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Investigating the Impacts of A Simulation-Based Learning Model Using Simulation Virtual Laboratory on Engineering Students

Hanapi Hasan[1)], Ambiyar[2)], Rizky Ema Wulansari[3)], Hasan Maksum[4)*], Tansa Trisna Astono Putri[5)]
[1)]Mechanical Engineering Education Department of Universitas Negeri Medan, Indonesia,
[2,3)]Mechanical Engineering Department of Universitas Negeri Padang, Indonesia,
[4)]Automotive Engineering Department of Universitas Negeri Padang, Indonesia,
[5)]Information Technology and Computer Education Study Program of Universitas Negeri Medan, Indonesia
[1)]hanapi_hasan@unimed.ac.id, [2)]ambiyar@ft.unp.ac.id, [3)]rizkyema@ft.unp.ac.id, [4)]hasan@ft.unp.ac.id, [5)]tansatrisna@unimed.ac.id

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Abstract: Considering electrical engineering students at Universitas Negeri Medan as a case study, this research looks at how an SVL affected their grades. Integrating the TAM with the ABET Laboratory Learning Objectives, it provides a comprehensive framework for quality engineering and technology education. This research is the first of its kind to theoretically compare the two concepts in a VL context. This research examines the relationship between student performance in the classroom and the TAM's usability components as well as the ABET's learning objectives. The results from the surveys given to first-year Electrical Engineering students are analyzed using Structural Equation Modeling (SEM) and Partial Least Squares (PLS). Because it enhances student performance and satisfies their learning goals, the results demonstrate that utilizing simulation-based virtual laboratories (SVL) in engineering education offers substantial educational benefits.

Keywords: engineering students, impact, Simulated Virtual Laboratory (SVL), Technology Acceptance Model (TAM), structural equation modeling

INTRODUCTION

Students enrolled in engineering programs are expected to demonstrate proficiency in both the theoretical and practical aspects of the field. Practical knowledge is gained by the execution of experimental exercises in physical labs (PLs), as opposed to theoretical information, which may be taught through classroom learning activities. Direct manipulation of real-world equipment during PL experiments can help students enhance their practical talents (Lei et al., 2018). To keep equipment in working order and cut down on time and materials used, they are not allowed to go beyond the experimental limits, but (Ens et al, 2019) However, engineering courses are notoriously challenging to study online due to the heavy reliance on both theoretical lectures and hands-on programming activities.

Because it provides a digital setting for engineering students to practice practical skills, the simulation-based virtual laboratory (SVL) is a vital resource for education in this field (Kapilan, Vidhya & Gao, 2021). Academics have debated SVLs extensively, discussing their benefits and drawbacks (Verawati et al., 2024) and wondering if engineering students would be just as engaged with virtual labs (VLs) as they would be with real ones. Some teachers think that pupils learn best when they use real-

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world tools in their physical laboratories (PLs) (Riches et al., 2019)(Schwind et al., 2019). However, there is evidence that virtual laboratories (VLs) and remote labs (RLs) could impede educational progress, according to some researchers (Hockings et al., 2018)(Raman et al., 2022). Virtual laboratory could also help students to explore their skills in order to encourage them in entrepreneurship in the future. Entrepreneurs contribute significantly to economic growth and job creation. A generation ago, few people felt that institutions had anything in common with business (Hasan et al., 2024). Several studies, however, have shown that students' conceptual knowledge in VLs is either equivalent to or even better than in conventional physical labs (PLs). Because of this, VLs might be useful in enhancing the education that PLs provide, based on study by (Cruz, Saunders-Smits & Groen, 2020)(Afacan Adanır, Akmatbekova & Muhametjanova, 2022).

The ability of VLs to stand in for PLs has been demonstrated in several investigations (Achuthan et al., 2021)(Moosvi, Reinsberg & Rieger, 2019)(Wang & Tseng, 2018). While several studies have examined VLs, most have concentrated on their technical components, including instructional design, hardware/software architecture, and VL implementation (Faulconer and Gruss, 2018)(El-Sabagh, 2021)(Cheong, K. H. and Koh, J. M., 2018). Additionally, in comparison to traditional physical learning environments (PLs) (Alsaleh et al., 2022)(Grodotzki, Ortelt & Tekkaya, 2018) and remote learning environments (RLs) (Pang, Cui & Yang, 2022)(Aramburu Mayoz et al., 2021)(Lavayssière, Larroque & Luthon, 2022), several studies have compared virtual learning environments (VLs) to RLs. However, academics have not focused much on conducting empirical research to evaluate the efficacy of virtual learning environments (VLs) in the classroom. Specifically, very little research has been found in the literature that examines the adoption and acceptability of VLs using theoretical models of technological acceptance (Altalbe, 2019)(Estriegana et al., 2019).

