Analysis of Factors Affecting Vocational Students' Intentions to Use a Virtual Laboratory Based on the Technology Acceptance Model

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Abstract—Virtual Laboratory (VL) is increasingly being used in the learning process, offering a variety of options. However, when choosing the appropriate type of VL, it is necessary to consider the factors that affect the successful implementation of the VL. This study discusses the factor analysis that affects the vocational students' intention to use a VL in remote learning. Based on the Technology Acceptance Model (TAM), Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Attitude towards VL (A) are factors that influence people's intention to use technology. This research was conducted on the learning process of the Power Electronics Practicum for Vocational students. This study involved 105 vocational students from the Industrial Electrical Engineering Study Program at Universitas Negeri Padang. A quantitative survey-based approach using a questionnaire was applied to obtain the research data. The research data was analyzed using Partial Least Square-Structural Equation Modeling (PLS-SEM). The results showed that all factors (PEU, PU, & A) had a significant and positive direct and indirect effect (through intervening variables) on the vocational students' intention to use VL to support remote learning. These factors can be considered in determining the appropriate virtual laboratory application to be implemented in the learning process.

Keywords—technology acceptance model, virtual laboratory, student intentions to use, remote learning, vocational students

1 Introduction

Vocational education (VE) is a specific form of education that focuses on providing students with practical skills and knowledge to prepare them for work in specific industries. Therefore, practical learning in the laboratory is more dominant than theoretical learning. The practical learning process in the laboratory provides students with hands-on learning experiences, allowing them to interact with materials and observe theoretical concepts in action [1], [2]. Practical learning aims to develop students' abilities and application skills, such as observing, measuring, planning, estimating, developing hypotheses, obtaining data, problem-solving, collaborating, interpreting results, and time management [2]–[4]. However, providing physical or real laboratories can be challenging for educational institutions due to the high investment costs for equipment and materials, as well as the time required for preparation [5]–[7]. Moreover, practical learning in the laboratory is not conducive to remote learning [8], [9].

The COVID-19 pandemic that began in 2020 has further hindered the implementation of practical learning in real laboratories due to restrictions on face-to-face interactions to prevent the spread of COVID-19 [8], [10]. As a result, remote learning has been implemented in every educational institution, including the implementation of practical learning [11], [12]. Remote learning has become increasingly popular during the COVID-19 pandemic era, leading to the development of various models, methods, approaches, and learning media for practical learning [13]–[15]. One such approach is the use of the virtual laboratory (VL), which provides easily accessible and flexible laboratory applications without the limitations of physical space and time. The VL simulates real laboratory environments through various computer software, allowing students to conduct experiments independently. Thus, students can comfortably design experiments, analyze and interpret data, and explore various concepts within a virtual environment [5], [9].

The implementation of VL in practical learning processes significantly contributes to achieving learning objectives and outcomes in remote learning and blended learning (a combination of face-to-face learning in a real laboratory with remote learning using VL) [16]–[18]. Moreover, the use of VL creates a different learning atmosphere that increases students' interest and motivation in learning. However, to benefit optimally from VL in the learning process, special care and consideration are necessary when selecting the type of VL technology [19], [20]. Previous studies have revealed that several cases of VL implementation were not optimal due to errors in selecting the type of VL. One of the indicators is the low intention of students to use the VL chosen by the lecturer. Consequently, the implementation of VL not being optimal, and the benefits offered by VL could not be fully realized [16], [20]. For that reason, lecturers need to comprehend the factors that influence students' intention to use or not use VL technology. Such comprehension will help ensure that VL is appropriately adopted and utilized by all students, enabling the effectiveness of practical learning implementation using VL to be optimal. Currently, there is a lack of references and research outcomes that specifically discuss the factors that influence students' intentions to use VL in the practicum learning process.

Based on the technology acceptance model (TAM), students' intention to use VL can be defined as Behavioral Intention (BI). In addition, perceived usefulness (PU) and perceived ease of use (PEU) are two important factors that influence BI [19], [21], [22]. These factors also have a direct influence on attitudes towards technology use (A), which also have a positive and significant influence on students' BI to use VL in practical learning [1], [19], [20]. Therefore, the TAM model was chosen as a framework for investigating the factors that influence vocational students' intention to use a VL in the learning process.

