Virtual Laboratory in Engineering Education: Investigating Its Impact on Students' Engagement and Learning Outcomes

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***Abstract*—Integrating Virtual Laboratory (VL) technology into engineering education is increasingly adopted to complement hands-on laboratory learning. However, comprehensive studies and empirical analyses are still required to understand its impact on students' Learning Engagement (LE) and Learning Outcomes (LO). This study investigates the effects of Virtual Laboratory Use (VLU) on students' LE and LO in an electrical machine course within the Industrial Electrical Engineering program, Faculty of Engineering, Universitas Negeri Padang, Indonesia. A quantitative, survey-based approach was employed, involving 117 second-year university students. Data were analyzed using Variance-Based Structural Equation Modeling (VB-SEM). The results indicated that the VLU had a positive and significant effect on students' LE across behavioral, cognitive, and emotional dimensions. Furthermore, VLU positively and significantly influenced students' perceived LO directly and indirectly through LE as a mediating variable. LO were simultaneously and significantly influenced by the variables of VLU, Cognitive Engagement (CE), Behavioral Engagement (BE), and Emotional Engagement (EE), with a strong effect size. These findings underscore the pedagogical value of the VL in enhancing the learning experience in engineering education.**

***Keywords*—quality education, virtual laboratory, learning engagement, learning outcomes, engineering education, electrical machine course**

I. Introduction

The digital revolution has brought fundamental changes to the implementation of learning in higher education, including engineering and vocational education [1, 2]. Digital-based learning technologies, such as Virtual Laboratory (VL), have emerged as strategic alternatives to address challenges related to limited access to physical equipment, time constraints, and safety risks in engineering practicum activities [2, 3]. VL facilitates interactive simulations replicating real-world experimental conditions, offering flexibility to explore technical concepts independently and repeatedly across time and space [4–6].

VL is particularly relevant as it provides practicum simulations that reflect real conditions of electrical systems without the risk of accidents or equipment damage, and it can be adapted to evolving technologies [7, 8]. These courses typically require a comprehensive understanding of the operating principles of motors, generators, transformers, control and protection systems, concepts that necessitate direct observation of current, voltage, torque, and machine efficiency [9, 10]. However, constraints such as limited equipment availability, restricted lab time, and high electrical hazard risks often hinder the implementation of hands-on laboratory practices [8, 11, 12]. The VL offers a solution by enabling students to conduct simulation-based experiments with unlimited repetitions, explore operational parameters flexibly, and receive immediate visual and numerical feedback [11, 13, 14]. As these technologies continue to advance, academic interest in their impact on learning processes and outcomes has grown, particularly in students' Learning Engagement (LE) and Learning Outcomes (LO) [15, 16].

LE plays a critical role as an indicator of the success of the learning process, as it reflects students' cognitive, emotional, and behavioral involvement in learning activities [16, 17]. High levels of LE are believed to enhance conceptual understanding, knowledge retention, and the ability to apply knowledge in practical contexts. In engineering education, which emphasizes theoretical knowledge and practical application, LE becomes even more essential in determining the effectiveness of technology-based approaches such as the VL [3, 17]. Therefore, a comprehensive understanding of the effect of Virtual Laboratory Use (VLU) on the various dimensions of LE and its implications for students' LO is necessary to inform effective pedagogical strategies.

Previous studies have highlighted the positive potential of VLU in enhancing students' motivation, self-efficacy, and LE [17–20]. However, a gap remains in the literature regarding the role of the LE as a mediating mechanism that bridges the relationship between VLU and LO. More specifically, there is a limited understanding of how the distinct dimensions of LE, such as behavioral, cognitive, and emotional, jointly function as mediators in this relationship. LO encompasses physical participation and cognitive involvement in problem-solving and emotional investment in the complex learning process [15, 21, 22]. Therefore, it is essential to investigate the role of the different dimensions of LE in explaining the impact of VLU on students' LO.

This study analyzes the effect of VLU on students' LE and LO in electrical machines courses within the context of engineering education. Furthermore, it investigates the mediating role of the three dimensions of LE in explaining the indirect effect of VLU on students' LO. Employing a Variance-Based Structural Equation Modeling (VB-SEM) approach, this study is expected to contribute empirically to the literature on educational technology in engineering education and offer practical insights for implementing and developing more effective and contextually relevant technology-based learning strategies. This study provides a novel contribution by integrating the three dimensions of LE as intervening variables within a structural model based on VB-SEM in engineering education, specifically in electrical machines courses. While prior research has predominantly focused on LO, often fragmented or limited to a single dimension of LE, this study adopts a holistic approach that synthesizes behavioral, cognitive, and emotional aspects of students' LE within a unified theoretical and empirical framework. By adopting a multidimensional approach to LE, this study addresses a critical gap and offers a more comprehensive understanding of how students interact with VL. This perspective captures the interrelated roles of BE, CE, and EE, all of which are essential for facilitating learning success, particularly in simulation-based, self-directed learning environments. The integrated model enables a more detailed analysis of the mechanisms through which VLU influences student LO, thereby enhancing both the theoretical framework and practical implications of the study.

