Exploring Student Acceptance of Virtual Laboratory in Learning: The Role of Perceived Relevance and Information Technology Experience

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***Abstract*—The application of Virtual Laboratory (VL) technology in learning is becoming increasingly popular and rapidly evolving. However, more comprehensive research is needed to understand student acceptance of this technology, particularly in laboratory learning. This research investigates the acceptance of VL technology among Industrial Electrical Engineering students in the Electrical Machinery Course (EMC). Student acceptance is measured through Behavioral Intention (BI) using the Technology Acceptance Model (TAM) framework. This framework was developed to empirically identify the factors influencing student acceptance, including Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Attitude Toward Use (AU), along with two additional external factors: Information Technology Experience (ITE) and Perceived Relevance (PR). This research employs a survey-based quantitative approach, utilizing a questionnaire distributed to 141 students. Data were analyzed using Variance-based Structural Equation Modeling (VB-SEM). The results indicate that Industrial Electrical Engineering students exhibit a high BI towards VL technology use in laboratory learning of the EMC. PEU, PU, and AU are empirically shown to positively and significantly impact the acceptance of VL technology. Additionally, ITE and PR positively and significantly influence PEU and PU, which, in turn, indirectly enhance BI. These findings have important implications for laboratory learning development, and integrating VL and hands-on laboratory. This research underscores the importance of considering factors within the TAM framework and the complementary roles of PR and ITE in designing, developing, selecting, and implementing VL technologies.**

***Keywords*—virtual laboratory technology, student acceptance, technology acceptance model, IT experience, perceived relevance**

I. Introduction

Information and communication technology development has revolutionized various aspects of life, including higher education [1, 2]. A significant innovation in higher education, particularly in industrial electrical engineering, is Virtual Laboratory (VL) technology [1, 3, 4]. This VL has emerged as a promising and increasingly popular alternative in laboratory learning processes, complementing and enhancing hands-on laboratory experiences [3, 5]. With a VL, students can conduct experiments and simulations interactively, without being constrained by location and time. This addresses various access and cost limitations that typically hinder the learning process in the hands-on laboratory [4, 6, 7].

Previous studies demonstrate that VL technology use can enhance students' understanding of concepts, practical skills, and engagement in the learning process [2, 5, 6, 8]. Several studies report that VL not only aids in improving conceptual comprehension but also provides opportunities for students to conduct safe and repeatable experiments [1, 4, 5, 9]. However, the discussion regarding student acceptance of the VL technology in a learning process, particularly in electrical engineering, remains limited. Therefore, more in-depth research is needed to understand student acceptance of the VL technology and the factors affecting their acceptance in laboratory learning.

In electrical machine learning, VL utilization holds significant potential to enhance the quality of learning, particularly in laboratory settings. Electrical machinery is a core course in the industrial electrical engineering curriculum, requiring a thorough understanding of both theoretical and practical applications of electrical machines [10–12]. The VL enables students to learn the basic principles of electrical machines, conduct simulation experiments, and develop technical skills more flexibly and innovatively than in hands-on laboratories [12–15]. However, implementing this VL technology has not yet achieved the expected level of effectiveness. The success or failure of VL-based learning is often related to errors in the selection and implementation of the technology, which are frequently caused by a lack of consideration of student acceptance and the factors influencing their acceptance as primary users of the VL in a learning process [3, 5, 16]. One model that is relevant for analyzing technology acceptance is the TAM. TAM provides a framework for understanding how users accept and use new technology, as well as the factors that influence their acceptance [4, 17–19]. Compared to other theoretical technology acceptance frameworks, the Technology Acceptance Model (TAM) focuses on core and critical variables, providing more targeted and actionable insights. Additionally, TAM has the flexibility to be expanded by incorporating additional factors, making it adaptable to more specific contexts, such as the application of virtual laboratory technology in the learning process within engineering education.

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This research uses TAM to analyze student acceptance of the VL technology and the factors affecting this acceptance. The model is also enhanced with two additional external factors, namely ITE and PR, to strengthen the analysis of factors affecting student acceptance [4, 16, 20]. These factors were selected over others, such as satisfaction, enjoyment, perceived support, and subjective norm, because they are directly related to students' capacities and perceptions of VL's relevance to their learning goals. This makes them more aligned with the personal and educational context of using VL in laboratory learning, particularly in EMC. This research investigates student acceptance of VL used in laboratory learning for EMC. The study aims to analyze the level of students' acceptance of VL and identify the factors influencing this acceptance by utilizing the Technology Acceptance Model (TAM). Additionally, the study considers the impact of two external variables, ITE and PR.

This research provides a deeper understanding of the factors that influence student acceptance of VL technology used for laboratory learning in EMC. This research offers valuable insights for engineering education development. that integrates technology into the learning process and provides an empirical basis for developing more effective strategic approaches to increase the adoption of emerging technologies in engineering education. This research will contribute to the existing literature by expanding the understanding of the TAM in the specific context of industrial electrical engineering, and by considering external factors crucial for understanding technology acceptance among college students. This will aid in selecting, implementing, or developing the appropriate VL technology for laboratory learning processes, ensuring that the effectiveness of this technology is achieved optimally.