The research questions for this study are: (1) What are the factors that influence vocational students' intention to use VL in remote learning, particularly in the process of power electronics practical learning, based on the TAM theory? (2) Are these factors positively and significantly influential? Therefore, the general objective of this study is to analyze the factors that influence vocational students' intention to use VL in the power electronics practicum learning process in remote learning. This study can contribute to the literature for educators and instructors about the factors that need to be considered in determining the appropriate type of VL to be applied in practical learning processes. The specific objectives of this study are to analyze: (1) the direct effect of PU on BI; (2) the direct effect of PEU on BI; (3) the direct effect of A on BI; (4) the direct effect of PU on A; (5) the direct effect of PEU on A; (6) the direct effect of PEU on PU; (7) the indirect effect of PU on BI through A as intervening variables; (8) the indirect effect of PEU on BI through A as intervening variables.

The study has several important implications. Firstly, it provides a better understanding of the factors that influence students' intentions to use VL applications. Secondly, this study shows that the factors that influence students' intentions to use VL applications are interrelated and influence each other. Thereupon, developers of VL applications must consider these factors in an integrated and comprehensive manner when designing, developing, and promoting VL applications. Thirdly, this research can also assist educational institutions and lecturers in selecting appropriate VL applications for use in practical learning. By considering the factors that influence students' intentions to use VL, lecturers can choose VL applications that are more suitable and effective in enhancing student learning.

2 Literature review

2.1 Vocational student

Vocational education is a type of education that focuses on providing students with specific practical skills and knowledge required for employment in certain industries [22], [23]. The primary goal of vocational education is to equip students with the skills and practical knowledge necessary to work in a particular field [24]–[26]. Vocational students are those who are enrolled in vocational education programs and undertake courses that focus on developing practical skills and knowledge in specific fields. They pursue expertise in their chosen fields, such as automotive mechanics, information technology, healthcare, and others [22], [25], [26]. Vocational students acquire practical skills through hands-on training and internships, allowing them to develop the skills necessary to work in specific industries. They have excellent employment prospects due to their practical and specific educational backgrounds. They possess industry-relevant skills and knowledge and are job-ready upon graduation [23], [27], [28].

2.2 Virtual laboratory

A virtual laboratory is a learning platform that allows users to perform laboratory experiments or practices in a virtual environment that closely resembles a physical environment. In a VL, users can simulate, observe, and interactively analyze experimental results safely without requiring actual laboratory materials or equipment [20], [29], [30]. The advantages of using VL in the learning process are as follows: (1) Time and place flexibility, as students can access the VL from anywhere and at any time without being tied to a strict laboratory schedule; (2) Cost-effectiveness, as in the VL, students do not need to buy or use actual laboratory materials and equipment, thus saving costs and reducing the risk of accidents; (3) Interactivity, as VL allows students to conduct interactive experiments and simulations, thereby increasing their engagement and understanding of the concepts being taught; (4) Safety, as students can conduct experiments and simulations safely without any danger or risks that may occur in the physical laboratory [31]–[33]. However, VL has some limitations, including the lack of hands-on experience which is crucial for certain scientific disciplines. Additionally, VL may have limited availability of equipment and materials, technical difficulties such as software crashes or internet connectivity issues, limited interaction, limited collaboration, and may lack authenticity in replicating real laboratory environments, which can impact the validity and reliability of experimental results obtained [31], [32], [34]. Despite these limitations, VL is a valuable tool for teaching and learning scientific concepts, and their use can be optimized by carefully considering the advantages and limitations, as well as choosing appropriate virtual laboratory applications based on the specific learning objectives and needs of the users [31], [32], [35].

2.3 Technology acceptance model

The Technology Acceptance Model (TAM) is a theory that explains the intention of individuals to use technology (BI) [22], [36]. This theory posits that an individual's intention to use technology is determined by two primary factors: perceived usefulness (PU) and perceived ease of use (PEU) [21], [22]. PU refers to the degree to which an individual believes that technology can provide benefits in their personal or professional life, while PEU refers to the degree to which an individual feels that technology is easy to use. According to TAM, the higher the PU and PEU, the greater the likelihood of an individual using it. Additionally, factors such as attitudes toward technology (A) and environmental conditions can also impact the intention to use technology. TAM has been widely employed in various studies on technology acceptance, particularly in the context of education and learning [10], [21]. Therefore, this study applied TAM to analyze the factors affecting vocational students' intention to use the VL.

