usage. The highest significant loading value is 0.929 for the PU construct with PU3 instrument regarding the enhancement of student learning effectiveness after using the device.

4.1.2. Convergent validity

The outcomes of the CV assessments, conducted via Cronbach's alpha, CR, and AVE, are displayed in Table 2. The assessment of CV using Cronbach's alpha, CR, and AVE calculations indicates that all computed values adhere to the established validity criteria of the respective calculation method. Specifically, when evaluating CV through Cronbach's alpha, all constructs exhibit values exceeding the recommended threshold of 0.7. The ATU construct attains the highest Cronbach's alpha value at 0.892, while the FC and SN constructs exhibit the lowest values at 0.783. Moreover, CR calculations consistently yield values exceeding the 0.7 benchmark across all constructs. Notably, the ATU and PU constructs exhibit the highest CR values at 0.925, with the SN construct registering the lowest CR value at 0.859. Additionally, the computation of AVE values for all constructs demonstrates their conformity to the stipulated validity standard, with each construct surpassing the minimum threshold of 0.5. The highest AVE value, 0.852, is observed in one of the constructs, while the lowest AVE value among the constructs is 0.604.

4.1.3. Discriminant validity

The assessment of DV utilized three different approaches. Findings from the Fornell-Larcker criterion method reveal that the square root of the AVE for each construct is higher in comparison to that of the other constructs. The square root of the AVE values for the constructs are as: ATU=0.869, BI=0.879, ANX=0.844, FC=0.835, OUT=0.923, PEOU=0.846, PEJ=0.882, PU=0.869, SE=0.804, and SN=0.777.

Subsequently, the cross-loading method was employed, yielding the following values: ANX (ANX1=0.884, ANX2=0.804, ANX3=0.842), ATU (ATU1=0.850, ATU2=0.879, ATU3=0.900, ATU4=0.846), BI (BI1=0.888, BI2=0.892, BI3=0.856), FC (FC1=0.869, FC2=0.824, FC3=0.811), OUT (OUT1=0.923, OUT2=0.923), PEJ (PEJ1=0.913, PEJ2=0.863, PEJ3=0.870), PEOU (PEOU1=0.843, PEOU2=0.835, PEOU3=0.876, PEOU4=0.828), PU (PU1=0.805, PU2=0.891, PU3=0.929, PU4=0.845), SE (SE1=0.792, SE2=0.721, SE3=0.874, SE4=0.822), and SN (SN1=0.703, SN2=0.780, SN3=0.819, SN4=0.803). From the evaluation with the cross-loading method, all construct values are above 0.7.

The third method used to assess DV involved the HTMT. The results of the DV calculation using HTMT show that all construct values are below 0.9. Based on the outcomes derived from the three methods employed to assess DV, it is evident that all constructs under scrutiny adhere to the prescribed validity criteria.

4.1.4. Predictive relevance

In the context of the ATU construct, the R² value stands at 0.596, signifying that 59.6% of the variance within ATU can be elucidated by the predictors or independent constructs influencing ATU. The predictors pertaining to the ATU construct exhibit a favorable fit, as indicated by the adjusted R² value of 0.587. Similarly, for the PEOU, PU, and BI constructs, their respective R² values are 0.502, 0.584, and 0.623, accompanied by adjusted R² values of 0.488, 0.569, and 0.615. These values collectively imply robust fits for these constructs.

