

PAPER

The Affecting Factors of Students' Attitudes Toward the Use of a Virtual Laboratory: A Study in Industrial Electrical Engineering

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ABSTRACT

Virtual laboratory (VL) has become increasingly popular in Post-COVID-19 to support practical learning in the remote learning system. The use of VL was responded to by students with different attitudes. This study discusses the factors that influence the perception of Industrial Electrical Engineering (IEE) students in responding to the use of the VL in the learning process of the Electrical Machines Practicum Course. Based on the technology acceptance model (TAM), students' attitudes toward using VL (are influenced by perceived ease of use (PEU) and perceived usefulness (PU). At the same time, PU also acts as an intervening variable. The research involved IEE students of the Electrical Engineering Department, at Universitas Negeri Padang. Data collection was carried out by survey using a questionnaire. Quantitative data were analyzed using variant-based structural equation modelling (SEM), with partial least square (PLS) or PLS-SEM. The results showed a significant positive effect between PEU and PU from the VL used against A. PU's role as an intervener was also positive in mediating the effect of PEU on A so it became more prominent. Thus, it can be concluded that PEU and PU are the factors that must be considered in choosing VL to be applied to a practical learning process in the remote learning system.

KEYWORDS

virtual laboratory (VL), students' attitudes toward use (A), perceived ease of use (PEU), perceived usefulness (PU), IEE Students

1 INTRODUCTION

The COVID-19 pandemic, which emerged at the end of 2019, has accelerated changes in the implementation of learning. With restrictions on activities, communication, and direct interaction during the learning process, the choice of implementing distance learning by using internet-based communication technology was the only option so that the implementation of learning could still occur. Remote learning

Putra Yanto, D.T., Ganefri, Hastuti, Candra, O., Kabatiah, M., Andrian, Zaswita, H. (2023). The Affecting Factors of Students' Attitudes Toward the Use of a Virtual Laboratory: A Study in Industrial Electrical Engineering. *International Journal of Online and Biomedical Engineering (iJOE)*, 19(13), pp. 4–16. <https://doi.org/10.3991/ijoe.v19i13.41219>

Article submitted 2023-05-08. Revision uploaded 2023-07-18. Final acceptance 2023-07-18.

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by utilizing internet-based communication technology has experienced a significant increase, followed by the emergence of learning applications that can support the implementation of remote learning in both cases and practice [1] [2]. In the practical or experimental learning process in engineering education, the learning process that was previously carried out in a hands-on laboratory must be carried out remotely by utilizing internet-based communication technology [2–4]. This change that is happening so fast certainly requires innovations to optimize the implementation of learning, such as innovations in methods, models, strategies, and learning media. Thus, remote learning can still be effectively implemented to achieve optimal learning outcomes even though the learning is not carried out in a hands-on laboratory [5] [6].

The changes in how to implement learning at the beginning of the COVID-19 pandemic also occurred in engineering education. Engineering education with practical learning certainly also requires innovations that can optimize the learning process, especially practical learning. Innovations have been made to ensure that the implementation of practical learning that is carried out remotely remains optimal, just like in a hands-on laboratory [6] [7]. Innovations in practicum learning media have emerged during the COVID-19 pandemic, such as animations, videos, and the use of a virtual laboratory (VL), which is more complete and represents a hands-on laboratory [8–10].

The VL is one of the practical learning media that has begun to be widely used and has experienced a significant increase in its use in the learning process after the COVID-19 pandemic. Practical learning based on VL is increasingly in demand to support the implementation of remote learning using Internet-based communication technology [4] [6] [10]. Learning that is carried out in a hands-on laboratory is then carried out remotely using VL technology. This implementation of practical learning can be done anytime and anywhere. The VL is a laboratory where the computer-operated application is used to observe or carry out practical and experimental activities that are designed to have the same form and function as a hands-on laboratory [10] [11]. In other words, a VL is a representation of a hands-on laboratory, so it is hoped that the experience of students carrying out practical and experimental learning will remain the same as learning in a hands-on laboratory. Some research results indicate that the VL is effectively used as a medium for practical learning in the practicum learning process for students of vocational, engineering, science, and nursing education [8–10]. In addition, the VL can also help optimize the implementation of practicum learning even though it is carried out remotely and not in a hands-on laboratory, which is indicated by achieving optimal learning objectives.

During the post-COVID-19 period, the learning process and activities were gradually carried out face-to-face through a 50–50 policy where the learning process was blended between face-to-face and online learning. The VL is still used as a medium for practical learning in combination with hands-on laboratory work [10] [12] [13]. Several studies have shown that the application of VL in the practical learning process makes an important contribution to achieving learning objectives and learning outcomes in remote learning and blended learning that combines hands-on laboratory learning with remote learning using VL [9] [14]. However, students respond with different attitudes towards the type of VL that is applied in the learning process. The learning process certainly requires a good and positive attitude response from students towards the applied VL so that the learning process can take place optimally [9] [15]. Therefore, lecturers or educators need to know the factors that influence students' attitudes toward the use of VL in the learning process. Understanding these factors will assist lecturers in ensuring that the VL selected and used in the learning process is responded to with a good and positive attitude by students so that VL implementation can be optimal.