2.4 Vocational students' intentions to use a virtual laboratory

The student's intention to use a VL refers to their willingness to use a VL in the learning process. The higher the students' intention to use a VL, the more optimal the implementation of a VL in the learning process will be. Therefore, it is important to consider students' intention to use a VL to optimize its implementation in the learning process. Based on TAM, students' intention to use VL is defined as BI, which is a person's intention to use and apply technology [19], [20]. In addition, PU and PEU are two important factors that influence BI. PU refers to the perceptions of vocational students regarding the benefits of using VL in remote learning [19], [36]. PEU refers to the perceptions of vocational students regarding the ease of use of VL in remote learning. PEU directly affects PU [19], [20]. Meanwhile, A refers to the attitude of vocational students towards the use of VL technology in remote learning, which is considered one of the important components in predicting BI [36], [37].

3 Methods

3.1 Research design

The study adopts a non-experimental [19], explanatory [38], and descriptive approach with a quantitative methodology [19]. In other words, a survey-based quantitative approach was utilized in this study. The survey method is a systematic collection of information that enables researchers to obtain accurate information on problems and the relationships between variables. It provides descriptive answers and reveals the influence between variables [39]. The research variables for this study are PU, PEU, A, and BI, and are illustrated in Figure 1, which represents the research model.

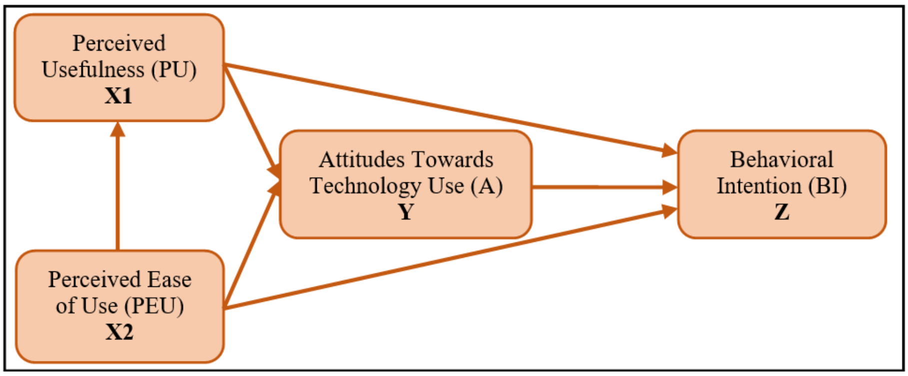

Fig. 1. Initial Research Model

3.2 Population and sample

The population for this study comprised 142 third-year vocational students who were enrolled in the power electronics course under the industrial electrical engineering study program, faculty of engineering, at Universitas Negeri Padang. The sample size was determined using the Slovin formula, which resulted in a sample of 105 students [40]. A simple random sampling technique was used for the selection of participants in this study [41].

3.3 Research instruments

The data collection technique used is a survey method using a research instrument. The data collection instrument used is a questionnaire with a Likert scale ranging from 1 to 5. The indicators for the questionnaire were obtained through a literature review and are presented in Table 1. This study uses reflective indicators where the indicators reflect the construct or variable [41]. PU has 4 indicators [22], [36], PEU has 5 indicators [21], [22], A has 4 indicators [19], [31], [36], and BI has 5 indicators [10], [19], [36].

Table 1. Dimensions and Indicators of Research Instrument

Dimensions	Theoretical Framework	Indicator
Perceived Ease of Use	[21], [22]	PEU.1. The VL used is easy to use. PEU.2. The VL used is easy to learn. PEU.3. The VL used is easy to access. PEU.4. The VL used is easy to understand. PEU.5. The VL used is convenient.
Perceived Usefulness	[22], [36]	PU.1. The VL used helps to save time. PU.2. The VL used helps me to be self-reliable. PU.3. The VL used helps to improve my knowledge. PU.4. The VL used helps to improve my performance.
Attitudes Toward Use	[19], [31], [36]	A.1. The VL used is enjoyable. A.2. I am pleased enough with the VL used. A.3. I am satisfied with the performance of the VL used. A.4. The VL used is pleasant to me
Behavioral Intention	[10], [19], [36]	BI.1. I tend to use VL which is applied in the learning process. BI.2. I believe that the use of VL in the learning process is available BI.3. I plan to use VL in the learning process. BI.4. I will use VL if available in the learning process. BI.5. I have a strong intention to use VL in the learning process.