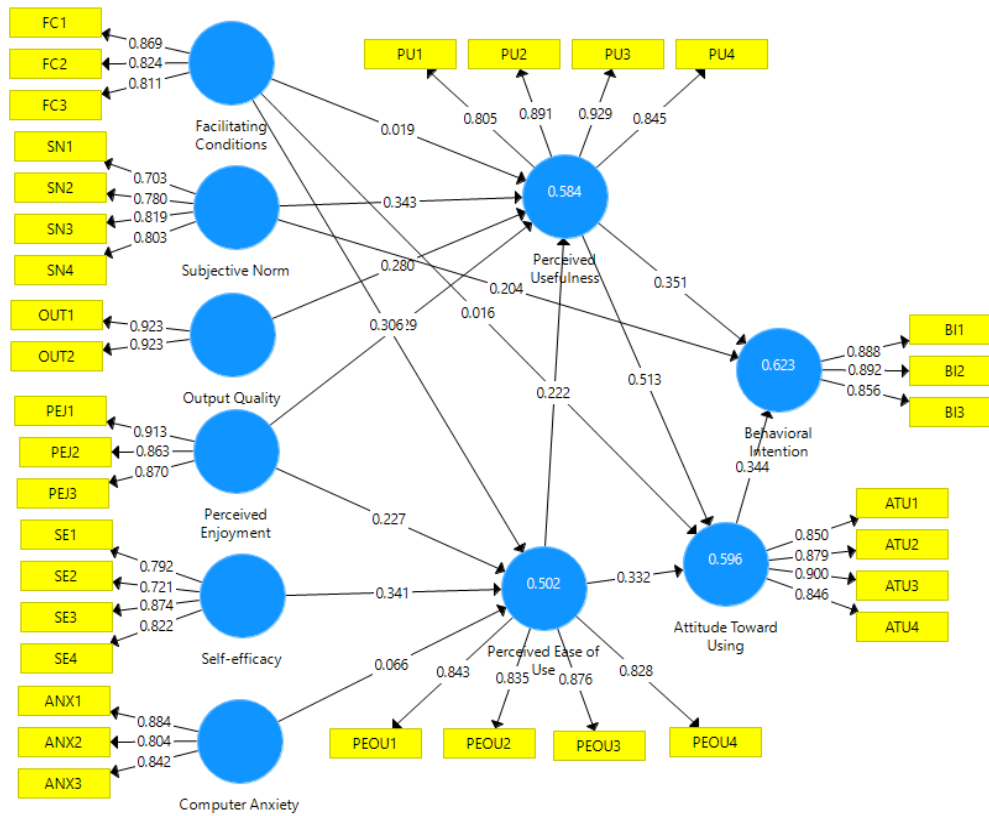


Figure 2. Results of significant loadings

Table 2. Result of CV test

Constructs	Cronbach's alpha	CR	AVE
ATU	0.892	0.925	0.755
BI	0.853	0.911	0.773
ANX	0.806	0.881	0.713
FC	0.783	0.873	0.697
OUT	0.827	0.920	0.852
PEOU	0.867	0.909	0.715
PEJ	0.858	0.913	0.779
PU	0.890	0.925	0.755
SE	0.817	0.880	0.647
SN	0.783	0.859	0.604

4.1.5. Hypotheses testing and final model

The hypotheses testing process involved the computation of path coefficients (β) for each hypothesis. Statistical significance was attributed to the relationships between constructs when the path coefficient (β) exceeded 0.2. Analysis of the measurement outcomes revealed hypotheses for which path coefficients (β) fell below the threshold of 0.2, specifically: H1 ($ANX \rightarrow PEOU$) with a coefficient of -0.032, H3b ($PEJ \rightarrow PU$) with a coefficient of 0.129, H6b ($FC \rightarrow PU$) with a coefficient of 0.019, and H6c ($FC \rightarrow ATU$) with a coefficient of 0.016. Subsequent analyses employed the t-statistic and p-values. A critical t-statistic value of 1.96 was used to indicate the presence of a significant relationship between constructs. Based on this criterion, four hypotheses yielded t-statistic values below 1.96: H1 (0.114), H3b (1.910), H6b (0.201), and H6c (0.151). The assessment of p-values required relationships between constructs to have values below 0.05 to be considered statistically significant. Hypotheses that failed to meet this criterion were H1 (0.909), H3b (0.057), H6b (0.841), and H6c (0.880). Consequently, four hypotheses (H1, H3b, H6b, and H6c) were rejected. Detailed information on the hypotheses (H), β coefficient values (β), standard deviations (SD), t-statistic values (t), p-values (p), and findings (F) are presented in Table 3. Within this final model, one construct, ANX, was excluded, along with the removal of three inter-construct associations, specifically, the connections between PEJ to PU, FC to PU, and FC to ATU.

Table 3. Hypotheses testing results

Hypotheses	Constructs	β	Standard deviation	t-statistics	p-values	Findings
H1	ANX→PEOU	-0.013	0.116	0.114	0.909	Rejected
H2	SE→PEOU	0.337	0.068	4.967	0.000	Accepted
H3a	PEJ→PEOU	0.230	0.068	3.354	0.001	Accepted
H3b	PEJ→PU	0.129	0.068	1.910	0.057	Rejected
H4	OUT→PU	0.280	0.085	3.303	0.001	Accepted
H5a	SN→PU	0.343	0.076	4.527	0.000	Accepted
H5b	SN→BI	0.204	0.069	2.968	0.003	Accepted
H6a	FC→PEOU	0.292	0.078	3.742	0.000	Accepted
H6b	FC→PU	0.019	0.094	0.201	0.841	Rejected
H6c	FC→ATU	0.016	0.106	0.151	0.880	Rejected
H7a	PEOU→PU	0.222	0.086	2.570	0.010	Accepted
H7b	PEOU→ATU	0.332	0.093	3.588	0.000	Accepted
H8a	PU→ATU	0.513	0.110	4.655	0.000	Accepted
H8b	PU→BI	0.351	0.089	3.935	0.000	Accepted
H9	ATU→BI	0.344	0.087	3.952	0.000	Accepted

4.2. Discussion

The analysis conducted using the PLS-SEM method on the measurement model, employing significant loading, CV, and DV assessments, has shown results affirming the fulfillment of the prescribed validity criteria for all proposed indicators. Significant loading calculations indicate that all constituent indicators contributing to the proposed constructs attain values exceeding the 0.7 thresholds. Furthermore, the CV computations, performed through three distinct methods (Cronbach's alpha, CR, and AVE), demonstrate that each construct surpasses the validity thresholds established by their respective methods. Additionally, DV calculations, aimed at assessing the distinctions among indicators across constructs through three methods (Fornell-Larcker criterion, cross-loadings, and HTMT), affirm that all constructs meet the validity criteria set forth by each of these approaches.