Based on the theory adopted from the technology acceptance model (TAM), student attitudes toward the use of VL in the learning process are defined as attitudes

towards use (A) [16]. A is influenced by two important factors, namely student perceptions of the perceived benefits of using VL, which are defined as perceived usefulness (PU), and student perceptions of the ease of use of VL, which are defined as perceived ease of use (PEU) [16] [17]. Other result studies also support that these two factors positively and significantly influence A [16] [18]. At the same time, PU also acts as an intervening variable that mediates the effect of PEU on A [16]. This study analyzes the factors affecting the attitudes of IEE students towards using VL in the practical learning process of the Electrical Machines Practicum Course (EMPC), which is held with remote learning systems. Specifically, this study analyzes and discusses: (1) the direct effect of PEU on PU; (2) PEU's direct influence on A; (3) PU's direct influence on A; (4) the indirect effect of PEU on A through PU as an intervening variable; and (5) the simultaneous effect of PEU and PU on A. The purpose of this study was to reveal the affecting factors of the attitudes of IEE students towards the use of VL in the learning process of EMPC in the electrical engineering department, faculty of engineering, Universitas Negeri Padang, during the post-COVID-19 period.

The benefit of this research is to generate information about the factors that influence students' attitudes toward the use of VL technology in the learning process. This study can serve as a valuable resource for lecturers and teaching staff in identifying and selecting the appropriate type of VL technology that aligns with the student's characteristics. Consequently, the implementation of VL-based practical learning can be optimized, enhancing the overall learning experience. In addition, the results of this study provide a foundation for further research to explore other factors that influence student attitudes toward using the VL and to enrich the literature on the use of technology in learning, thus providing a broader view of the factors that impact student attitudes toward technology in learning.

2 LITERATURE REVIEW

2.1 Industrial electrical engineering students

Industrial electrical engineering (IEE) students are students who engage in learning about the design, development, and application of electrical technology to solve problems in the industry [6] [19]. They generally study a wide variety of electrical engineering subjects, including the basics of electrical engineering, mathematics, physics, control systems, instrumentation, and measurement. They also learn about industrial technology such as automation, robotics, production systems, and industrial management [6] [20]. After graduation, IEE students have various career options, such as becoming control system engineers, industrial mechanical engineers, or working in other fields related to industrial electricity. In the era of Industry 4.0 and digitalization, the role of IEE students is increasingly important, as electrical technology has become an inseparable part of modern industrial systems. Therefore, IEE students are expected to become a workforce capable of facing challenges and innovating to create new solutions in the industry.

2.2 Virtual laboratory

A VL is a computer-based simulation of a physical laboratory environment or equipment that enables users to perform experiments and manipulate digital equipment in a virtual space [10] [11]. VLs provide a flexible, cost-effective, and secure alternative to traditional laboratory settings, especially in situations where access to

a physical laboratory is limited or restricted. Students and researchers can use VLS to learn and practice laboratory procedures, test hypotheses, and analyze data in a controlled, iterative environment [6] [10]. VLS are extensively used in various fields, including science, engineering, medicine, and education, and they are constantly advancing with the development of new technologies [8–10]. The VLS used in this study is the Power SIM (PSIM) application.

Power SIM is a software application used for simulation and design in the fields of electrical engineering and electronics. It is a user-friendly and powerful tool that allows for the simulation, analysis, and optimization of various electrical and electronic systems such as electric machines, motor drives, power electronics, rectifiers, inverters, power supplies, and other electrical field simulations [21] [22]. This application provides various analysis tools, including transient analysis, frequency analysis, and parameter sweep. It is widely used in industry and education, particularly in engineering education, for designing, testing, and analyzing electrical and electronic systems. Electrical engineers, researchers, and educators also prefer this software for its simplicity, accuracy, and versatility. Furthermore, this application can be integrated with other software, such as MATLAB or Simulink, for more sophisticated and comprehensive simulations [21] [23]. Figure 1 presents the display of the PSIM application when EMPC is used in this study.