The assumption that students will embrace and make good use of VLs has been made without enough scrutiny in previous research. Not taking into consideration the reality that students' attitudes toward these teaching tools, in addition to the technological aspects of VLs, impact their efficacy. Consequently, in order to empirically examine the impact of SVL in electrical engineering education and to acquire a deeper grasp of students' learning objectives, a thorough assessment is required.

The purpose of this research is to shed light on the theoretical and quantitative aspects of SVL's instructional design and how it impacts students' views of the tool's usefulness and ease of use, as well as the tool's ability to achieve its learning goals and improve engineering education outcomes.

This study suggests a theoretical model that integrates certain laboratory learning objectives from the Accreditation Board for Engineering and Technology (ABET) with the usability aspects of the technology acceptance model (TAM) (Mezhuyev et al., 2019). This study aims to examine the impact of a SVL environment on the academic achievement of Electrical Engineering students at Universitas Negeri Medan. Using VL as a framework, this study is the first of its kind to compare and contrast TAM and ABET's laboratory learning goals. This study aims to explore the effects of SVL technology on student performance by examining the causal links between TAM's usability features, ABET's laboratory learning objectives, and these factors. For the study to be successful, the model takes into account not only the needs and results of each participant, but also their learning goals. A thorough assessment of their mental health is required to achieve this goal (perceptions and needs). It looks into how productivity is affected by users' sense of self-fulfillment and how effectively the SVL fits their aims and desires. This inquiry is intended to answer the following questions:

1) Does implementing the ABET laboratory learning objectives improve performance outcomes?
2) How does the use of a virtual laboratory based on simulation affect students' academic performance?
3) What are the educational benefits of using simulation-based virtual laboratory technologies in the field of electrical engineering?

METHOD

The information we provided was analyzed using the variance-based structural equation modeling (SEM) technique for hypothesis assessment and the partial least squares (PLS) approach for model validation. Reason being, PLS does route analysis using the ordinary least squares method with multiple linear regressions, presupposes a multivariate normal distribution, and imposes minimal restrictions on

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little samples. Hence, the dependent variables' residual variance decreases (Chin et al., 2020)(Sarstedt, Ringle & Hair, 2021). That is why the PLS-SEM method is a great substitute for our inquiry.

Creating a survey

This study's quantitative methodology is in line with other relevant research on online education and technology adoption and use. The goals of the lab, the features of the students' usability, and the impact of SVL on their performance were to be measured in two phases of online questionnaires.

For each survey issue, participants used a 5-point Likert-type scale that went from "Strongly disagree (1)" to "Strongly agree (5)" to express their level of agreement or disagreement. Several parts were adjusted from earlier studies so they could work with the SVL platform that was being tested. To provide an example, we adapted the usability factors (PEOU and PU) from prior studies (Mezhuyev et al., 2019)(Estriegana, Medina-Merodio & Barchino, 2019) to fit the needs of SVL users. Previous research was used to modify the laboratory learning objectives (INSTR & IC) and IMPT items according to ABET's specified learning objectives (Altalbe, 2018).

Information Gathering

Universitas Negeri Medan's first-year electrical engineering students taking the Sensor and Transducer course are the subjects of this population-based and longitudinal cohort research. By tracking the shifts in students' perceptions of SVL across time, this study hopes to shed light on the development of the concept. As an auxiliary tool, the breadboard simulator is available to students in this class.

The research was carried out in a two-part fashion, with two distinct online surveys administered three months apart. It is common practice to conduct a post-deployment survey in the first half of the academic year. The purpose of this survey is to collect student opinions on the tool and their views on the usability criteria of perceived ease of use (PEOU) and perceived utility (PU).

In the latter weeks of the academic year, the second phase took place, and it was called the post-production implementation survey. At this point, we mainly wanted to see how the students felt about the breadboard simulator after three months of actual usage.

We collected data from online questionnaires that students took as part of our Sensor and Transducer course and used SVL. Twelvety students enrolled in the course were contacted by email with an invitation to participate in the SVL online survey at their own discretion. Eighty students regularly utilized SVL and participated in the inaugural poll, according to the platform's web usage data. Afterwards, the second stage survey was sent out and students were asked to take part again.