The assessment of the structural model was executed through two methods: the calculation of R² and the measurement of inter-construct impacts employing path coefficients (β), t-values, and p-values. The outcomes derived from the R² calculations indicate that all values associated with the dependent constructs surpass the threshold of 0.1, signifying a notable and statistically significant influence of independent constructs on the dependent counterparts. The validation of hypotheses was performed by measuring the relationships between constructs, resulting in the rejection of four out of the 15 proposed hypotheses. The assessment of inter-construct relationships resulted in the elimination of one construct (namely, ANX) and the exclusion of four inter-construct relationships from the proposed model. Significantly, in the context of this study, there was an absence of observable influence emanating from the ANX construct on the PEOU construct. This observation contrasts with findings from studies regarding the acceptance and adoption of e-learning in Indonesia [38] and in Taiwan [38]. In an alternative research context focused on the measurement of e-portfolios among students in the United Kingdom, the influence of ANX on PEOU was noted, albeit without achieving statistical significance [37]. The ANX construct is inherently associated with individuals' apprehensions and fears regarding the utilization of computer-based digital technology. In this study, the participants, who constitute the subject of investigation, possessed an average age range of 13-16 years and were born between 2007 and 2010, classifying them as belonging to generation Z. Members of generation Z, often referred to as the digital generation, are characterized by their early exposure to information technology, which has rendered them highly adept at using various types of information technology in their daily routines [39]. Consequently, their familiarity and comfort with diverse information technology types may account for the observed absence of fears related to its use.

In this investigation, the utilization of the camera simulator construct within the context of PE exhibits a significance impact on PEOU, aligning with findings from several prior studies [35]–[37], [60]. Nonetheless, distinctive outcomes emerge when examining the relationship between PE and PU, as the hypothesis linking these two constructs is rejected in this study, despite the t-values and p-values calculated being in close proximity to the predefined threshold. Two other relationships, namely FC towards PU and ATU, also yield rejected hypotheses. This outcome holds particular interest, especially given the prior publication by Fathema *et al.* [39], which posited that FC exerted no influence on PEOU. Despite the diverse functionalities and modes available in photography, camera simulators often exhibit relative simplicity and limited functionality compared to other technological models such as LMS, MOOCs, or e-learning platforms. Consequently, the utilization of camera simulators tends to be confined to specific learning activities, potentially contributing to lower perceptions of usefulness when compared to perceptions of ease of use among students.

From the practical implication perspective, this study equips educators and vocational institutions with the means to formulate appropriate strategies when selecting or implementing simulator-based learning tools. This involves a focus on the influential factors and constructs that can be effectively managed and controlled to enhance the educational experience for vocational-level students. From a theoretical implications standpoint, this study's results elaborate on the integration of the adapted TAM 3 and UTAUT models, providing a detailed view of the factors or constructs that support student acceptance of camera simulator technology for educational purposes in the Indonesian vocational school context. These results have implications, serving as a valuable reference and source of insight for other researchers and the deployment of simulator-based learning technology among vocational school students.

This research has a limitation, primarily stemming from its exclusive focus on a single educational institution. Within the context of vocational education in Indonesia, a challenge arises from the significant disparity between schools located in urban and remote areas [8]. This situation presents an opportunity for future research endeavors aimed at conducting comparative analyses of the factors influencing the acceptance of simulator technology among VHS students in urban and remote areas. Such studies have the potential to provide valuable insights into the dynamics at play across diverse educational environments, shedding light on the factors that influence technology acceptance among VHS students in varying contexts, subjects, and different types of technologies.

5. CONCLUSION

This study has identified the factors that influence the acceptance of camera simulator technology among vocational high school students in Indonesia. These factors have been derived from two well-established acceptance models: TAM 3 and UTAUT, which have undergone empirical validation in prior research within the education sector. The examination has revealed ten factors estimated to exert significant influence on camera simulator acceptance: facilitating conditions, subjective norms, output quality, self-efficacy, computer anxiety, perceived enjoyment, perceived usefulness, perceived ease of use, attitude toward using, and behavioral intention. The proposed acceptance model in this study is rooted in the interrelationships among these constructs. Using PLS-SEM as the analytical method, a thorough evaluation of the proposed model was carried out, covering both the measurement of the model and the measurement of the structural model. The results of the measurement model analysis confirm that all indicators and their respective constructs align with the validity criteria. In the evaluation of the structural model, among the initially considered ten constructs, one of construct (namely computer anxiety), and four inter-construct relationships have been excluded from the final model. The research has culminated in the formulation of a comprehensive model that integrates elements of TAM 3 and the UTAUT model. This model offers a framework to assess the acceptance of camera simulator technology among students in Indonesian VHS.

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