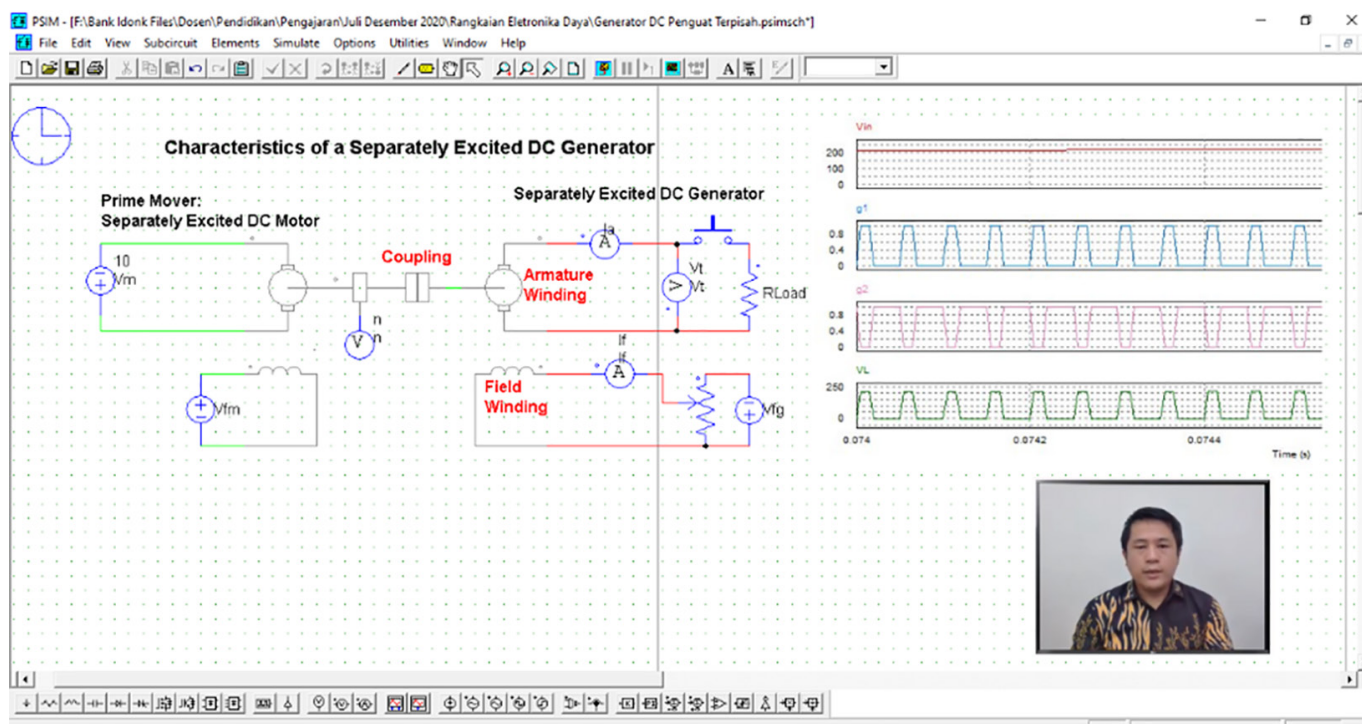


Fig. 1. The display of the PSIM application when EMPC is used

2.3 Attitudes toward the use of a virtual laboratory

Attitudes toward the use of a VLS refer to students' attitudes toward laboratory applications used in the learning process. It is important to consider students' attitudes toward VLS because they can influence the success of using them in the learning process and achieving learning objectives [16]. Based on the TAM, students' attitudes toward using VLS in the learning process (A) are influenced by two factors: PEU and

PU [16] [17]. Several studies have found that these two factors significantly and positively affect A. PU also acts as an intervening variable that mediates the effect of PEU on A [16] [18]. This study analyzes the factors that influence the attitudes toward the use of the VL by IEE students in the EMPC, which is held via remote learning systems.

3 METHODS

Non-experimental, explanatory, and descriptive research with a quantitative approach is the type of research applied in this study [24] [25]. Survey-based quantitative research has been applied to achieve research objectives [25] [26]. The research variables in this study include PU, PEU, and A. Partial least squares-structural equation modeling (PLS-SEM) was used to analyze the research data. PLS-SEM analysis was carried out using the Smart PLS application to determine the direct, indirect, total, and simultaneous effects of exogenous variables on endogenous variables.

3.1 Participants

Participants in this research were 118 IEE students who took part in the practical learning process of EMPC in the IEE study program, electrical engineering department, faculty of engineering, Universitas Negeri Padang, Indonesia. They are students who underwent the learning process for an electric machine practicum using a VL, specifically the PSIM application, through a remote learning system for one semester. The responses they provided through research instruments served as reference data for the data analysis conducted in this study.

3.2 Research instruments

The data collection instrument used in this research was a questionnaire using a Likert scale (1–5) with indicators obtained based on a literature review as presented in Table 1.

Table 1. Variables and indicators of research instrument

Variables	Theoretical Framework	Indicators
Perceived Ease of Use	[16]–[18]	PEU.1. The PSIM application used in EMPC is easy to use PEU.2. The PSIM application used in EMPC is easy to learn PEU.3. The PSIM application used in EMPC is easy to access PEU.4. The PSIM application used in EMPC is easy to understand PEU.5. The PSIM application used in EMPC is convenient
Perceived Usefulness	[16], [18]	PU.1. The PSIM application used in EMPC helps to save time PU.2. The PSIM application used in EMPC helps to save cost PU.3. The PSIM application used in EMPC helps me to be self-reliable PU.4. The PSIM application used in EMPC helps to improve my knowledge PU.5. The PSIM application used in EMPC helps to improve my performance PU.6. The PSIM application used in EMPC is effective PU.7. The PSIM application used in EMPC is efficient
Attitudes Toward Use	[16], [18], [27]	A.1. The PSIM application used in EMPC is enjoyable A.2. I am pleased enough with the PSIM application used in EMPC A.3. I am satisfied with the performance of the PSIM application used in EMPC A.4. The PSIM application used in EMPC is pleasant to me A.5. The PSIM application used in EMPC gives me self-confidence