II. Literature Review

A. Technology Acceptance Model

The TAM is a theoretical model created to understand how users adopt and utilize technology, along with the factors that affect this adoption [18, 19, 21]. TAM proposes that two main factors influence technology acceptance: PEU and PU. PEU refers to the degree to which an individual believes a specific technology is easy to use and operates according to their requirements. PU refers to the degree to which an individual believes that the technology will be beneficial in enhancing their performance [18, 19, 21]. This model also includes A, which is influenced by PEU and PU. These attitudes, in turn, influence users' BI to use the technology. BI indicates the likelihood that the technology has been accepted or will be well-utilized by users [9, 19, 22]. Therefore, PEU and PU are essential factors that shape user attitudes toward technology, subsequently affecting their intentions to use the technology [9, 18, 19, 23].

In this research, TAM is employed to investigate student acceptance of VL technology for laboratory learning in EMC. PEU denotes the degree to which students believe the VL used in laboratory learning is easy to use and operate during the learning process. PU signifies the extent to which students believe VL technology will be beneficial and enhance their performance in EMC laboratory learning. A represents students' overall attitudes toward VL technology use, shaped by their perceptions of its ease of use and usefulness. This research focuses on measuring engineering students' BI, specifically their intention to use VL technology. By utilizing the TAM framework, this study aims to identify and analyze factors such as PEU, PU, and A influencing students' BI to use VL technology in engineering education.

B. Information Technology Experience

Information Technology Experience (ITE) refers to a person's experience in using various information and communication technologies [24, 25]. This factor is considered important in technology acceptance studies because previous experience with technology can influence an individual's perception of the ease of use and benefits derived from a technology [25, 26]. Broader and deeper experience with information technology generally increases user confidence and facilitates adaptation to new systems, thereby reducing resistance and increasing technology acceptance [26–30]. In this research, the TAM framework is strengthened and enriched by adding additional external factors, namely ITE. ITE encompasses student experience using software, simulation tools, and digital learning platforms relevant to the VL technology used in EMC. Students with extensive experience using information technology tend to have more positive Perceptions of Ease of Use (PEU) and benefits (PU) of VL. They are more likely to feel comfortable and confident in using the VL, which ultimately enhances their attitudes and intentions to use the VL [26, 28, 31].

C. Perceived Relevance

Perceived Relevance (PR) is a factor that indicates the extent to which users feel that a technology or system meets their specific needs, tasks, and context [32–34]. Previous studies show that PR is a significant factor in technology acceptance [32–35]. When users perceive a system as relevant to their tasks, it enhances their perception of the ease of use and the perceived benefits of the technology, thereby supporting their work [32, 34, 35]. In this research, the TAM framework, which is used to reveal student acceptance of the VL technology, is further strengthened by adding another external factor, namely PR. PR refers to the extent to which industrial electrical engineering students feel that the VL utilization for laboratory learning is relevant to their learning in the EMC.

D. The Virtual Laboratory for Laboratory Learning in Electrical Machine Course

A virtual laboratory is a digital platform that simulates a physical or hands-on laboratory environment, allowing users to perform experiments and practical exercises interactively via a computer or other device [3, 4, 20, 36]. This technology offers various benefits, including greater accessibility, lower costs, and the ability to perform complex, repeatable experiments without physical or material risks [1, 2, 27]. The VL has been applied in a variety of disciplines, including engineering, chemistry, biology, and physics, to improve the quality and effectiveness of laboratory learning [1, 2, 5, 27].

This research uses the PSIM application (PowerSIM) as a VL for laboratory learning in EMC. PSIM is simulation software specifically designed for the simulation and analysis of power electronic circuits and control systems [12, 37, 38].

This VL allows students to design, simulate, and analyze the characteristics of various types of electrical machines and power systems, providing in-depth practical experience in a safe and controlled environment [3, 39]. The display of the PSIM application as a VL for Laboratory learning in EMC is presented in Fig. 1. The use of this VL in learning enables students to test theories learned in class, deepen their understanding of the dynamics of electrical machines, and develop analytical skills that are important in the field of electrical engineering.