3.4 Technique of data analysis

The research data collected using research instruments were analyzed to determine research findings in line with the research objectives. Variant-based Structural Equation Modeling (SEM) was employed to analyze the research data [5], [40], [41]. PLS-SEM analysis was conducted using the SmartPLS application to determine the direct and indirect effects of several exogenous variables on endogenous variables. This allowed for the identification of the factors that influence vocational students' intention to use the VL in the practical learning process of Power Electronics courses. Before this, a validity analysis of variables and instrument indicators was also included in the PLS-SEM analysis.

4 Results and discussion

4.1 Results

This study employs the PLS-SEM model to investigate the factors affecting the vocational education students' intention to use a VL in the practical learning process of the power electronics course. Specifically, this study uncovers the direct, indirect, and total effects of PU, PEU, and A on BI. The direct effect in this study includes the effect of PU & PEU on A, the effect of PU & PEU on BI, and the effect of A on BI. Meanwhile, the indirect effect is the impact of PU and PEU on BI through A as an intervening variable. The significance of each influence is also analyzed. The initial PLS-SEM model, which was compiled based on the literature review of each research variable, is presented in Figure 2.

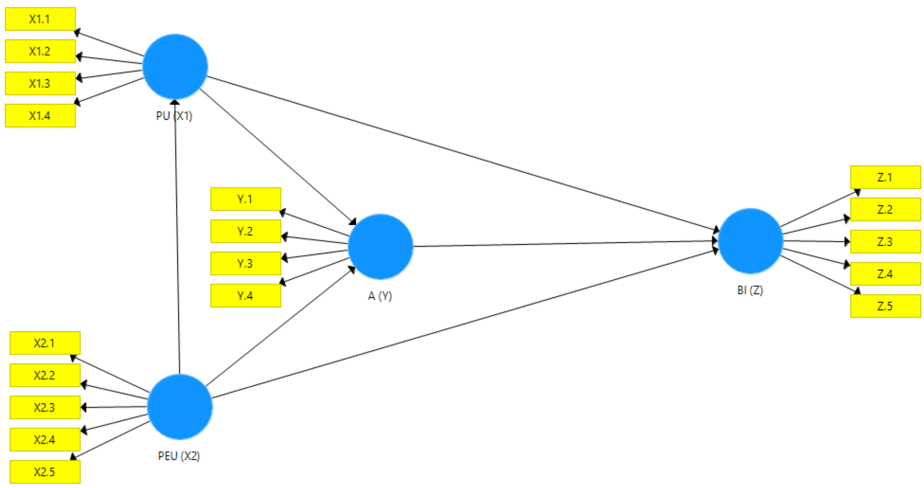

Fig. 2. Initial PLS-SEM Model

The Preliminary Research Model is analyzed to ensure that each indicator meets the assumptions and requirements of the analysis. There is no problem of multicollinearity, which is an assumption that must be met in the inner and outer model analysis. Multicollinearity is indicated by the Variance Inflating Factor (VIF) value exceeding 5. If the VIF value is greater than 5, then a multicollinearity problem occurs. Otherwise, if the VIF value is less than 5, there is no multicollinearity problem [42], [43]. Table 2 presents the results of the Outer VIF Values analysis.

Table 2. The Outer VIF Values Analysis

PU		PEU		A		BI	
Indicator	***VIF***	***Indicator***	***VIF***	***Indicator***	***VIF***	***Indicator***	***VIF***
PU.1	1.678	PEU.1	2.387	A.1	1.532	BI.1	1.575
PU.2	2.017	PEU.2	5.418	A.2	1.724	BI.2	1.487
PU.3	1.654	PEU.3	2.060	A.3	1.402	BI.3	1.545
PU.4	2.477	PEU.4	5.628	A.4	1.387	BI.4	1.580
		PEU.5	1.855			BI.5	1.371

The results of the outer VIF Value analysis indicate that two indicators, PEU.2 and PEU.4, have VIF values above 5 (VIF > 5), indicating the presence of multicollinearity. Therefore, the two indicators need to be eliminated, and a second analysis is conducted for the Outer VIF Values as presented in Table 3.