4 RESULTS

4.1 Research model analysis

In this study, the factors that influence IEE students' attitudes toward the use of VL technology in the practical learning process are revealed and analyzed using PLS-SEM analysis. In detail, this study reveals the direct effect of PEU on PU, PEU on A, and PU on A. In addition, it also reveals the indirect effect of PEU on A through PU as an intervening variable and the simultaneous effect of PEU and PU on A. The initial research model based on the study of the literature is presented in Figure 2. This study uses reflective indicators, namely indicators that are embodiments or reflections of the variables. Table 1 shows detailed indicators for each variable studied.

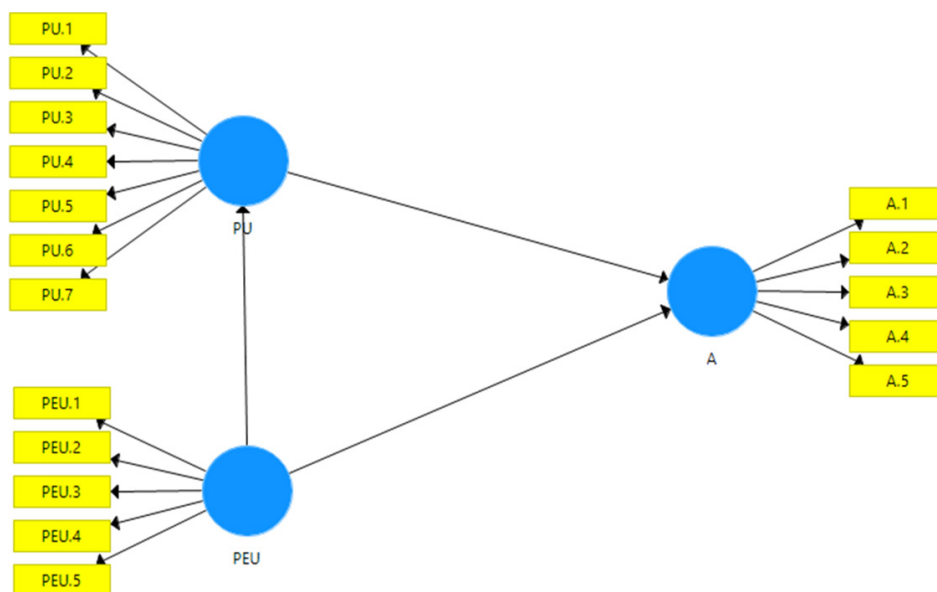


Fig. 2. Initial research model

The initial research model is then analyzed to ensure that it meets the assumptions and pre-requirements of the analysis. That is, each variable (inner model) and indicator (outer model) does not have a multicollinearity problem and meets the goodness of fit (GoF) criteria. The results of the outer VIF value analysis are presented in Table 2. The results of the outer VIF value analysis in Table 2 show that all VIF values for each indicator are below 5 ($VIF < 5$), so it can be seen that there are no multicollinearity problems for each indicator [24] [28].

Table 2. The outer VIF values analysis

Indicators	VIF	Indicators	VIF	Indicators	VIF
PEU.1	1.758	PU.1	2.332	A.1	2.388
PEU.2	2.117	PU.2	2.163	A.2	2.589
PEU.3	2.344	PU.3	2.457	A.3	1.789
PEU.4	3.417	PU.4	1.755	A.4	1.675
PEU.5	1.989	PU.5	2.765	A.5	2.430
		PU.6	3.234		
		PU.7	2.236		

The next step is to test multicollinearity for latent variables. As with indicator measurements, latent variables must also be ensured that they do not have multicollinearity between variables. Inner VIF value analysis results are presented in Table 3. It shows that all VIF values between latent variables are below 5 ($VIF < 5$), so it can be seen that there are no multicollinearity problems between latent variables [24] [28].

Table 3. The inner VIF values analysis

	PEU	PU	A
PEU	–	1.231	1.220
PU	–	–	1.294

The next analysis is the GoF analysis presented in Table 4 to ensure the research model meets the GoF criteria. The results of the GoF analysis show that when viewed from the standardized root mean square (SRMR) value which is less than 0.08 [24] [25], the NFI value is greater than 0.9 [24] [25], and the root mean square theta (RMS Theta) value is less than 0.102 [24] [25] the research model meets the GoF criteria. After the initial model meets the requirements, assumptions, and GoF criteria, further analysis can be carried out, such as analysis of indicators and analysis of research variables. The results of the PLS-SEM analysis are presented in Figure 3.