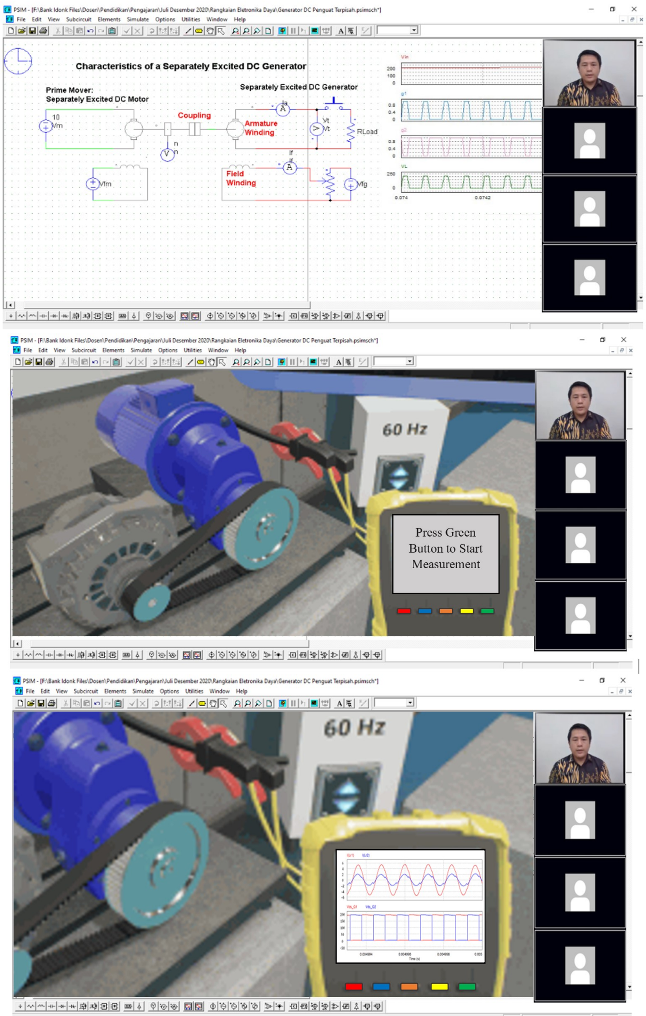

Fig. 1. The VL used for laboratory learning in EMC.

The PSIM as VL offers several significant advantages. First, it provides flexibility in terms of time and place, allowing students to carry out experiments anytime and anywhere without needing to be physically present in the hands-on laboratory. Second, This VL offers clear and interactive visualization of complex phenomena, which can improve the intuitive understanding of concepts. Third, this VL allows for unlimited repetition of experiments, which is crucial for strengthening students' understanding and practical skills. Additionally, the VL reduces the costs and risks associated with using expensive and sensitive physical equipment [12, 38, 40].

III. METHODS

A. Research Design

In line with the research objectives, this study utilized survey-based quantitative research [3, 16, 20]. Surveys represent a systematic research method employed to gather data and information, offering solutions to encountered problems in both descriptive and relational forms between variables while ensuring data accuracy and reliability [4, 20, 41]. The research variables include those within the TAM framework: PEU, PU, A, and BI. Additionally, TAM is enhanced with two external variables, ITE and PR, as illustrated in Fig. 2. VB-SEM is employed for data analysis. The analysis is conducted using the SmartPLS application, a form of VB-SEM, to assess model validity and reliability, and to analyze the effects of exogenous variables on endogenous variables such as direct, indirect, total, and simultaneous effects [41–43]. Consequently, this research aims to elucidate industrial electrical engineering students' acceptance of VL technology for laboratory learning in EMC.

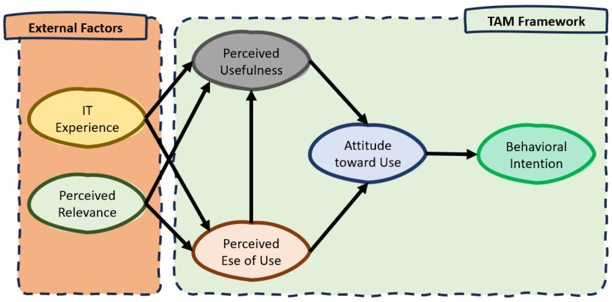

Fig. 2. The framework of student acceptance through a virtual laboratory for laboratory learning.

B. Research Instruments

This research uses a Likert scale-based questionnaire, with responses ranging from a minimum score of "1" for "Strongly Disagree" to a maximum score of "5" for "Strongly Agree", as the research instrument [4, 41, 44]. The indicators in the research instrument, presented in Table 1, were adapted from relevant literature sources identified through a comprehensive review. Likert scale questionnaires provide a standardized method for capturing respondents' perceptions on specific research topics, particularly in empirical survey-based studies [4, 20, 45, 46]. The collected data will contribute to enhancing understanding of the variables central to this research focus.

Table 1. Research instrument details

Variables	Indicators	Source
ITE	ITE.1. Experienced in using computers. ITE.2. Proficient in operating computer-based applications. ITE.3. Skilled in using simulator applications. ITE.4. Experienced in utilizing similar virtual laboratory technologies.	[25, 47, 48]
PR	PR.1. Using the VL directly related to the laboratory learning objectives at EMC. PR.2. Using the VL enhances the understanding of practical concepts in laboratory learning at EMC. PR.3. Using the VL helps bridge the gap between theory and practice in laboratory learning at EMC. PR.4. Using the VL provides practical experience relevant to real-world situations in laboratory learning at EMC.	[32, 34, 35]
PEU	PEU.1. The VL in laboratory learning at EMC is easy to learn. PEU.2. The VL in laboratory learning at EMC is easy to understand.	[16, 19, 20]