For the purpose of further data processing, 116 out of 120 survey replies were determined to be genuine and comprehensive. The results are relevant in a similar situation even if some individuals drop out of the research. As per the suggestion in reference (Wang & Ji, 2020) a sample size of 116 is considered sufficient for data analysis when the following conditions are met: a population size of 120, a sample percentage of 10%, a margin of error of 5%, and a confidence level of 95%. In terms of age, academic level, and major, the class's demographics were quite homogeneous. Furthermore, males made up the bulk of the student population. Therefore, the sample is really a reflection of the whole class.

RESULT

Utilizing the SmartPLS 3 tool, the structural model was computed, measured, and data processed. We used the PLS method for 300 iterations with 5000 bootstrap subsamples to make sure the parameters were stable. The 95% confidence intervals and 5% 2-tailed significance level were determined in accordance with references (Ramayah, 2018) and (Ali et al, 2018).

The parameter fits of the proposed structural model were evaluated using partial least squares (PLS). Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI) are two commonly used metrics in SmartPLS for assessing model fit. SRMR has a maximum threshold of 0.08 (Lopez-Fernandez et al., 2023) while NFI has a minimum threshold of 0.9 (Cho et al., 2020). With SRMR (0.065) and NFI (0.905) both above the fit indices' cutoffs, the results demonstrate a strong degree of concordance between the model and the fitness indices.

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Table 1. Descriptive Results of Questionnaire

Construct / Item	**Mean**	**Std**	**Loading**	**t-value**
Perceived Ease of Use (PEOU)	4,21			
PEOU1. I find SVL wonderful to use	4,22	0,63	0,789	15,7
PEOU2. I find SVL easy to use	4,17	0,65	0,813	17,5
PEOU3. My overall experience using SVL is satisfying	4,60	0,60	0,853	23,4
PEOU4. I find SVL flexible to use	3,90	0,62	0,910	38,5
PEOU5. I find the software's interface of SVL is user-friendly	4,18	0,80	0,873	35,2
Perceived Usefulness (PU)	4,20			
PU1. SVL assists me in acquiring the necessary skills to operate the equipment	4,50	0,85	0,875	25,8
PU2. SVL facilitates my comprehension of theoretical concepts and models.	4,30	0,80	0,903	35,1
PU3. SVL enables me to enhance my analytical and critical thinking skills.	4,00	0,88	0,825	18,9
PU4. SVL assists me in the development of my experimental design skills.	4,00	0,91	0,821	19,2
Instrumentation (INSTR)	4,18			
INSTR1. SVL makes me aware of what instruments should be used to measure a physical quality	4,20	0,88	0,922	53,8
INSTR2. SVL allows me to operate instruments and components with precision and efficiency.	4,15	0,92	0,938	69,8
INSTR3. SVL enables me to see the instrument structure and examine its different features	4,20	0,89	0,915	38,9
Creativity and Innovation (CI)	4,26			
CI1. SVL increases levels of independent thought and creativity	4,50	0,73	0,890	32,8
CI2. SVL helps solve real-world problems	4,30	0,73	0,852	28,3
CI3. SVL allows more time for creativity	4,10	0,75	0,855	29,9
CI4. SVL provides autonomy to deal with problems using innovative methods	4,15	0,75	0,855	32,3
Performance Impact (IMPT)	3,92			
IMPT1. Better understanding of lab equipments	4,30	0,77	0,897	33,8
IMPT2. SVL develops my ability to design experiments	4,20	0,80	0,862	24,8
IMPT3. SVL enables me to undersatnd and perform the experiment easily	3,75	0,92	0,781	18,9
IMPT4. SVL develops critical and creative thinking skills	3,62	0,89	0,801	18,9
IMPT5. Using SVL, I have learned how to use lab equipments effectively	3,72	0,88	0,802	24,9
IMPT6. SVL stresses the importance of working safely with equipments	3,90	0,85	0,780	16,8

Validity and reliability were the two metrics used to assess the measurement model. Obtaining Cronbach's alpha, composite reliability (CR), and outer loadings for each item is the initial step in testing the model's dependability. By using these metrics, we can examine the consistency and dependability of the model. Table 1 displays the descriptive statistics, statistical t-values, and factor loadings of the indicator items. Outside loadings for all indicator items are greater than the minimum requirement of 0.70, falling on the range of 0.774 to 0.943 (Tarka, 2018). For every construct, you can see the

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Cronbach's alpha and CR values in Table 2. There was no building with a coefficient alpha below the 0.70 cut-off value. The values varied from 0.882 to 0.915. Comparable to coefficient alpha is the concept of CR, which shows the degree of internal consistency among the items utilized to test a specific construct. With CR scores between 0.915 and 0.945 across all builds, we hit the target threshold of 0.70.