Table 4. The GoF analysis results

	SRMR < 0.08 [24], [28]	NFI > 0.9 [24], [25], [28]	RMS Theta < 0.102 [24], [25]	GoF
Saturated Model	0.057	0.993	0.079	Fit
Estimated Model	0.057	0.993	0.079	Fit

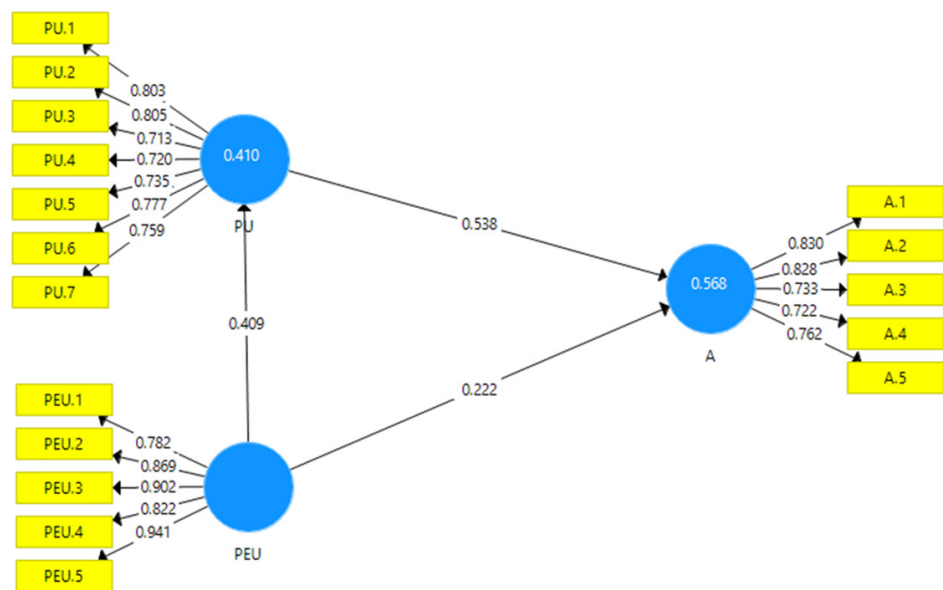


Fig. 3. PLS-SEM analysis of the final research model

4.2 Indicator analysis

The indicator analysis in PLS-SEM is called the outer model analysis. The analysis of the indicators includes convergence validity, construct reliability, AVE, discriminant validity, cross-loading, and the unidimensionality of the model. The ability of the indicators to measure their variables is called internal consistency reliability, which can be seen from the value of Cronbach's Alpha. Table 5 shows that Cronbach's Alpha value for each tested variable is > 0.6. So, all tested variables are declared reliable [24] [25]. Unidimensionality tests are also needed to ensure that there are no problems with measurement. Based on Table 5, all constructs fulfill the unidimensional requirements because the composite reliability value is greater than 0.7. All variables tested have also been declared valid and meet the convergent validity criteria [25] [28]. This is because the AVE value for each variable is greater than 0.50, as presented in Table 5.

Table 5. The results of outer model analysis results

	Cronbach's Alpha (> 0.7)	Rho_A (> 0.7)	Composite Reliability (> 0.7)	AVE (> 0.5)	Internal Consistency Reliability	Unidimensionality of the Model	Convergent Validity
PU	0.838	0.848	0.816	0.673	Reliable	Reliable	Valid
PEU	0.804	0.815	0.886	0.722	Reliable	Reliable	Valid
A	0.777	0.725	0.816	0.528	Reliable	Reliable	Valid

4.3 Variable analysis

Variable analysis in PLS-SEM is known as inner model analysis. The inner model analysis is an analysis conducted to determine the relationship between variables and reveal direct effects (path coefficient), indirect effects, total effects, and simultaneous effects of exogenous variables on endogenous variables. The results of the inner model analysis are presented in Table 6.

Table 6. The results of inner model analysis

	PU			A			R Square	R Square Adjusted
	Path Coefficients	Indirect Effects	Total Effect	Path Coefficients	Indirect Effects	Total Effect		
PEU	0.409	–	0.409	0.222	0.381	0.603	0.568	0.564
PU	–	–	–	0.538	–	0.538		
P-Value	0.001	0.003	0.011	0.001	0.000	0.008	0.000	0.002

Direct effects analysis is based on the direct influence of an exogenous variable on endogenous variables. In PLS-SEM analysis, this direct effect value is indicated by the path coefficient value, which ranges from –1 to +1. The value that gets closer to +1 means that the relationship between the two variables is getting stronger and more positive. Whereas a value close to –1 indicates a weak and negative relationship [24] [25] [28]. The results of the inner model analysis in Table 6 show that: (1) The direct effect of PEU on PU is 0.409, which means that if PEU increases by one unit, PU can also increase by 40.9% (positive influence). The influence given is also expressed

as significant because the P-value is less than 0.05 (P-value < 0.05) [24] [28]; (2) The direct effect of PEU on A is 0.222, which means that if PEU increases by one unit, A can also increase by 22.2% (positive influence). The influence exerted by PEU on A is also significant because the P-value is less than 0.05 (P-value < 0.05) [24] [25]; and (3) The direct effect of PU on A is 0.538, which means that if PU increases by one unit, A can also increase by 53.8% (positive influence). The influence exerted by PEU on A is also significant because the P-value is less than 0.05 (p-Value < 0.05) [24] [25].