II. Literature Review

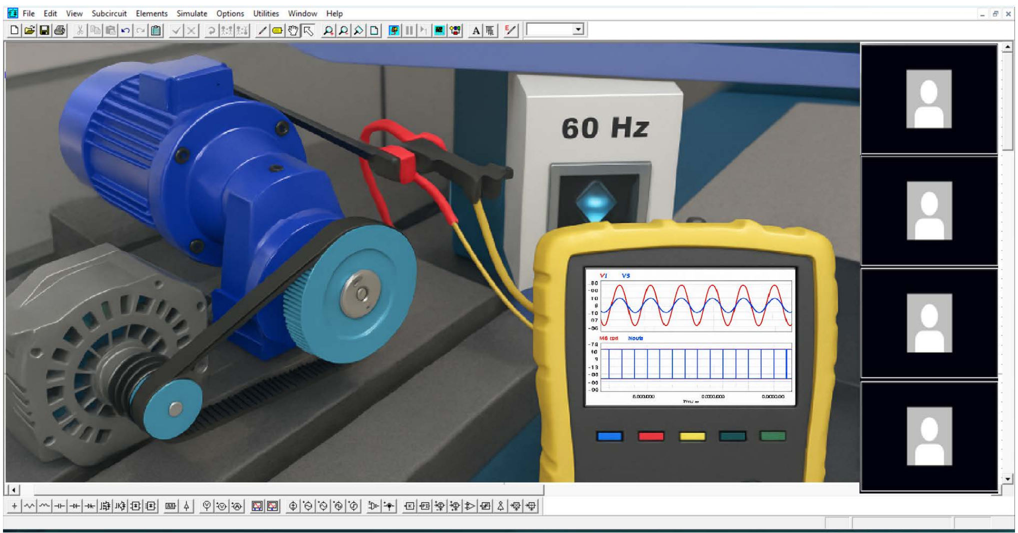
A. Pedagogical Foundation

The design and integration of VL in engineering education can be grounded in several pedagogical theories that offer a comprehensive understanding of how students engage with, process, and retain knowledge. First, Constructivist Theory (CT) posits that individuals actively construct knowledge through direct experience and engagement in learning activities. Learning is most effective when students participate in problem-solving, experimentation, and reflective practices. VL provides an interactive environment that enables exploration and simulation of engineering phenomena, aligning well with constructivist principles. Second, Cognitive Load Theory (CLT) emphasizes the role of instructional design in managing the cognitive demands placed on working memory. CLT differentiates among intrinsic, extraneous, and germane cognitive loads. In the context of the VL, tools such as PSIM offer dynamic visualizations of abstract engineering concepts and support gradual, iterative learning. This approach helps reduce extraneous load and enhance germane load, thereby facilitating deeper knowledge internalization. Third, Self-Determination Theory (SDT) underscores the significance of intrinsic motivation and the satisfaction of three basic psychological needs, competence, autonomy, and relatedness, in fostering LE and achievement. VL offers students opportunities for autonomous learning, confidence-building through experimentation (competence), and collaboration with peers (relatedness). In this study, SDT provides a conceptual framework for understanding LE as a multidimensional construct encompassing behavioral, cognitive, and emotional dimensions.

B. Virtual Laboratory

The VL is a technology-based learning platform that enables students to perform experiments or practical activities in a digital environment. VL offers a learning experience comparable to hands-on practice in a hands-on laboratory, but with greater flexibility in time and location [8, 23]. This technology allows students to conduct repeated experiments without the risk of damaging equipment or materials, while also addressing the resource constraints commonly encountered in hands-on laboratories [24–26]. In engineering education, VL provides opportunities for students to comprehend complex concepts through interactive visualizations and simulations, thereby deepening their understanding of engineering theories and real-world applications [11, 12, 27].

This study employs a PSIM (PowerSIM) as the VL application to support practical learning in the electrical machine course. PSIM is an advanced simulation software that digitally models and analyzes electrical systems and power devices [23, 24]. With PSIM, students can access a variety of simulations and models, including electric motors, transformers, and other power systems that typically require expensive hardware and time-intensive experimentation [8, 23]. This application enables students to visualize the performance of electrical systems in real time, enhancing their understanding of the fundamental principles and practical applications related to electrical machines [11, 23, 24]. The use of PSIM in this study aims to examine the effect of VL implementation on students' LE and LO, as well as to explore the potential of this technology to improve the effectiveness of instruction in industrial electrical engineering. The PSIM application utilized as a VL in this study is illustrated in Fig. 1.



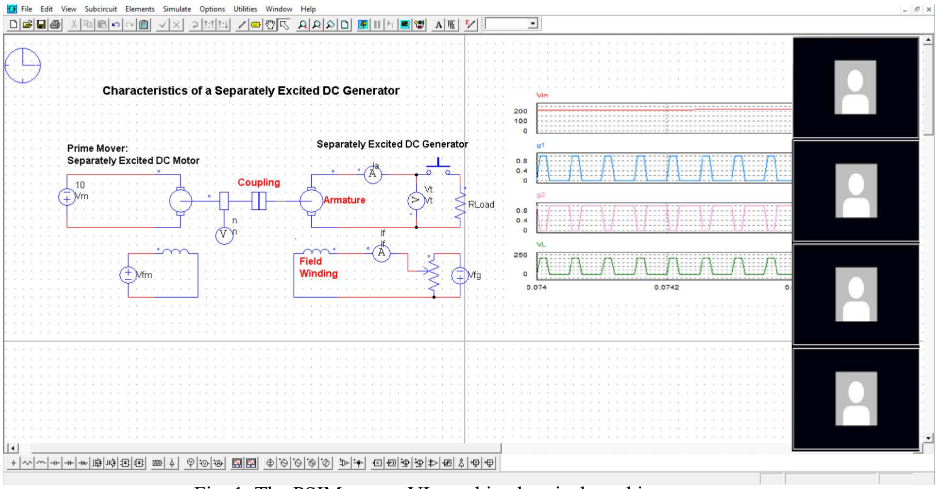


Fig. 1. The PSIM app as VL used in electrical machine course.

C. Learning Outcomes

LO describes the knowledge, skills, and attitudes students are expected to acquire upon completing the learning process [15, 23, 28]. In this study, LO is operationalized as students' perceived LO, which refers to their perceptions of the achievements gained after engaging in learning activities involving the VL [21, 29]. This concept emphasizes the extent to which students feel they have attained conceptual understanding, enhanced technical skills, and strengthened positive attitudes toward the subject matter, particularly in electrical machines courses. Perceived LO encompasses objectively measurable results and subjective dimensions derived from students' learning experiences [15, 21, 29]. These include the degree to which students feel supported by technology in understanding the material, completing practical assignments, and connecting theoretical knowledge to real-world applications [15, 23, 30]. In this study, students' perceived LO serves as a key indicator for evaluating the effectiveness of VLU and examining how LE, comprising behavioral, cognitive, and emotional dimensions, contributes to shaping students' perceptions of their learning success.

While perceived LO differs from objective LO, that are typically assessed through standardized tests or performance evaluations, it offers valuable insights into the cognitive and affective dimensions of learning that are not easily quantifiable. By capturing students' self-assessed progress, confidence, and engagement, perceived LO provides a critical lens into the effectiveness of learning technologies such as VL. Moreover, in educational settings where students' motivation, autonomy, and emotional responses play a central role in shaping learning behaviors, perceived LO can serve as a valid and meaningful proxy of learning effectiveness. For future research, a combined approach integrating both perceived and objective measures could offer a more comprehensive understanding of how the VL influences learning.