	PEU.3. The VL in laboratory learning at EMC is easy to use. PEU.4. The VL in laboratory learning at EMC is easy to access. PEU.5. The VL in laboratory learning at EMC is easy to apply to the practical process.	
PU	PU.1. Using the VL in laboratory learning at EMC helps save time. PU.2. Using the VL in laboratory learning at EMC has helped me become independent. PU.3. Using the VL in laboratory learning at EMC has improved my knowledge. PU.4. Using the VL in laboratory learning at EMC has improved my performance. PU.5. Using the VL in laboratory learning at EMC has helped me achieve laboratory learning objectives. PU.6. Using the VL in laboratory learning at EMC streamlines the laboratory learning process.	[18, 19, 41]
A	A.1. The VL used in laboratory learning at EMC is enjoyable for students. A.2. The performance of the VL used in laboratory learning at EMC meets the students' expectations. A.3. Students enthusiastic about using the VL in laboratory learning at EMC. A.4. The VL used laboratory learning at EMC makes learning interesting for students.	[3, 18, 20]
BI	BI.1. Students regularly use the VL in laboratory learning at EMC. BI.2. The VL is necessary for students to support laboratory learning at EMC. BI.3. Students believe that the VL used in laboratory learning at EMC supports the learning objectives achievement. BI.4. Students strongly intend to use the VL in laboratory learning at EMC	[16, 17, 19]

C. Research Participant

This study involved 141 second-year Industrial Electrical Engineering students at the Faculty of Engineering, Universitas Negeri Padang as research respondents, because that is the total population under study. They participated in the laboratory learning process on EMC, utilizing a virtual laboratory.

D. Analysis Technique

The research data were analyzed using VB-SEM or PLS-SEM analysis [41–43]. The SmartPLS application facilitated VB-SEM analysis, allowing for empirical examination of VL technology acceptance from engineering students in laboratory learning, as well as exploration of factors influencing this acceptance [41, 42]. Before the main analysis, the validity and reliability of research variables and indicators were assessed using VB-SEM analysis [4, 42]. Additionally, descriptive analysis was employed to offer insights into how students of industrial electrical engineering perceive and accept the use of VL technology in EMC [4, 5, 31]. This analytical approach contributes to a comprehensive understanding of the research focus and aids in interpreting the study's findings.

IV. Results

This research investigates student acceptance of VL technology for laboratory learning in EMC, as indicated by the students' BI level based on the TAM framework. Additionally, this study examines the factors influencing student intentions through VB-SEM analysis. Specifically, the research analyzes the direct effects between (1) ITE and PR on PEU and PU; (2) PEU on PU; (3) PEU and PU on A; and (4) A on BI.

Furthermore, the study explores the indirect effects between (1) ITE and PR on PU through PEU as an intervening variable; (2) ITE and PR on A through PU as an intervening variable; (3) PEU on A through PU as a mediating or intervening variable; and (4) PU on BI through A as a mediating variable. The research also includes an analysis of the simultaneous effects between (1) ITE and PR on PEU and PU; and (2) the simultaneous influence of PEU and PU on A. The preliminary research model, shown in Fig. 3, illustrates the conceptual framework used in this study. Reflective indicators, which act as representations or manifestations of variables, are employed in this research. Specific indicators for each variable are detailed in Table 1.

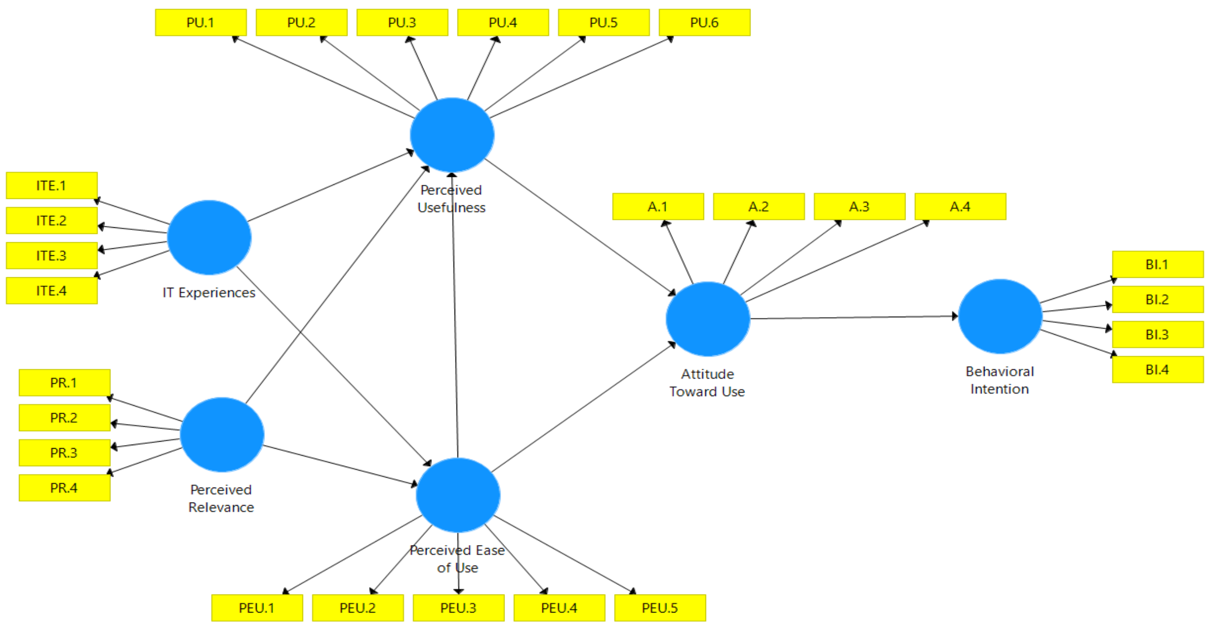

Fig. 3. Preliminary model.