Indirect effects analysis is based on the indirect influence of an exogenous variable on endogenous variables through an intermediary variable called an intervening variable. The results of the inner model analysis in Table 6 show that the indirect effect of PEU on A through PU as the intervening variable is 0.381, which means that if PEU increases by one unit, A can increase indirectly by 38.1% through PU as the intervening variable (influence positive). The indirect effect exerted by PEU on A is also significant because the P-value is less than 0.05 (P-value < 0.05) [24] [25]. Total effects analysis is an analysis of the total effect or overall effect, which is the result of the sum of the direct and indirect effects. The direct effect of the exogenous variables is then summed up with the indirect effects of the intervening variables on the endogenous variables. In this study, an analysis of the total effect of PEU on A was carried out. Based on the results of the inner model analysis in Table 6, it can be seen that the total effect of PEU on A is 0.603. If PEU increases by one unit, A in total can increase by 74.2% (positive effect). The total influence exerted by PEU on A is also significant because the P-value is less than 0.05 (P-value < 0.05) [24] [25].

The criterion for the R square value is if the value is ≥ 0.67 (strong category), $0.33 \leq R \text{ square} < 0.67$ (medium category), or ≥ 0.19 (weak category) [24] [25]. Whereas the adjusted R square value is used as a reference in assessing the ability of the variables (PEU and PU) to influence variable A. Table 6 shows that the R square value of the joint effect of PU and PEU on A is 0.568, with an adjusted R square value of 0.564. Thus, it can be explained that all exogenous constructs (PEU and PU) simultaneously affect A by 0.564, or 56.4% (moderate category). The joint influence exerted by PEU and PU on A is also significant because the P-value is less than 0.05 (P-value < 0.05) [24] [25].

5 DISCUSSION

The analysis of the effect of PEU on PU revealed a significant and positive direct effect of PEU on PU from IEE students. The amount of influence given is 40.9% (moderate category). When PEU increases by one unit, PU will also experience an increase as a result of the effect of an increase in PEU of 40.9%. This finding aligns with previous studies that also show the positive and significant influence of the ease of use of technology on individuals' perceptions of its usefulness in facilitating their daily activities [8] [11] [15]. Moreover, other studies have also yielded similar outcomes, highlighting the impact of PEU on PU of technology adoption in educational environments [16] [18] [27]. The convergence of findings across studies enhances the robustness and generalizability of the observed association between PEU and PU. These results further substantiate the notion that enhancing the user-friendliness of VL technology can heighten its perceived usefulness among students.

The analysis results also indicated a positive and significant influence of PEU on A from IEE students. The total influence given is 60.3% (medium category), comprising direct effects (22.2%) and indirect effects mediated by PU as an intervening variable (38.1%). These findings are consistent with previous studies that have also

observed a significant and positive impact of PEU on A in the context of technology adoption within educational environments [9] [16]. Moreover, similar results have been reported in studies examining the relationship between PEU and A across different fields, further emphasizing the positive influence of PEU on A [9] [10] [16]. The role of PU as an intervening variable, mediating the effect of PEU on A, is particularly noteworthy. PU plays a crucial role in mediating the effect of PEU on A, increasing from 22.2% to 38.1%. This finding aligns with previous research that has identified PU as an important mediator between PEU and A [8] [11] [15]. Collectively, these findings provide robust evidence supporting the significant influence of PEU on A among IEE students. Additionally, they underscore the important role of PU as an intermediary variable in shaping students' attitudes. Understanding this relationship can aid educators and practitioners in designing interventions that enhance PEU and, subsequently, improve students' attitudes toward the use of the VL in the learning process.

Additionally, another factor that influences variable A is PU. The analysis results revealed a significant and positive direct effect between PU and A among IEE students, which amounts to 53.8% (medium category). This implies that a one-unit increase in PU results in a corresponding 53.8% increase in A. When the application of the VL can assist and facilitate students in comprehending learning materials effectively, it enhances their attitude toward the use of the VL. These findings are consistent with previous studies conducted in the context of technology acceptance in education, which also found a significant and positive influence between PU and A [3] [8] [10] [16]. Additionally, studies investigating technology acceptance in different environments have yielded consistent results with the findings of this study, emphasizing the positive impact of PU on A. The consistency of the findings strengthens the robustness and generalizability of the observed relationship between PU and A [3] [10] [16]. These results further support the notion that when university students perceive VL as useful for their learning experience, it positively influences their attitude toward its use. Understanding the significant influence of PU on A has practical implications for educators and practitioners. By focusing on enhancing the perceived usefulness of VL and aligning them with students' learning needs, educators can foster positive attitudes and engagement among students. This, in turn, may lead to more effective utilization of VL in the learning process and improved learning outcomes [10] [11] [29].