D. Learning Engagement

LE is a critical indicator that reflects the extent to which students are actively involved in the learning process, physically, cognitively, and emotionally [16, 31]. In this study, LE refers to the degree of students' participation and involvement during practical learning in the electrical machines course through the VL technology. Such involvement is crucial, as higher levels of LE are associated with more profound understanding and improved LO.

The BE dimension encompasses students' participation in observable learning activities, including attendance in practical sessions, active use of the VL, and completion of assigned tasks [16, 31, 32]. CE refers to students' mental investment in processing information and comprehending the learning content. In VL, this is demonstrated by how students utilize VL, such as PSIM, to explore technical concepts in depth, manipulate experimental variables, and analyze results to solve engineering problems [17, 32]. Meanwhile, EE involves students' feelings and motivation toward the learning process. In the PSIM usage, EE is reflected in students' interest, motivation, and satisfaction with the virtual experiments conducted [16, 31, 33]. The VLU is expected to enhance EE by offering a more interactive and stimulating learning experience. Students emotionally connected to the learning material are generally more motivated to participate in practicum activities and report greater satisfaction with their learning experience.

III. Methods

A. Research Design

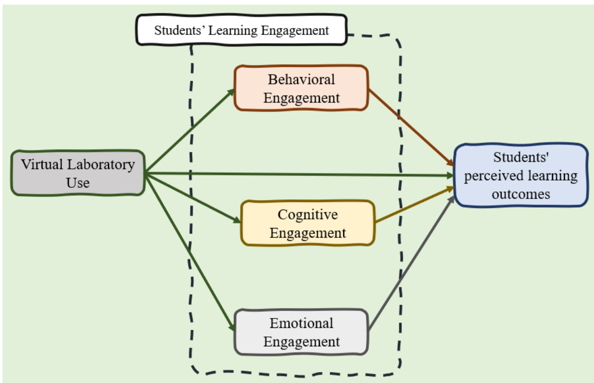


Fig. 2. The research framework.

Following the research objectives, a quantitative survey-based approach was employed in this study [7, 34]. The survey method was selected as a systematic means of collecting data to obtain relevant information and formulate solutions to the research problem, both descriptively and in terms of revealing relationships between variables [34, 35].

This approach also aimed to ensure the accuracy and reliability of the collected data. Moreover, this approach is relevant for examining the complex mediation model employed in this study, as it allows for the standardized collection of data from a large number of respondents.

The use of VB-SEM via SmartPLS offers advantages in handling models with numerous latent constructs, relatively small sample sizes, and no strict requirement for normally distributed data. Therefore, the combination of a survey approach and VB-SEM is considered appropriate and efficient for testing both direct and indirect relationships within the framework of this study. The variables analyzed in this study include VLU, BE, CE, EE, and LO, as illustrated in the conceptual framework presented in Fig. 2. The data were analyzed using VB-SEM. For this purpose, the SmartPLS software was utilized, a widely used tool in VB-SEM. This approach enables researchers to assess the validity and reliability of the model, as well as to analyze both the direct and indirect effects of exogenous variables on endogenous variables. In this way, the study empirically evaluates the impact of VLU on students' LE and LO in the practicum of the electrical machines course.

B. Research Instruments

The instrument used in this study was a questionnaire employing a five-point Likert scale (1–5) [34, 36, 37]. The indicators included in the instrument, as presented in Table 1, were developed through adaptations from various relevant literature sources identified via a comprehensive literature review. These indicators were contextually adapted and customized to suit the specific objectives of this study, aiming to capture students' unique experiences in using PSIM software within the context of electrical machinery courses. The Likert scale provides a standardized method for capturing respondents' perceptions of the studied phenomena, particularly in survey-based research aimed at conducting empirical analysis [31, 36]. The data collected through this instrument are expected to enhance understanding of the key variables investigated in this study.

Table 1. Research instrument details

Contructs	Indicators	Source
VLU	VLU.1. The VL is regularly integrated into learning activities. VLU.2. The VL is utilized to support the completion of practical assignments. VLU.3. Access to the VL is carried out independently based on individual learning needs. VLU.4. VLU.4: Simulations provided in the VL accurately represent real-world practical activities. VLU.5. The VL is used to review and reinforce practical learning materials. VLU.6. The VL usage enhances students' understanding of practical concepts.	[1, 11, 35, 38]
BE	BE.1. Participates in practical activities consistently and with discipline. BE.2. Actively engages in discussions and group work during practical sessions. BE.3. Completes practical assignments following the given schedule and instructions. BE.4. Seeks additional learning resources to support practical activities. BE.5. Performs practical procedures following established guidelines.	[16, 17, 31, 32]
CE	CE.1. Demonstrates understanding of relevant theoretical concepts before conducting the practicum. CE.2. Establishes connections between theoretical concepts and the practicum implementation. CE.3. Analyzes practicum results to deepen conceptual understanding. CE.4. Evaluates errors encountered during the practicum as part of the learning process.	[3, 16, 17]
EE	EE.1. Feels enthusiastic when participating in practicum activities. EE.2. Feels satisfied after completing practicum activities. EE.3. Feels motivated to learn after using the VL. EE.4. EE.4: Feels comfortable using the VL while engaging in practicum activities. EE.5. EE.5: Feels proud of the results achieved in the practicum activities.	[3, 16, 17, 31]
LO	LO.1. Demonstrates a solid understanding of the electrical machines' working principles. LO.2. Applies learned concepts effectively in practical learning. LO.3. Shows improved technical skills in conducting practicum activities. LO.4. Analyzes and evaluates experimental results logically and critically. LO.5. Exhibits responsibility and teamwork during practicum activities. LO.6. Demonstrates increased readiness to face challenges in the professional engineering field.	[15, 18, 30, 32]

The research instrument was initially piloted with 30 students outside the primary research participants to ensure its validity and reliability before full implementation. Validity was assessed using Pearson's Product-Moment Correlation [39–41], while reliability was evaluated through Cronbach's Alpha [40, 42]. Before these tests, a content validity assessment was conducted, involving eight experts who reviewed each item in the instrument and provided feedback regarding the relevance, clarity, and completeness of the questionnaire items. The expert evaluations and subsequent revisions confirmed that the instrument met the criteria for content validity.