Table 3. The Second Outer VIF Values Analysis

PU		PEU		A		BI	
Indicator	***VIF***	***Indicator***	***VIF***	***Indicator***	***VIF***	***Indicator***	***VIF***
PU.1	1.678	PEU.1	2.454	A.1	1.532	BI.1	1.575
PU.2	2.017	PEU.3	1.613	A.2	1.724	BI.2	1.487
PU.3	1.654	PEU.5	2.320	A.3	1.402	BI.3	1.545
PU.4	2.477			A.4	1.387	BI.4	1.580
						BI.5	1.371

The results of the second outer VIF Value analysis in Table 3 show that all VIF values are already below 5 (VIF <5). Therefore, it can be concluded that there is no multicollinearity problem. The next step is to test multicollinearity for latent variables (inner model). As with measuring indicators (outer models), inner models must also be ensured that they do not have multicollinearity between variables. Table 4 presents the results of the inner VIF value analysis.

Table 4. The Inner VIF Values Analysis

	A	BI
PU	1.220	2.342
PEU	1.294	1,847
A		1.278

The Inner VIF Value analysis in Table 3 indicates that all VIF values are 5 (VIF <5). Therefore, it can be concluded that there is no multicollinearity problem among the latent variables. The next step is to analyze the Goodness of Fit (GoF) criteria to ensure that compiled model meets the required standards. The GoF analysis results for the models used in this study are presented in Table 5.

Table 5. The GoF Analysis Results

	SRMR < 0,08 [41], [42]	**NFI > 0,9** [41], [42]	**Rms theta < 0,102** [41], [42]	**GoF**
Saturated Model	0,057	0,993	0,079	Fit
Estimated Model	0,057	0,993	0,079	Fit

The results of the GoF analysis show that the research model has met the GoF criteria, where the Standardized Root Mean Square Residual (SRMR) value is 0.067, The Normed Fit Index (NFI) value is 0.989, and the Root Mean Square Theta (RMS Theta) value is 0.049 [42], [44]. Therefore, based on these three values, the path model has met the GoF criteria. The PLS-SEM analysis results of the final research model are presented in Figure 3.