Table 2. Reliability and Convergence Test

Constructs	**Cronbach Alpha**	**CR**	**AVE**
PEOU	0,907	0,925	0,725
PU	0,882	0,915	0,729
INSTR	0,915	0,945	0,861
CI	0,882	0,927	0,742
IMPT	0,895	0,922	0,675

Consequently, the results of the three criterion assessments are very trustworthy. First, the average variance extracted (AVE) for each concept; second, composite reliability (CR); and third, the exterior loadings of separate questions were used to evaluate convergent validity (Tarka, 2018). Factor loadings for all items and CR values in all constructs were higher than the predetermined threshold of 0.70. Also, the AVE values (ranging from 0.675 to 0.861) were higher than the allowed limit of 0.5 (Tarka, 2018).

DISCUSSION

The results of this investigation offer important new information about the efficacy of simulation-based virtual labs (SVLs) in engineering education, especially in relation to electrical engineering. The findings imply that via strengthening students' practical skills, theoretical concept understanding, and critical thinking abilities, SVLs can significantly improve their learning experiences and outcomes.

According to the research, pupils had high levels of perceived utility (PU) and ease of use (PEOU). This is consistent with other studies (Mezhuyev et al., 2019)(Estriegana, Medina-Merodio & Barchino, 2019) that show how beneficial and intuitive well-designed virtual learning resources can be for students. The PU and PEOU concept mean scores were higher than 4, indicating that most students thought the SVL platform was helpful for their learning and simple to use. According to Esteriegana et al. (2019), adopting and successfully utilizing new instructional tools depend heavily on this favorable view.

The integration of SVLs with the Accreditation Board for Engineering and Technology's (ABET) laboratory learning goals is further validated by this study. The high mean ratings for the instrumentation (INSTR) and creativity and invention (CI) constructs indicate that students thought the SVL promoted creative thinking while assisting them in understanding and using lab instruments. This lends credence to the idea that SVLs can provide instructional value on par with or perhaps better than traditional physical labs (Cruz, Saunders-Smits & Groen, 2020) (Afacan Adanır, Akmatbekova & Muhametjanova, 2022).

Positive scores were also given to the performance impact (IMPT) construct, suggesting that students thought the SVL improved their overall academic performance. This conclusion aligns with previous research (Alsaleh et al., 2022)(Grodotzki, Ortelt & Tekkaya, 2018) that shown the potential of virtual laboratories to improve learning outcomes. These encouraging outcomes were probably influenced by SVLs' capacity to offer a flexible and secure learning environment that freed students from the limitations of traditional lab settings and allowed them to conduct experiments.

Future research should address the limitations of this study, although the encouraging results. Although the sample size is appropriate for this study, it might be increased to encompass a wider range of engineering fields and student populations. Long-term research may also shed further light on the long-term effects of SVLs on students' learning paths and preparedness for the workforce. To further improve the SVL experience, future studies should also investigate the integration of cutting-edge technology like artificial intelligence (AI) and augmented reality (AR).

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CONCLUSION

While numerous studies has concentrated on the technical features of virtual laboratories, the adoption of simulated virtual labs (SVLs) has received comparatively little attention. This study does, however, get over these restrictions and provides extensive information on the consequences of SVL technology use. The proposed model investigates the interconnections among IMPT use results, ABET lab learning objectives (INSTR & CI), and usability characteristics (PEOU & PU). By considering the users' psychological states and learning objectives, we hope to gain a better understanding of their usage results and individual requirements. The model also considers the extent to which SVL satisfies the needs of individual users and the impact of this self-fulfillment on the outcomes of their usage. An evaluation of SVL's (Simulated Virtual Learning) efficacy in the classroom found that it significantly improved students' electrical engineering coursework.

Despite CI's lesser impact on student achievement, the truth remains that INSTR and PU variables are the most significant indicators of IMPT. Lab learning goals also alter the known link between usability attributes and usage outcomes, according to this study. In conclusion, the results demonstrate that SVL experimentation may be a viable teaching activity to supplement conventional laboratory work and enhance student learning. The use of this SVL gadget enhances students' opportunities for hands-on learning, facilitates the completion of pre-laboratory fitness regimens, and supports their academic success.

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