Based on the post-pilot validity analysis, all item correlation coefficients (r-calculated) exceeded the critical r-value (0.619 > 0.3610), with significance levels below 0.05, indicating that all items were statistically valid [39, 40]. Additionally, the reliability test yielded a Cronbach's Alpha of 0.785, surpassing the acceptable threshold of 0.60 (0.785 > 0.600), thus confirming the instrument's reliability [42, 43]. These findings affirm the research instrument's validity and reliability, supporting its appropriateness for use in this study.

C. Research Participant

A purposive sampling technique was employed, involving all second-year students (117) enrolled in the electrical machine course, from the Industrial Electrical Engineering Study Program, Faculty of Engineering, Universitas Negeri Padang, Indonesia, as respondents. The students participated in learning activities using a VL. After completing the learning process, they were asked to fill out a research questionnaire based on their learning experiences during the activity.

D. Analysis Technique

The data obtained in this study were analyzed using the

VB-SEM approach, also known as Partial Least Squares Structural Equation Modeling (PLS-SEM). The analysis was conducted using SmartPLS software. This analytical technique was selected based on several methodological considerations. First, VB-SEM offers greater flexibility regarding data distribution assumptions. Second, VB-SEM is particularly well-suited for testing exploratory conceptual models. Third, this approach supports robust predictive analysis. Additionally, VB-SEM is more accommodating of smaller sample sizes, making it a practical choice for this research context.

Before conducting the primary structural analysis, the validity and reliability of all research constructs and their associated indicators were assessed within the VB-SEM framework [36, 44]. The analysis was then carried out in two key stages: the outer model analysis and the inner model analysis [36, 44]. The outer model analysis aimed to evaluate the quality of the measurement model by examining several critical parameters, including Internal Consistency Reliability (ICR), Unidimensionality Model (UM) to ensure that each construct is measured by indicators that represent a single concept, Convergent Validity (CV) to confirm that indicators strongly reflect the underlying construct, and Discriminant Validity (DV) to ensure that each construct is conceptually different from the others [35, 36, 44].

The inner model analysis was conducted to examine the structural relationships among latent variables. This analysis focused on identifying the direct, indirect (mediated), total, and simultaneous effects of exogenous variables on endogenous variables [24, 44]. Through this approach, the study aimed to comprehensively explain the mechanisms by which VLU influences students' LE and LO in engineering education.

IV. Results

This study investigates the influence of VL technology on students' LE and LO within the context of engineering education, specifically in the electrical machines course. Furthermore, the study explores the mediating role of LE, which includes BE, CE, and EE, in explaining the indirect relationship between VLU and LO. Specifically, the study examines the direct effects of VLU on BE, CE, EE, and LO. Additionally, the direct impacts of BE, CE, and EE on LO were analyzed to understand how different dimensions of LE contribute to students' perceived learning success. Moreover, the study evaluates the indirect effects of VLU on LO through BE, CE, and EE as intervening variables. The simultaneous impacts of VLU, BE, CE, and EE on LO were also assessed. To provide a more comprehensive understanding. The initial conceptual model of this study, which visually represents the research framework, is illustrated in Fig. 3 All constructs in the model are measured using reflective indicators, the detailed list of which is provided in Table 1.

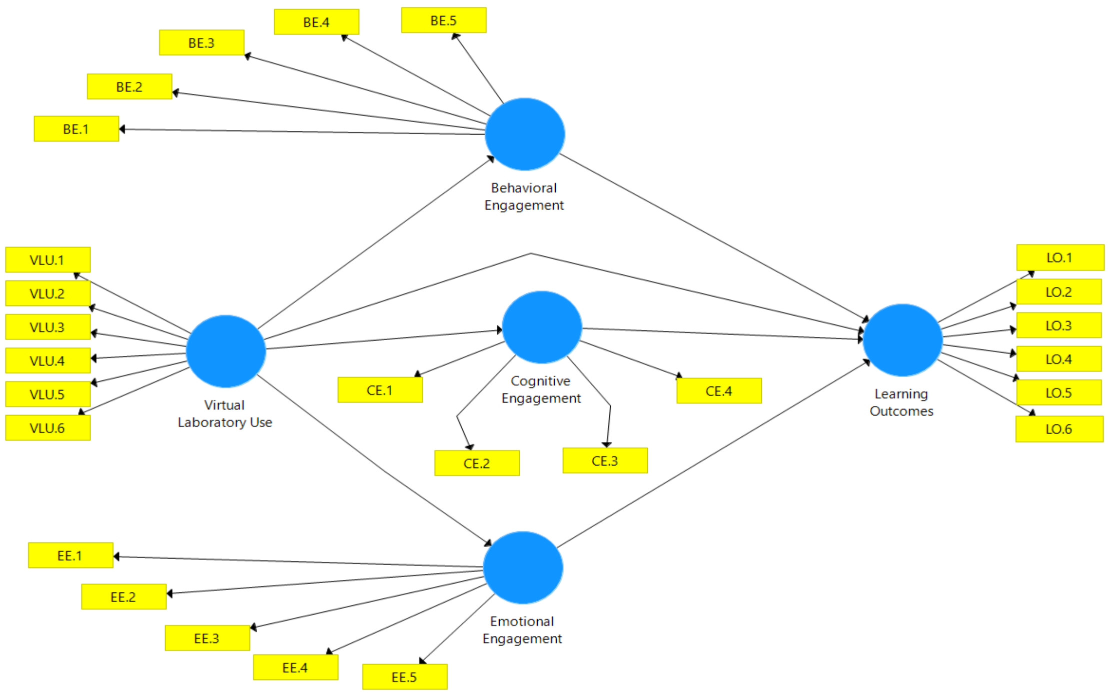


Fig. 3. Initial concept model.

The initial model in Fig. 3 was evaluated to ensure its compatibility with the underlying assumptions and analytical requirements of the VB-SEM approach. This evaluation included both the inner model (constructs) and the outer model (indicators), with the primary aim of confirming the model's validity and absence of statistical issues such as multicollinearity, as well as its compliance with Goodness of Fit (GoF) standards.