The preliminary research model presented in Fig. 3 was first validated to ensure it met the assumptions and requirements of VB-SEM analysis [3, 42]. This evaluation included all variables (inner model) and indicators (outer model) within the model. The purpose was to confirm the absence of multicollinearity issues and adherence to Goodness of Fit (GoF) criteria, which are essential for analysis [3, 43]. The absence of multicollinearity among indicators in a model is indicated by a Variance Inflation Factor (VIF) below 5 (VIF < 5) [41–43]. The outer VIF analysis results, shown in Table 2, indicate that the VIF of all indicators is less than 5. This demonstrates that there are no multicollinearity issues among the indicators in the initial research model used in this study.

Multicollinearity testing was also performed among the variables in the model (inner model). Ensuring there are no multicollinearity issues among the research variables is crucial. An examination of the inner VIF values in Table 3 shows that all VIF values between the research variables are less than 5. This indicates no multicollinearity issues among the research variables in this model.

The next prerequisite test verifies that the research model meets the GoF criteria, as demonstrated in Table 4. The GoF analysis results indicate that the Standardized Root Mean Square Residual (SRMR) value is below 0.08, the Normed Fit Index (NFI) is above 0.9, and the Root Mean Square Theta (RMS Theta) is under 0.102 [41–43]. These results demonstrate that the research model satisfies the GoF criteria. After confirming that the assumptions and analytical requirements of the research model are met, the main analysis using VB-SEM can proceed. Fig. 4 displays the results of the VB-SEM analysis conducted with SmartPLS on the final research model for this study.

Table 2. The outer VIF analysis

Indicators	VIF
ITE.1	1.021
ITE.2	1.011
ITE.3	1.211
ITE.4	1.144
PR.1	1.522
PR.2	1.122
PR.3	1.004
PR.4	1.122
PEU.1	2.421
PEU.2	1.113
PEU.3	1.422
PEU.4	1.842
PEU.5	1.912
PU.1	1.322
PU.2	1.111
PU.3	1.010
PU.4	1.561
PU.5	1.004
PU.6	1.121
A.1	1.321
A.2	1.855
A.3	1.553
A.4	1.342
BI.1	1.578
BI.1	1.883
BI.1	1.643
BI.1	1.321

Table 3. The inner VIF values analysis

	PEU	PU	A	BI
ITE	1.411	1.611	-	-
PR	1.512	1.719	-	-
PEU	-	1.552	1.251	-
PU	-	-	1.285	
A	-	-	-	1.243

Table 4. The goodness of fit analysis

	Rms theta	NFI	SRMR
Sat. Model	0,088	1,184	0,061
Esti. Model	0,093	1,189	0,066

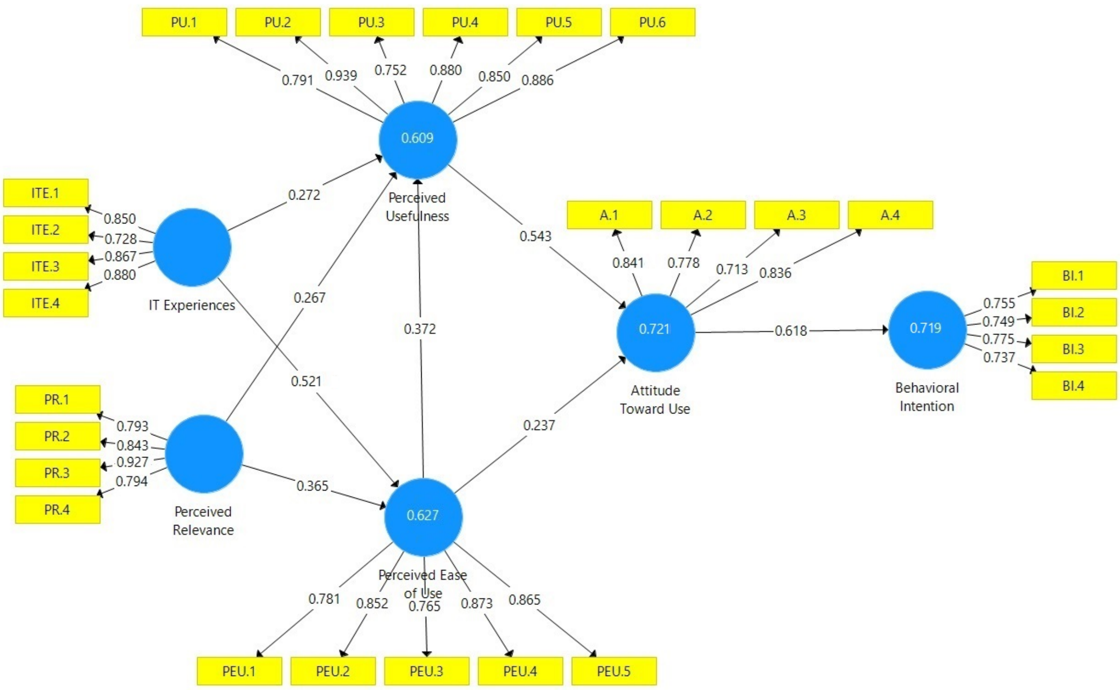

Fig. 4. The VB-SEM analysis using SmartPLS.