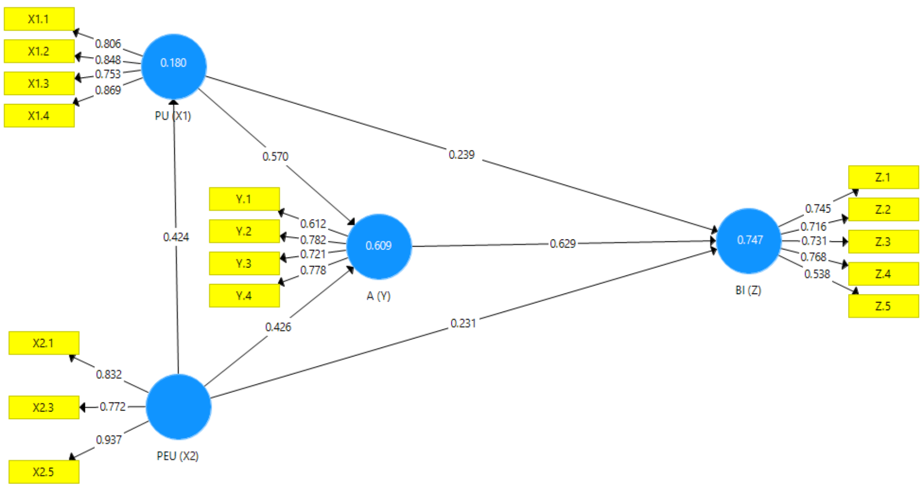

Fig. 3. The PLS-SEM Analysis Results of the Final Research Model

Indicator measurements (Outer model). The results of the construct validity and reliability analysis are presented in Table 6. Internal Consistency Reliability (ICR) is an analysis used to determine the ability of indicators to measure variables or their latent variables[41], [42]. In PLS-SEM, ICR is indicated by the values of composite reliability and Cronbach's alpha. Table 6 shows that all variables have a Cronbach's Alpha value greater than 0.6 and a composite reliability value greater than 0.7, indicating that all variables meet the ICR criteria (reliable) [41], [42]. A unidimensionality test is also required to ensure that there are no problems in the measurement, which is indicated by the composite reliability and Cronbach's alpha value [37], [42], [44]. Table 6 shows that all variables meet the unidimensionality criteria, with composite reliability and Cronbach's alpha greater than 0.7 [42], [44]. The next aspect to consider is convergent validity (CV). CV for variables that have reflective indicators is evaluated based on the AVE value. Table 6 presents that the AVE value for each variable is greater than 0.50, indicating that all variables are valid and meet the convergent validity criteria [42], [44].

Table 6. Construct Reliability and Validity Analysis

	Cronbach 's Alpha (> 0,7)	rho_A (> 0,7)	Composite Reliability (> 0,7)	AVE (> 0,5)	Internal Consistency Reliability	Unidimensionalitas Model	Convergent Validity
PU	0.714	0.748	0.708	0.633	Reliable	Reliable	Valid
PEU	0.706	0.815	0.756	0.612	Reliable	Reliable	Valid
A	0.757	0.725	0.716	0.528	Reliable	Reliable	Valid
BI	0.774	0.796	0.729	0.577	Reliable	Reliable	Valid

Inner model analysis. The analysis of the inner model is conducted to determine the relationship between variables and to reveal the direct effect (path coefficient), indirect effect, and total effect. Moreover, it is used to determine the simultaneous effect of exogenous variables based on the R Square, and Adjusted R Square [41], [42]. The results of the analysis of latent variables or inner model analysis are presented in Table 7.

Table 7. The Inner Model Analysis

	A (Y)			BI (Z)			R Square	R Square Adjusted
	Path Coeff.	*Ind. Effects*	*Tot. Effects*	*Path Coeff.*	*Ind. Effects*	*Total Effect*		
PU	0.570	-	0.570	0.239	0.503	0.742	-	-
PEU	0.426	-	0.426	0.231	0.437	0.668	-	-
A	-	-	-	0.629	-	0.629	0.609	0.604
BI	-	-	-	-	-	-	0.747	0.742

Direct effect analysis. In PLS-SEM analysis, the values of direct effects can be observed in the path coefficient. Path coefficient values range from -1 to +1, with values closer to +1 indicating a stronger and more positive relationship between the two constructs, while values closer to -1 indicate a negative effect [41], [42]. Table 7 presents that: (1) The direct effect of PU on A is 0.570 (Path Coefficient = 0.570) and the effect is positive, meaning that if PU increases by one unit, A will also increase by 57.0%; (2) The direct effect of PEU on A is 0.426 (Path Coefficient = 0.426) and the effect is positive, meaning that if PEU increases by one unit, A will also increase by 42.6%; (3) The direct effect of PU on BI is 0.239 (Path Coefficient = 0.239) and the effect is positive, meaning that if PU increases by one unit, BI can also increase by 23.9%; (4) The direct effect of PEU on BI is 0.231 (Path Coefficient = 0.231) and the effect is positive, meaning that if PEU increases by one unit, BI can also increase by 23.1%; and (5) The direct effect of A on BI is 0.629 (Path Coefficient = 0.629) and the effect is positive, meaning that if A increases by one unit, BI can also increase by 62.9%.

Indirect effect analysis. Indirect effects are the effects of an exogenous variable on an endogenous variable through an intervening variable. In PLS-SEM analysis, as well as the Path Coefficient, the indirect effect values range from -1 to +1, with values closer to +1 indicating a stronger and more positive relationship between the two constructs, and values closer to -1 indicating a negative relationship [41]–[43]. Table 7 shows that: (1) The indirect effect of PU on BI through A as an intervening variable is 0.503, which means that if PU increases by one unit, BI can indirectly increase through A by 50.3%; and (2) The indirect effect of PEU on BI through A as an intervening variable is 0.437, which means that if PEU increases by one unit, BI can indirectly increase through A by 43.7%.