A key for assessing multicollinearity is the Variance Inflation Factor (VIF) [44, 45]. In this study, the results of the VIF analysis, as summarized in Table 2, demonstrate that all indicators exhibit VIF values below the threshold of 5 ($VIF < 5$). This indicates that the model does not suffer from multicollinearity issues, affirming the appropriateness of the initial measurement model for further analysis [36, 44].

A multicollinearity test was conducted for the inner model to examine potential collinearity among the latent variables. This step is essential to ensure the robustness of the structural model and the validity of the path coefficient estimates. As presented in Table 3, all constructs in the inner model exhibited VIF values below 5, indicating no multicollinearity issues were detected among the endogenous and exogenous variables [24, 44]. These results support the appropriateness of the structural model for further hypothesis testing and path analysis within the VB-SEM framework.

Table 2. The VIF analysis for Indicators

Indicators	VIF
VLU.1	1.373
VLU.2	1.509
VLU.3	1.464
VLU.4	1.501
VLU.5	1.633
VLU.6	1.460
BE.1	1.662
BE.2	1.291
BE.3	1.314
BE.4	1.251
BE.5	1.525
CE.1	1.206
CE.2	1.356
CE.3	1.314
CE.4	1.288
EE.1	1.154
EE.2	1.423
EE.3	1.305
EE.4	1.423
EE.5	1.423
LO.1	1.284
LO.2	1.500
LO.3	1.562
LO.4	1.249
LO.5	1.520
LO.6	1.533

The assessment results, summarized in Table 4, indicate that the Normed Fit Index (NFI) exceeds the recommended threshold of 0.90, the Standardized Root Mean Square Residual (SRMR) value is below 0.08, and the Root Mean Square Theta (RMS Theta) is below 0.102. These values collectively suggest that the model demonstrates an acceptable overall fit [36, 44, 46]. The fulfillment of these GoF criteria confirms that the model is structurally sound and appropriate for further hypothesis testing. Having met all underlying assumptions and analytical requirements, the study proceeded to the core analysis stage using the VB-SEM approach. The final structural model, along with the path coefficients and indicator relationships, is illustrated in Fig. 4, which presents the visualization of the final research model analysis results.

Table 3. The VIF values analysis for the Inner Model

Variable	BE	CE	EE	LO
VLU	1.325	1.770	1.881	1.920
BE	-	-	-	1.819
CE	-	-	-	1.782
EE	-	-	-	1.911

Table 4. The GoF analysis

Item	SRMR	NFI	Rms theta	GoF
Saturated Model	0,061	1,131	0,089	Fit
Estimated Model	0,065	1,138	0,092	Fit

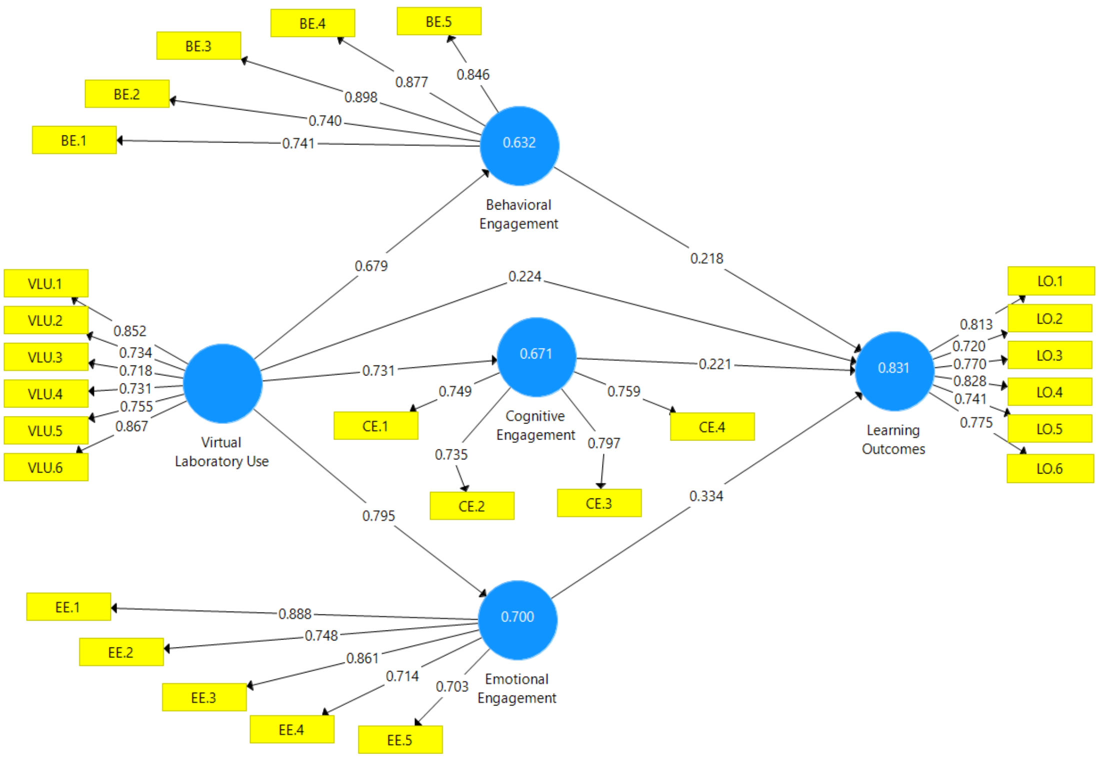


Fig. 4. The visualization of the final research model analysis results.

A. Outer Model

The outer model analysis in the VB-SEM approach involves evaluating the indicators within the research model using several key parameters, including Outer Loading (OL), Composite Reliability (CR), Average Variance Extracted (AVE), Cronbach's Alpha (CA), and rho_A. This analysis aims to assess ICR, UM, and CV of the measurement model. ICR evaluates the extent to which indicators consistently measure the intended construct, typically indicated by the CA value [7, 44].

The analysis results in Table 5 show that all variables exhibit CA values above 0.7, indicating that all indicators are considered reliable [36, 44, 46]. The assessment of unidimensionality ensures that there are no structural issues in the measurement model [36, 44]. Table 5 demonstrates that all constructs fulfill the UM criteria, as both CR and CA values exceed the threshold of 0.7 [35, 44]. Meanwhile, CV assesses whether indicators within a single construct are sufficiently correlated. The analysis results confirm that all constructs meet the criteria for CV, as evidenced by AVE values exceeding 0.50 for each variable.