A. *Outer Model*

Outer Model analysis in VB-SEM includes testing the indicators in the research model by evaluating several values, including Average Variance Extracted (AVE), Composite

Reliability (CR), Cronbach's Alpha (CA), and rho_A. This analysis, or indicator measurement, assesses Internal Consistency Reliability (ICR), Model Unidimensionality (UM), and Convergent Validity (CV). ICR measures the reliability of indicators for their respective variables, indicating the level of an indicator's ability to measure its corresponding variable, as shown by the CA value [42, 43]. Table 5 displays the CA for all variables, all of which are higher than 0.7. Thus, it means that all indicators for each tested variable are considered reliable.

UM is tested to ensure there are no measurement problems or issues [41, 42]. Table 5 shows that all variables meet the unidimensional requirements, as the CR value exceeds 0.7 and CA exceeds 0.7. Meanwhile, CV is analyzed to ensure that indicators measuring the same variable have a high level of consistency [41, 43]. The analysis results indicate that all variables are valid and meet the CV criteria. This is evidenced by the AVE for each tested variable, as presented in Table 5, which is higher than 0.50.

Table 5. Outer model analysis

	AVE	CR	rho_A	CA
ITE	0.671	0.824	0.799	0.813
PR	0.666	0.851	0.823	0.977
PEU	0.733	0.877	0.8552	0.963
PU	0.692	0.863	0.753	0.826
A	0.788	0.817	0.788	0.853
BI	0.677	0.964	0.892	0.922

B. Inner Model

This analysis tests the relationships between variables and reveals the effects of exogenous variables on endogenous variables in the research model, including direct influence, indirect influence through intervening variables, total influence, and simultaneous influence [41–43]. The direct effect between exogenous and endogenous variables in this research model is represented by the path coefficient value, which ranges from −1 to +1. A value near +1 signifies a stronger and more positive impact of exogenous variables on endogenous variables, whereas a value close to -1 indicates a weaker and negative effect [41, 42].

Table 6. Inner model analysis for direct effect

No.	Path	Path coefficient	P-value
1	ITE → PEU	0.521	0.000
2	ITE → PU	0.272	0.001
3	PR → PEU	0.365	0.000
4	PR → PU	0.267	0.002
5	PEU → PU	0.372	0.000
6	PEU → A	0.237	0.002
7	PU → A	0.543	0.000
8	A → BI	0.618	0.000

Based on Table 6, the following direct influences were observed: (1) ITE has a positive direct influence on PEU with a path coefficient value of 0.521. This indicates that an increase in ITE by one unit causes an increase in PEU by 52.1%; (2) ITE has a positive direct influence on PU with a value of 0.272; (3) PR has a positive direct influence on PEU with a value of 0.365; (4) PR has a positive direct influence on PU with a value of 0.267; (5) PEU has a positive direct influence on PU with a value of 0.372; (6) PEU has a positive direct influence on A with a value of 0.237; (7) PU has a positive direct influence on A with a value of 0.543; and (8) A has a positive direct influence on BI with a value of 0.618. All direct effects in this research model are proven to be statistically significant. This is indicated by the p-value of all direct effects in this research model, which is lower than the significance level of 0.05.

Indirect influence is part of the inner model analysis using VB-SEM, which functions to determine how an exogenous variable influences an endogenous variable indirectly by utilizing an intervening variable [41–43]. Table 7 shows that: (1) ITE has a positive indirect influence on PU through PEU as a mediating variable, with a coefficient value of 0.194. This indicates that an increase in ITE by one unit causes an indirect increase in PU by 19.4% through PEU mediation; (2) ITE has a positive indirect influence on A through PU as a mediating variable, with a coefficient value of 0.148; (3) PR has a positive indirect influence on PU through PEU as a mediating variable, with a coefficient value of 0.136; (4) PR has a positive indirect influence on A through PU as a mediating variable, with a coefficient value of 0.145; (5) PEU has a positive indirect effect on A through PU, with a coefficient value of 0.202; (6) PEU has a positive indirect impact on BI through A as a mediating variable, with a coefficient value of 0.147 (7) PU has a positive indirect impact on BI through A as a mediating variable, with a coefficient value of 0.336. All indirect influences through the intervening variables in this study were proven to be statistically significant. This is indicated by the p-values of all indirect effects being lower than the significance level of 0.05.

Table 7. Inner model analysis for indirect effect

No.	Path	Path coefficient	P-value
1	ITE → PEU → PU	0.194	0.003
2	ITE → PU → A	0.148	0.004
3	PR → PEU → PU	0.136	0.004
4	PR → PU → A	0.145	0.004
5	PEU → PU → A	0.202	0.002
6	PEU → A → BI	0.147	0.004
7	PU → A → BI	0.336	0.000

Additionally, the total effect can be examined and computed to assess the overall impact, encompassing both direct and indirect effects [42, 43]. Table 8 shows that: (1) The total impact of ITE on PU is 0.466, meaning an increase in ITE by one unit can result in an overall increase in PU by 46.6%; (2) The total impact of PR on PU is 0.403, indicating that PR influences PU by 40.3%; (3) The total effects of PEU on A is 0.439, meaning an increase in PEU by one-unit results in an overall increase in A by 43.9 %. These total influences are statistically significant, as all p-values for the influences are below the significance level of 0.05.