Total effect analysis. Total effects are the sum of indirect and direct effects. In this study, the total influence analyzed is the total influence of PU on BI and the total influence of PEU on BI. So, it is known how much PU and PEU variables can affect BI in total [41]–[43]. Table 7 shows that: (1) The total influence of PU on BI is 0.742, which means that if PU increases by one unit, BI can increase either directly or indirectly through A as the intervening variable by 74.2%; and (2) The total influence of PEU on BI is 0.668, which means that if PEU increases by one unit, BI can increase either directly or indirectly by 66.8%.

R square and adjusted square analysis. The R Square value is between 0 and 1, with values greater than 0.67 considered the strong category, values between 0.33 and 0.67 considered the moderate category, and below 0.33 considered the weak category) [41], [42]. The Adjusted R Square value is used as a reference to assess the ability of exogenous latent variables to influence endogenous latent variables. Table 7 shows that: (1) The simultaneous influence of PU and PEU on A is 0.609 (R Square is 0.609) and the adjusted r square value is 0.604, which means that PEU and PU simultaneously affect A by 0.604 or 60.4% (moderate category); (2) The simultaneous effect of PEU, PU, and A on BI is 0.747 (R Square is 0.747) and the adjusted r square value is 0.742, which mean that PEU, PU, and A variables simultaneously affect BI by 0.742 or 74.2% (strong category).

Significance analysis. The significance analysis aims to determine whether the effects obtained through the analysis of the Inner Model are significant or insignificant. Specifically, it is done to determine the significance of each effect of exogenous latent variables on endogenous latent variables. The results of the significance analysis in Table 8 show that the overall significance value of each effect is less than 0.05 (P value <0.05), indicating that all the tested influences in this study are significant.

Table 8. The Results of Significance Analysis

Path Coefficients/ Direct effect			
	Original Sample (O)	***Sample Mean (M)***	***P Values***
PU → A	0.570	0.575	0.000
PU → BI	0.196	0.202	0.019
PEU → A	0.426	0.420	0.000
PEU → BI	0.178	0.185	0.007
A → BI	0.629	0.616	0.000
Indirect Effect			
PU → A → BI	0.358	0.354	0.010
PEU →A → BI	0.268	0.259	0.008
Total Effect			
PU → BI	0.554	0.556	0.006
PEU → BI	0.681	0.688	0.020

4.2 Discussion

Perceived Usefulness (PU). The analysis results demonstrated that PU had a direct and significant effect on A, with a positive influence of 57.0% (moderate category). Additionally, PU had a positive and significant effect on BI, with a direct effect of 23.9 (weak category) and an indirect effect of 50.3% (moderate category) through A, acting as an intervening variable. Therefore, the total impact of PU on BI was 74.2% (strong category). These findings are consistent with prior research, which also identified the positive and significant influence of technology's perceived usefulness on attitudes toward its use and intentions to use the technology [22], [36], [43], [45]. In the context of using VL for learning, these outcomes suggest that PU exerts a positive and significant impact on vocational students' intention to use VL for learning. The results also highlight the importance of focusing on the perceived benefits of using VL to increase its adoption among vocational students. By offering a useful VL application, vocational students will develop a more favorable attitude toward its use and higher intentions to use it in the learning process.

Perceived Ease of Use (PEU). The results of the analysis showed that PEU had a direct and significant effect on A, with a positive influence of 42.6% (moderate category). PU also had a positive and significant effect on BI, with a direct effect of 23.1 (weak category) and an indirect effect through A as an intervening variable of 43.7% (moderate category). Therefore, the total influence of PU on BI was 66.8% (strong category). The results showed that perceived ease of use had a significant effect on the attitude towards the use of technology and behavioral intention among vocational students in the Industrial Electrical Engineering Study Program. This is in line with previous research, which also demonstrates the positive and significant effects of the ease of using technology on attitudes towards technology use and intention to use technology [17], [46], [47]. In the case of using VL in the learning process, this result indicates that PU has a positive and significant influence on the intention of vocational students to use VL in the learning process. Furthermore, the results showed that to increase VL adoption in the learning process among vocational students, it is important to focus on the ease of using the VL application. By providing VL applications that are easy to use, vocational students will have a more positive attitude towards the use of VL and higher intentions to use it.