Table 5. The results of the outer model analysis

Variable	OL	CR	CA	rho_A	AVE
VLU		0.812	0.765	0.673	0.699
VLU.1	0.852				
VLU.2	0.755				
VLU.3	0.731				
VLU.4	0.718				
VLU.5	0.734				
VLU.6	0.852				
BE		0.803	0.713	0.722	0.683
BE.1	0.741				
BE.2	0.740				
BE.3	0.898				
BE.4	0.877				
BE.5	0.846				
CE		0.815	0.869	0.821	0.712
CE.1	0.749				
CE.2	0.735				
CE.3	0.797				
CE.4	0.759				
EE		0.834	0.842	0.731	0.681
EE.1	0.888				
EE.2	0.748				
EE.3	0.861				
EE.4	0.714				
EE.5	0.703				
LO		0.835	0.877	0.753	0.771
LO.1	0.813				
LO.2	0.720				
LO.3	0.770				
LO.4	0.828				
LO.5	0.741				
LO.6	0.775				

DV is assessed by comparing the square root of the AVE, following the Fornell-Larcker criterion, with the correlation coefficients between latent variables. As shown in Table 6, the square root of the AVE for each construct exceeds its correlations with other constructs. For instance, for VLU, the square root of the AVE is 0.878, which is greater than its correlations with BE = 0.469, Cognitive Engagement CE = 0.519, Emotional Engagement EE = 0.521, and Learning Outcomes LO = 0.518.

Table 6. The results of the Fornell-Larcker criterion

Variable	VLU	BE	CE	EE	LO
VLU	0.878				
BE	0.469	0.836			
CE	0.519	0.614	0.826		
EE	0.521	0.491	0.461	0.844	
LO	0.518	0.477	0.569	0.560	0.825

B. Inner Model

The purpose of this analysis is to examine the relationships among variables and to assess the influence of exogenous variables on endogenous variables within the structural model. These effects are evaluated in terms of direct, indirect (via mediating variables), total, and simultaneous impacts. The strength and direction of direct effects are indicated by path coefficients, ranging from -1 to +1. Coefficients approaching +1 reflect a strong positive relationship, while those nearing -1 indicate a strong negative association [7, 35, 44].

Based on the results of the inner model analysis using the VB-SEM approach, as presented in Table 7, the following findings were obtained: (1) The effect of VLU on BE was found to be positive and statistically significant ($\beta = 0.679$, $p < 0.05$); (2) The path from VLU to CE was found to be positive and statistically significant ($\beta = 0.731$, $p < 0.05$); (3) The effect of VLU on EE was found to be positive and statistically significant ($\beta = 0.795$, $p < 0.05$); (4) The effect of VLU on LO was found to be positive and statistically significant ($\beta = 0.224$, $p < 0.05$) ; (5) The effect of BE on LO was found to be positive and statistically significant ($\beta = 0.218$, $p < 0.05$); (6) The effect of CE on LO was found to be positive and statistically significant ($\beta = 0.221$, $p < 0.05$); and (7) The path from EE to LO was found to be positive and statistically significant ($\beta = 0.334$, $p < 0.05$).

Table 7. The direct effect analysis in the inner model

No.	Direct Effect	Path coefficient	P-value
1	VLU → BE	0.679	0.001
2	VLU → CE	0.731	0.001
3	VLU → EE	0.795	0.001
4	VLU → LO	0.224	0.006
5	BE → LO	0.218	0.006
6	CE → LO	0.221	0.006
7	EE → LO	0.334	0.005

A comparison graph of the magnitude of the direct influence (β) for each path in this model is presented in Fig. 5. This graph presents the comparison of β-values across all paths in the structural model. The highlighted pathways (VLU → EE and EE → LO) indicate the stronger roles of EE both as a direct outcome of VLU and as a predictor of LO, underscoring its central position in the model.

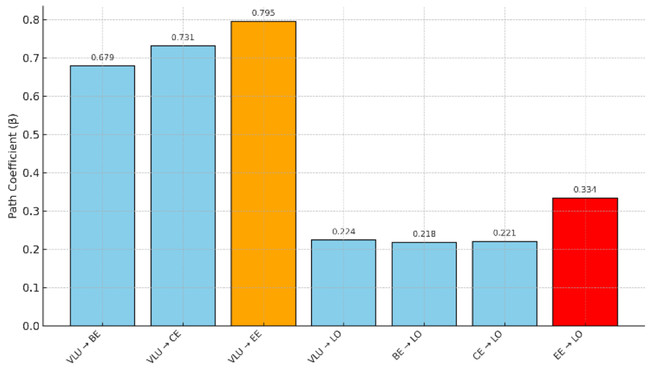


Fig. 5. Path coefficients of direct effects in the SEM model.

The β values in Table 7 indicate that VLU influences the multidimensional LE. EE shows the highest path coefficient, followed by CE and BE, as visualized through the radar chart in Fig. 6. This visualization emphasizes the dominant role of EE in mediating the relationship between VLU and LO.

The analysis of indirect effects in the inner model using the VB-SEM approach aims to determine the extent to which exogenous variables influence endogenous variables through mediating variables. Based on the results presented in Table 8, the following findings were obtained: (1) The indirect effect of VLU on LO through BE was found to be positive and statistically significant ($\beta = 0.148$, $p < 0.05$); (2) The indirect effect of VLU on LO through CE was found to be positive and statistically significant ($\beta = 0.162$, $p < 0.05$); and (3) The indirect effect of VLU on LO through EE was found to be positive and statistically significant (β = 0.265, p < 0.05). Therefore, the total indirect effect of VLU on LO, mediated through the three dimensions of LE, is 0.575.

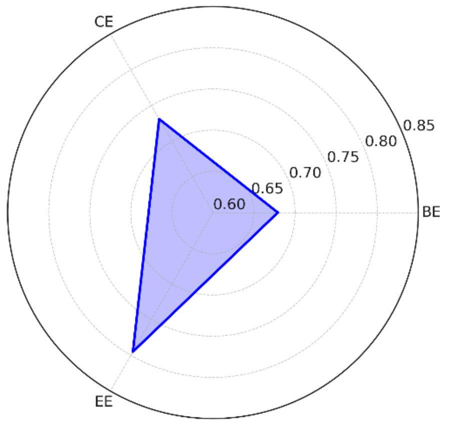


Fig. 6. Comparison of BE, CE, and EE influenced by VLU.