Table 8. Inner model analysis for total effect

No.	Path	Path coefficient	P-value
1	ITE → PU	0.466	0.000
2	PR → PU	0.403	0.000
3	PEU → A	0.439	0.000

In VB-SEM, the simultaneous influence is also explored through the R-squared value (R^2) and the Adjusted R-squared value (Adj. R^2). When assessing the R^2 value, specific criteria are applied. An R^2 value of ≥ 0.67 is considered a strong effect, whereas a value ranging from 0.33 to < 0.67 is deemed moderate. If the R^2 value is < 0.33, then the effect is considered weak [41–43]. Analysis results show that the simultaneous influence of variables (ITE and PR) on PEU is 62.7%, as indicated by the R^2 value of 0.627. This means that ITE and PR have a positive simultaneous influence on increasing PEU. Other simultaneous influences include (1) The simultaneous influence of ITE, PR, and PEU on PU, which is 0.609; (2) The simultaneous influence of ITE, PR, PEU, and PU on A, which is 0.721; (3) The simultaneous influence of ITE, PR, PEU, PU, and A on BI, which is 0.719. These values show a positive influence with relatively high numbers. The simultaneous impact of multiple variables in this research was statistically significant, as the *p*-value was below the established significance level.

C. Student Acceptance of a Virtual Laboratory in Laboratory Learning

This research specifically examines student acceptance of the use of VL technology in EMC, measured through the level of student BI based on the TAM framework. The research results show that students have a high intention to use the VL in their learning activities. Four indicators were used to measure students' BI regarding the VL technology, and overall, they obtained high average scores.

The first indicator, BI.1, reveals that students routinely use the VL technology in their learning. The average score for this indicator is 4.90, indicating a high level of use. This shows that students feel comfortable and accustomed to using the VL as part of their learning routine. The second indicator, BI.2, indicates that students need VL technology for their learning activities. The average score for this indicator is 4.81, which is also in the very high category. These findings suggest that VL is considered important and relevant for students' learning needs, allowing them to do experiments and learn electrical machine concepts practically. The third indicator, BI.3, shows that students believe that VL technology supports them in achieving the expected learning goals. The average score for this indicator is 4.77, which is still in the very high category. Students feel they can understand the learning material clearly through experimental experiences using the VL which is used to strengthen experimental experiences in hands-on laboratory for laboratory learning. Finally, indicator BI.4 reveals that students have a strong intention to continue using VL in their learning process in the future. The average score for this indicator was 4.75, indicating that students see long-term value in using this technology in their education.

Overall, the results of this study confirm that student acceptance of VL is very positive. The high scores on each indicator of behavioral intention show that students not only accept this technology but also recognize the practical benefits and relevance of the VL in supporting their learning process in electrical machinery courses. These findings are important for the further development of educational technology, suggesting that the VL integration can enhance student's learning experiences and facilitate a deeper understanding of course material.

V. Discussion

Research findings indicate that industrial electrical engineering students are highly accepting of using the VL for laboratory learning in EMC. The high average values of the BI indicators suggest that students not only routinely use the VL (BI.1), but also consider it essential for their laboratory learning activities (BI.2). Furthermore, they believe that the VL supports and helps them achieve the expected learning objectives (BI.3) and demonstrate a strong intention to continue using the VL for the laboratory learning process in the EMC (BI.4). These results confirm that PSIM, as an implemented VL, has succeeded in meeting students' needs and expectations, reflected in their positive attitudes and strong intentions to integrate this technology into their learning. This high acceptance shows the potential of PSIM as a VL to become an effective and sustainable learning tool, enhancing hands-on laboratory experiences for electrical engineering students, particularly in EMC.

The study results highlight the important role of ITE and PR in influencing student acceptance of VL technology for laboratory learning. Findings indicate that students with greater ITE tend to have more positive PEU and PU of VL technology. These perceptions, in turn, influence their attitudes toward the technology and their intentions to use it. Additionally, students who perceive the VL as relevant to their learning needs demonstrate higher levels of acceptance, indicating that PR plays a critical role in increasing the PU and PEU of VL technology. This research confirms that both ITE and PR are important factors that must be considered in the design and implementation of learning technology to ensure the successful adoption and optimization of the student learning experience.

This research also highlights how the TAM framework, reinforced with ITE and PR, is used to reveal student acceptance of VL technology and analyze the factors influencing this acceptance. The direct effect of PEU on PU and A is proven to be significant and positive. This demonstrates that PEU not only influences PU but also affects students' attitudes towards the VL. Furthermore, PU had the strongest direct influence on A, confirming that when students find the VL useful, they develop more positive attitudes toward their use. The simultaneous influence of these variables also shows significant and positive results. ITE and PR together have a significant and positive influence on PEU in the medium category, as well as the simultaneous influence on PU and A, which also have a significant and positive effect in the medium category from several exogenous variables. Finally, the factors tested (ITE, PR, PEU, PU, and A) simultaneously have a significant and positive effect on BI in the strong influence category. These findings confirm the complexity of interactions between variables in the extended TAM model, providing deeper insight into the factors influencing technology acceptance in the context of electrical engineering education.