Attitudes towards technology use. The results of the analysis showed that A had a direct and significant effect on BI, with a positive influence of 62.9% (medium category). The direct effect of A on BI is larger when compared to the direct impact of PU and PEU on BI. However, A is influenced by PU and PEU, meaning that the strength of the influence of A on BI is also influenced by PU and PEU. The results found that attitudes toward use had a significant effect on behavioral intention among vocational students in the Industrial Electrical Engineering Study Program. This is in accordance with previous research, which also shows the positive and significant influence of a person's attitude towards technology on the intention to use the technology [1], [10], [19]. Attitudes themselves are influenced by the previous two factors, namely perceived usefulness, and perceived ease of use. [1], [22] In the case of the use of VL in the learning process, this result shows that A has a positive and significant influence on the intention of vocational students to use VL in the learning process. The results also showed that to increase VL adoption in the learning process among vocational students, in addition to focusing on the usefulness and ease of use of the VL application, student attitudes towards the use of the VL application used need to be considered. By providing a VL application that positively affects students' attitudes towards VL, vocational students will have a higher intention to use it.

Factors affecting vocational students' intentions to use a virtual laboratory. The results of the analysis show that there are three main factors influencing the intention of vocational students to use VL in the learning process, namely PU, PEU, and A. At the same time, A also acts as an intervening variable that mediates the influence of PU and PEU on BI, making it stronger. The strength of A's influence on BI is also influenced by PU and PEU. The study found that perceived usefulness, perceived ease of use, and attitudes towards technology use significantly influenced the behavioral intention of vocational students in the Industrial Electrical Engineering study program to use VL. This is consistent with previous studies that also showed a positive influence of perceived usefulness, perceived ease of use, and attitudes toward technology use on behavioral intention [22], [45], [48]. To increase the adoption of virtual laboratories among vocational students, it is essential to focus on perceived benefits, ease of use, and students' attitudes toward the VL application to be used [20], [22]. By providing VL applications that are perceived as useful, perceived as easy to use, and make students' attitudes more positive towards them, students' intentions to use the VL will be higher [36], [46], [49]. These findings may have implications for the development and implementation of VL applications to optimize the implementation of practical learning in vocational education. Additionally, they can also help lecturers and educational institutions determine the appropriate VL application to be used in the learning process as an effort to optimize learning implementation when a real laboratory is unavailable and a remote learning system is implemented.

5 Conclusion

The study aims to investigate the factors influencing students' intention to use a VL in remote learning practicum activities. It examines the factors that affect vocational students' intention to use a VL in their learning process. The study identifies three main factors: Perceived Usefulness (PU), Perceived Ease of Use (PEU), and Attitudes toward the Use of Technology (A). The results indicate a significant and positive influence on (1) the direct effect of PU on BI, (2) the direct effect of PEU on BI, (3) the direct effect of A on BI, (4) the direct effect of PU on A, (5) the direct effect of PEU on A, (6) the direct effect of PEU on PU, (7) the indirect effect of PU on BI, through A as an intervening variable, and (8) the indirect effect of PEU on BI, through A as an intervening variable. These findings indicate that PU, PEU, and A have a significant and positive impact on vocational students' intention to use a VL for learning. To increase the adoption of a VL in vocational education, it is crucial to focus on the perceived benefits, ease of use, and attitudes of students toward the VL application. By providing a VL application that is considered useful, and user-friendly, and improving students' attitudes toward a VL, the intention to use a VL among students will increase. These findings have implications for the development and implementation of VL technology in vocational education, and they can assist lecturers and educational institutions in determining appropriate VL applications for use in the learning process.

The study focuses solely on the factors that influence the intention of vocational students to use a VL, which includes PU, PEU, and A Other factors such as social influence, perceived risk, and trust were not considered in this study. Future research could examine the effect of these factors on vocational students' intention to use a VL. Additionally, this research only pertains to vocational students in the Industrial Electrical Engineering Study Program. Therefore, caution should be taken when generalizing the findings to other vocational programs.

Future studies could expand on the current research by examining the impact of other factors, such as social influence, perceived risk, and trust, on vocational students' intention to use VL. Moreover, this study could be broadened to other vocational programs to determine the generalizability of findings across different vocational programs. Lastly, future research could explore the factors that influence students' intentions to use VL by utilizing other models of perceived technology.

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