Table 8. The indirect effect analysis in the inner model

No.	Indirect Effect	Path coefficient	P-value
1	VLU → BE → LO	0.148	0.009
2	VLU → CE → LO	0.162	0.009
3	VLU → EE → LO	0.265	0.006

Subsequently, the total effect was examined and calculated to determine the overall impact of the exogenous variable on the endogenous variable, encompassing both direct and indirect effects. The analysis results indicate that the total effect of VLU on LO was found to be positive and statistically significant (β = 0.799, p < 0.05). In the VB-SEM framework, simultaneous effects are further evaluated using the R-squared (R^2) and Adjusted R-squared (Adj. R^2) values [36, 44]. Based on the analysis, the simultaneous effect of VLU, BE, CE, and EE on LO is strong (Adj. R^2 = 0.831).

V. Discussion

The VL can be strategically combined with hands-on laboratory activities through constructivist instructional design and competency-based learning approaches, which encourage students to develop conceptual understanding and technical skills through exploratory experiences independently. In the context of blended learning, the VL serves as an effective bridge between online and offline instruction by enabling students to engage in self-directed practice before and after face-to-face sessions. Lecturers can deliver theoretical and technical content during online sessions, grant students access to VL environments for independent exploration, and subsequently conduct in-person sessions for discussion, feedback, or hands-on practice using physical equipment. This integrated approach promotes flexibility, autonomy, personalized learning, and timely feedback. It is also aligned with the principles of student-centered learning, in which students take an active role in managing their learning process, while instructors serve as facilitators.

The main findings indicate that the effect of VLU on students' LE and LO was found to be positive and statistically significant. The results suggest that VL implementation significantly influences students' LE, which encompasses behavioral, cognitive, and emotional dimensions. These forms of LE represent the intensity of students' interactions with learning materials, the mental strategies employed in understanding concepts, and the positive emotional responses experienced during the learning process. These findings demonstrate that VL technology not only serves as a complementary tool to hands-on laboratory, but also acts as a catalyst for creating an interactive and immersive learning environment, thereby supporting the achievement of more meaningful LO within the context of engineering education.

In terms of BE, the VL (PSIM) interactive features enable students to independently and flexibly explore circuit parameters, conduct iterative simulations, and observe real-time system responses without safety risks. Regarding CE, PSIM facilitates the understanding of complex electrical concepts through visual representations, simulated experiments, input/output manipulation, and immediate feedback, thereby strengthening conceptual understanding and critical thinking skills. For EE, PSIM fosters a motivating and enjoyable learning experience by promoting a sense of autonomy, reducing anxiety about making errors, and enhancing learning satisfaction through dynamic visualizations and flexible scheduling. Together, these three dimensions synergistically reinforce students' LE in engineering education.

This study finds that the VLU enhances EE, partly by reducing students' anxiety about making errors, thereby directly addressing the "risk of harm" that often undermines motivation in hands-on laboratory. Likewise, the evidence that VLU supports flexible and independent exploration offers a concrete solution to the challenge of "limited laboratory time," as students can repeat experiments anytime without being constrained by equipment availability. Moreover, the observed increase in CE suggests that students develop a deeper conceptual understanding, reducing their reliance on face-to-face instruction, which is frequently hindered by "limited instructors and equipment." The improvement in BE, reflected in active participation and timely completion of lab assignments, further demonstrates that VL can mitigate the issue of "limited laboratory resources," where students often lack equal opportunities for hands-on practice.

Furthermore, LE plays a crucial role as a mediating factor between the VLU and the achievement of LO. High levels of students' LE across behavioral, cognitive, and emotional dimensions contribute significantly to improved LO, both in knowledge acquisition and practical skills development. This implies that VL not only offers access to instructional content and practical simulations but also creates a learning experience that fosters student focus, cognitive, and emotional involvement.

EE is the most influential dimension of students' LE in predicting LO. This is attributable to the complex and cognitively demanding nature of the electrical machine course. Consequently, an emotionally safe, enjoyable, and motivating learning environment is essential to support students' focus and persistence throughout the learning process. Moreover, in self-directed digital learning contexts, affective factors play a critical role in reinforcing the instructor's function of fostering motivation and sustaining EE. This finding supports the notion that affective factors such as interest, satisfaction, and intrinsic motivation play a critical role in academic achievement, as emphasized in affective learning theories. In self-paced virtual learning environments, students encounter both cognitive and emotional challenges. Consequently, learning success depends on the virtual system's ability to evoke positive emotions, provide enjoyable learning experiences, and foster emotional attachment to the content and the medium.

According to CLT, positive emotional states can reduce extraneous cognitive load and enhance germane load, thereby improving the efficiency of knowledge processing. In this context, the VL can stimulate EE while simultaneously reinforcing students' conceptual understanding. Furthermore, the enhancement of BE and CE is underpinned by CT. The VL offers students opportunities to conduct repeated experiments, test hypotheses, and reflect on outcomes without the time constraints or potential risks. This process enables students not only to acquire information but also to develop deeper conceptual understanding through active meaning-making. In addition, the role of EE in fostering learning motivation aligns with SDT. The VL promotes autonomy through the flexibility of self-directed learning, strengthens competence through the successful completion of experiments, and fosters relatedness by facilitating virtual collaboration with peers.

These findings also underscore the importance of instructional strategies that integrate VL not merely as technological tools, but as pedagogical instruments. The VLU should be oriented toward enhancing students' active participation in the learning process, thereby fostering deeper LE. In this context, VL holds the potential to deliver immersive, adaptive, and contextually relevant learning experiences, which ultimately contribute to the achievement of higher LO. Therefore, the success of VL implementation in engineering education depends not only on the availability of the technology but also on how effectively it is employed to activate and support students' holistic LE.

The effectiveness of VL in engineering education largely depends on its capacity to enhance LE, which collectively influences students' LO. The findings contribute significantly to the development of technology-enhanced learning designs and support a paradigm shift, from the digital tools' mere use toward the creation of a digital learning ecosystem that empowers students as active participants in the learning process. Furthermore, this study reinforces the relevance of VL as a strategic solution for overcoming limitations in access and flexibility of practical learning amid the digital transformation of higher education.