This research found that industrial electrical engineering students showed high acceptance of the use of the VL for laboratory learning in EMC, as measured through the BI indicator. These findings align with previous research, which also observed that students' high acceptance of virtual learning technology, as indicated by BI, was significantly impacted by their perceptions of the technology's usefulness and ease of use [4, 9, 20, 45]. However, this study extends these findings by including ITE and PR variables as additional factors that significantly influence the acceptance of VL technology within the TAM framework. Other studies using TAM have found that PEU and PU are the main predictors of technology acceptance in a learning process [9, 20, 43]. The results of these previous studies are consistent with the findings of this study, where PEU and PU were proven to significantly influence A and BI. However, this research makes a new contribution by showing that ITE directly influences PEU and PU, reinforcing the finding that broader technology experience can increase the acceptance of VL technology, especially in Engineering Education.

In addition, other previous studies introduced TAM extensions by including factors such as user experience and social support [3, 9, 32, 43, 49]. The results of this research support this concept by showing that ITE and PR not only have a direct influence on PEU and PU but also an indirect influence on A and BI through intervening variables. Previous research also found that users with broader technology experience exhibited more positive attitudes and stronger intentions to use new technology [4, 29, 30, 49]. This aligns with the findings of this research, which reveal that ITE has a positive and significant effect on PEU and PU, which in turn influences A and BI. These findings emphasize the importance of technological experience in increasing the acceptance and adaptation of new technologies in the context of engineering education. This research also reveals that PR plays an important role in the acceptance of VL technology. These results align with prior studies, which demonstrate that PR is a strong predictor of technology acceptance [32–35]. In this research, students who felt that the VL was relevant to their learning in the EMC exhibited a positive attitude and a strong intention to use this technology. This suggests that increasing the PR of technology can enhance its acceptance and use in electrical engineering education.

In this research, a significant contribution is made to understanding the factors that influence engineering students' acceptance of VL technology in the field of electrical engineering education. The research results confirm that ITE and PR paired with the TAM framework play a crucial role in analyzing student acceptance of the utilization of VL technology and the factors that influence this acceptance. Several previous studies support this finding [29–35]. Analysis using VB-SEM also reveals complex relationships between the variables involved, highlighting direct and indirect influences through intervening variables such as PEU, PU, and A. The practical implication is that factors such as ITE, PR, PEU, PU, and A should be taken into account when selecting and determining the type of VL technology for laboratory learning in electrical engineering education. This approach aims to enhance the effectiveness of VL technology in improving the quality of engineering education and preparing students for the demands of a progressively digital industry.

VI. Conclusion

This research successfully investigated student acceptance of the utilization of VL technology for laboratory learning in EMC using the TAM framework. Through VB-SEM analysis, it reveals that the ITE and PR factors significantly influence PEU and PU, which in turn affect students' A and BI towards the utilization of VL technology. The analysis results show that industrial electrical engineering students have a high intention to use PSIM as an implemented VL for laboratory learning in EMC, with all BI indicators showing very high average scores. These findings indicate that VL Technology is well-received by students, considered relevant and useful in supporting learning objectives, and routinely adopted in their learning activities. This research provides strong evidence that the integration of the VL, which is expected to improve the quality of practical learning in EMC, support theoretical understanding through practical application, and strengthen students' analytical skills, can be accepted and effectively used by students.

The practical implications of these findings underscore that the implementation of Virtual Laboratory (VL) technology can effectively address the limitations of physical laboratories. VL enables students to independently conduct experimental simulations and accelerate their mastery of concepts without the constraints of time and space. Educators can leverage VL to enhance teaching methods and perform more comprehensive evaluations. Additionally, educational institutions should invest in digital infrastructure to improve resource efficiency and competitiveness. An analysis of student acceptance is also crucial before selecting VL technology to ensure its alignment with learning needs and effectiveness in achieving educational objectives.

Although this research has revealed important findings regarding student acceptance of the VL in EMC, several limitations need to be considered. First, this research only involved industrial electrical engineering students from one educational institution. To generalize the findings, it is necessary to include a larger population from diverse educational institutions. Second, this research strengthens the TAM framework by focusing on two external variables, namely PR and ITE, leaving room for further research on other external variables, such as self-efficacy, perceived support, or subjective norm, which might influence student acceptance of VL technology in laboratory learning in engineering education. Longitudinal research could provide deeper insight into how student acceptance of virtual laboratories develops over time and under different learning conditions. By expanding the research focus and analysis methods, future studies could provide a more comprehensive and in-depth understanding of technology adoption in higher education, as well as practical recommendations for more effective implementation.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization: D.T.P.Y., G., S., and J.P.Y.; Methodology: D.T.P.Y., G., S., H.H., and M.K.; Validation: G., S., H.Z., and J.P.Y.; Formal Analysis: D.T.P.Y., G., and M.K.; Original Draft Preparation: D.T.P.Y, G., S., and H.Z.; Writing Review and Editing: S., H.Z. and J.P.Y. All authors had approved the final version.

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