6 CONCLUSION

The application of VL in practical learning has become increasingly popular after the COVID-19 pandemic. The results of the research analysis show that two factors positively and significantly influence students' attitudes toward using the PSIM application as the VL, their perceptions of the ease of use of the VL applications and the benefits they can feel when using the VL. These two factors collectively exert both direct and indirect influence on students' attitudes towards the use of VL in the learning process. At the same time, students' perceptions of the benefits that can be felt from the use of the VL also play an excellent role as an intervening variable in mediating the influence exerted by students' perceptions of the ease of use on their attitudes towards the use of the VL in the EMPC. These factors can be considered when determining the type of VL that will be applied in a practicum learning process.

The study was conducted within a specific context, namely IEE students at EMPC, and therefore, the results cannot be generalized to other fields or contexts.

Additionally, this study only focused on one VL application, namely PSIM, and did not consider other virtual laboratories. Therefore, future research can investigate the factors that influence students' attitudes toward the use of the VL in other fields or disciplines to determine the generalizability of the findings. Furthermore, future research can compare different VL applications to identify their strengths and weaknesses in improving students' attitudes toward the use of the VL. This can provide insight into the most effective types of VLs and inform the development of more effective VL applications.

7 REFERENCES

- [1] S. M. Banjo-Ogunnowo and L. A. J. Chisholm, "Virtual versus traditional learning during COVID-19: Quantitative comparison of outcomes for two articulating ADN cohorts," *Teaching and Learning in Nursing*, vol. 17, no. 3, pp. 272–276, 2022. <https://doi.org/10.1016/j.teln.2022.02.002>
- [2] Y. P. Yuan, G. Wei-Han Tan, K. B. Ooi, and W. L. Lim, "Can COVID-19 pandemic influence experience response in mobile learning?" *Telematics and Informatics*, vol. 64, p. 101676, 2021. <https://doi.org/10.1016/j.tele.2021.101676>
- [3] D. T. P. Yanto, M. Kabatiah, H. Zaswita, N. Jalinus, and R. Refdinal, "Virtual laboratory as a new educational trend post COVID-19: An effectiveness study," *Mimbar Ilmu*, vol. 27, no. 3, 2022. <https://doi.org/10.23887/mi.v27i3.53996>
- [4] D. May, G. R. Alves, A. A. Kist, and S. M. Zvacek, "Online laboratories in engineering education research and practice," in *International Handbook of Engineering Education Research*, New York: Routledge, pp. 525–552, 2023. <https://doi.org/10.4324/9781003287483-29>
- [5] D. Menon, "Uses and gratifications of educational apps: A study during COVID-19 pandemic," *Computers and Education Open*, vol. 3, p. 100076, 2022. <https://doi.org/10.1016/j.caeo.2022.100076>
- [6] D. Karahoca, Z. F. Zaripova, A. R. Bayanova, L. S. Chikileva, S. V. Lyalyaev, and X. Baoyun, "During the COVID-19 pandemic, students' opinions on distance education in department of engineering," *International Journal of Engineering Pedagogy*, vol. 12, no. 2, pp. 4–19, 2022. <https://doi.org/10.3991/ijep.v12i2.29321>
- [7] M. V. Gomez, "Open higher education for refugees to access: Virtual learning in the COVID-19 pandemic," *International Journal of Instruction*, vol. 15, no. 2, pp. 715–736, 2022. <https://doi.org/10.29333/iji.2022.15239a>
- [8] M. Seifan, N. Robertson, and A. Berenjian, "Use of virtual learning to increase key laboratory skills and essential non-cognitive characteristics," *Education for Chemical Engineers*, vol. 33, pp. 66–75, 2020. <https://doi.org/10.1016/j.ece.2020.07.006>
- [9] J. Ramírez et al., "A virtual laboratory to support chemical reaction engineering courses using real-life problems and industrial software," *Education for Chemical Engineers*, vol. 33, pp. 36–44, 2020. <https://doi.org/10.1016/j.ece.2020.07.002>
- [10] C. Peechapol, "Investigating the effect of virtual laboratory simulation in chemistry on learning achievement, self-efficacy, and learning experience," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 20, pp. 196–207, 2021. <https://doi.org/10.3991/ijet.v16i20.23561>
- [11] A. Torres-Freyermuth, G. Medellín, G. U. Martín, and J. A. Puleo, "A virtual laboratory for conducting 'hands-on' experiments on water wave mechanics," *Cont Shelf Res*, vol. 243, p. 104760, 2022. <https://doi.org/10.1016/j.csr.2022.104760>
- [12] A. A. Del Savio, L. Z. Carrasco, E. C. Nakamatsu, K. G. Velarde, W. Martinez-Alonso, and M. Fischer, "Applying project-based learning (PBL) for teaching virtual design construction (VDC)," *International Journal of Engineering Pedagogy (ijEP)*, vol. 13, no. 2, pp. 64–85, 2023. <https://doi.org/10.3991/ijep.v13i2.35877>