The research findings indicating that the VLU can enhance students' LE are consistent with several previous studies, which report that VL increases student motivation and active participation in engineering education [3, 16, 17]. Moreover, findings from other studies also confirm that integrating VL into engineering courses fosters deeper student LE through independent exploration and experimentation, thereby reinforcing the CE and BE [12, 23, 25]. Consequently, the results of this study further support the existing literature on the effectiveness of VL in promoting more active and meaningful learning interactions.

The findings demonstrating the mediating role of LE in the relationship between VLU and LO align with several previous studies, which have identified LE as a significant predictor of academic achievement in digital learning environments [3, 17, 32]. Additionally, other studies support the central role of LE as a transitional mechanism linking technology experience to LO [32, 47, 48]. Through behavioral, cognitive, and emotional involvement, students become not merely passive users of technology but active participants in constructing meaningful learning experiences. Regarding its impact on LO, this finding corroborates prior research indicating that students who use VL alongside hands-on laboratory achieve better outcomes than those relying solely on hands-on laboratory, particularly in conceptual understanding and analytical thinking skills [1, 2, 8]. Similarly, other studies have shown that the combination of virtual and physical laboratories results in higher learning gains compared to hands-on laboratory alone, offering increased time efficiency and flexibility [2, 7, 34]. The results indicate that VL functions not merely as alternatives, but as practical and evidence-based learning solutions in engineering education.

Furthermore, the study results contribute to the broader scientific discourse on VL-based learning in engineering education. Unlike previous studies that primarily focused on technical aspects or system design [1, 11, 49], this research emphasizes psychopedagogical dimensions, particularly students' LE as a critical mediating factor in the success of technology-enhanced learning. Therefore, this study advances the development of a more comprehensive theoretical framework that explains how technology influences LO through students' affective and cognitive processes. It also allows future research to explore the mediating variables' role within digital learning approaches.

However, this study was conducted in a single institution, focusing on one course with a limited sample. It restricts the generalizability of the findings to broader contexts, particularly across interdisciplinary engineering programs. This limitation implies that caution should be exercised in transferring the results directly to other settings. Accordingly, future research is encouraged to replicate the study in diverse institutions, disciplines, and cultural contexts to validate and extend the applicability of the findings.

Thus, the VLU in engineering education, particularly in electrical machines courses, significantly enhances student LE, which positively affects LO. This study confirms that the success of technology-based learning depends not only on the system's sophistication but also on its ability to foster behavioral, cognitive, and emotional involvement of students throughout the learning process. These findings reinforce the theoretical premise in the literature that LE is a crucial mechanism mediating the relationship between digital learning experiences and academic achievement. Thus, integrating VL should be seen not just as implementing a learning tool but as adopting a teaching approach that promotes active, thoughtful, and impactful learning experiences.

VI. Conclusion

This study demonstrates that the VLU has a significant impact on students' LE and LO in engineering education, particularly in electrical machines courses. The analysis results indicate that VLU directly enhances BE, CE, and EE, and exerts both direct and indirect effects on LO through these LE dimensions as intervening variables. LE plays a critical role as a bridge that connects VL-based learning experiences with optimal LO. Furthermore, the simultaneous influence of VLU, BE, CE, and EE on LO underscores that the success of engineering education in the digital era is primarily determined by the strategic integration of learning technologies and the holistic activation of students' LE.

These findings offer valuable implications for the design of technology-enhanced engineering education, highlighting the importance of not only implementing digital tools but also fostering learning experiences that promote active participation, cognitive reflection, and emotional involvement among students. The findings of this study provide a solid foundation for engineering education institutions to integrate the VL into technology-enhanced practical learning. For instance, in the electrical machines course, lecturers can employ the PSIM application to simulate electric motor circuit parameters before conducting physical laboratory sessions. This approach allows students to develop an initial conceptual understanding while minimizing the risks of injury or equipment damage.

As a practical implication, educators are encouraged to select or design VL that not only conveys technical content but also fosters optimal cognitive engagement. Several strategies can be employed to achieve this goal: (1) aligning the VL design with the characteristics and content of the learning material; (2) integrating problem-solving tasks based on real-world industrial contexts to promote critical and reflective thinking; (3) incorporating interactive, simulation-based features that support autonomous exploration and active manipulation of experimental variables; and (4) including guiding questions that stimulate conceptual reasoning and reflective thinking.

This study provides a valuable contribution to understanding the impact of VLU on student LE and LO within the context of engineering education. However, several limitations should be acknowledged. First, the study employs a cross-sectional design and is confined to a single course, a limited sample size, at one engineering education institution, and does not involve a control group design. Consequently, caution must be exercised in generalizing the findings. Second, future research should adopt a longitudinal approach to examine objective LO over an extended period, to assess how students' performance evolves with sustained use of VL. As a follow-up, it is recommended that future studies employ longitudinal or experimental designs to investigate causal relationships and the progression of LO over time. A longitudinal approach enables researchers to observe the progression and changes in the dimensions of LE as students gain experience with VL technology. This allows for a more rigorous examination of the mediating role of students' LE on LO, particularly by accounting for temporal precedence, an essential criterion for establishing causal inference.

Therefore, future research employing longitudinal or experimental designs is strongly recommended to strengthen the evidence for causal relationships and to assess the long-term effects of the VL integration in engineering education. Broadening the scope to include other engineering courses, diverse types of institutions, and more heterogeneous student populations is also essential to enhance the external validity of the findings. Moreover, future research could explore additional mediating or moderating factors, such as digital self-efficacy, instructional design quality, or collaborative learning dynamics, that may further enrich the understanding of how VL contributes to effective learning in engineering education.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization: D.T.P.Y., O.C., H., and C.D.; Methodology: D.T.P.Y., O.C., C.D., A.D.S., and S.R.; Validation: D.T.P.Y., A.D.S., T.D., and S.R.; Formal Analysis: D.T.P.Y., C.D., and H.; Original Draft Preparation: D.T.P.Y., H., C.D., and A.D.S.; Writing Review and Editing: T.D., and S.R. All authors had approved the final version.

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