- [13] A. Fensie, "A conceptual model for meeting the needs of adult learners in distance education and e-learning," *International Journal of Advanced Corporate Learning (IJAC)*, vol. 16, no. 2, pp. 37–56, 2023. <https://doi.org/10.3991/ijac.v16i2.35729>
- [14] H. Abuhassna, F. Awae, K. Bayoumi, D. U. Alzitari, A. H. Alsharif, and N. Yahaya, "Understanding online learning readiness among university students: A bibliometric analysis," *International Journal of Interactive Mobile Technologies*, vol. 16, no. 13, pp. 81–94, 2022. <https://doi.org/10.3991/ijim.v16i13.30605>
- [15] N. Shaheerani, A. K. Putra, D. Soelistijo, and B. Yembuu, "The development of mobile geography virtual laboratory for rock and soil practicum studies," *International Journal of Interactive Mobile Technologies*, vol. 16, no. 22, pp. 142–156, 2022. <https://doi.org/10.3991/ijim.v16i22.36163>
- [16] R. Estriegana, J. A. Medina-Merodio, and R. Barchino, "Student acceptance of virtual laboratory and practical work: An extension of the technology acceptance model," *Comput Educ*, vol. 135, pp. 1–14, 2019. <https://doi.org/10.1016/j.compedu.2019.02.010>
- [17] S. Acharya and M. Mekker, "Public acceptance of connected vehicles: An extension of the technology acceptance model," *Transp Res Part F Traffic Psychol Behav*, vol. 88, pp. 54–68, 2022. <https://doi.org/10.1016/j.trf.2022.05.002>
- [18] C. Antonietti, A. Cattaneo, and F. Amenduni, "Can teachers' digital competence influence technology acceptance in vocational education?" *Comput Human Behav*, vol. 132, p. 107266, 2022. <https://doi.org/10.1016/j.chb.2022.107266>
- [19] O. Candra, A. Putra, S. Islami, D. T. P. Yanto, R. Revina, and R. Yolanda, "Work willingness of VHS students at post-industrial placement," *TEM Journal*, vol. 12, no. 1, pp. 265–274, 2023. <https://doi.org/10.18421/TEM121-33>
- [20] D. Beneroso and J. Robinson, "Online project-based learning in engineering design: Supporting the acquisition of design skills," *Education for Chemical Engineers*, vol. 38, pp. 38–47, 2022. <https://doi.org/10.1016/j.ece.2021.09.002>
- [21] E. Garces, C. J. Franco, J. Tomei, and I. Dyner, "Sustainable electricity supply for small off-grid communities in Colombia: A system dynamics approach," *Energy Policy*, vol. 172, p. 113314, 2023. <https://doi.org/10.1016/j.enpol.2022.113314>
- [22] J. Morcillo, M. Castaneda, M. Jiménez, S. Zapata, I. Dyner, and A. J. Aristizabal, "Assessing the speed, extent, and impact of the diffusion of solar PV," *Energy Reports*, vol. 8, pp. 269–281, 2022. <https://doi.org/10.1016/j.egy.2022.06.099>
- [23] J. Arias-Gaviria, V. Valencia, Y. Olaya, and S. Arango-Aramburo, "Simulating the effect of sustainable buildings and energy efficiency standards on electricity consumption in four cities in Colombia: A system dynamics approach," *J Clean Prod.*, vol. 314, p. 128041, 2021. <https://doi.org/10.1016/j.jclepro.2021.128041>
- [24] G. Dash and J. Paul, "CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting," *Technol. Forecast Soc. Change*, vol. 173, p. 121092, 2021. <https://doi.org/10.1016/j.techfore.2021.121092>
- [25] X. Xie and X. Guo, "Influencing factors of virtual simulation experiment teaching effect based on SEM," *International Journal of Emerging Technologies in Learning*, vol. 17, no. 18, pp. 89–102, 2022. <https://doi.org/10.3991/ijet.v17i18.34489>
- [26] D. T. P. Yanto, Sukardi, M. Kabatiah, H. Zaswita, and O. Candra, "Analysis of factors affecting vocational students' intentions to use a virtual laboratory based on the technology acceptance model," *International Journal of Interactive Mobile Technologies*, vol. 17, no. 12, pp. 94–111, 2023. <https://doi.org/10.3991/ijim.v17i12.38627>
- [27] E. Attié and L. Meyer-Waarden, "The acceptance and usage of smart connected objects according to adoption stages: An enhanced technology acceptance model integrating the diffusion of innovation, uses and gratification and privacy calculus theories," *Technol. Forecast Soc. Change*, vol. 176, p. 121485, 2022. <https://doi.org/10.1016/j.techfore.2022.121485>

- [28] J. Hair and A. Alamer, "Partial least squares structural equation modeling (PLS-SEM) in second language and education research: Guidelines using an applied example," *Research Methods in Applied Linguistics*, vol. 1, no. 3, p. 100027, 2022. <https://doi.org/10.1016/j.rmal.2022.100027>
- [29] F. J. M. Veiga and A. M. V. de Andrade, "Critical success factors in accepting technology in the classroom," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 18, pp. 4–22, 2021. <https://doi.org/10.3991/ijet.v16i18.23159>

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