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V-LAMOT: A Cognitive-Load Optimized Virtual Lab for Three-Phase Motor Control

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ABSTRACT

Purpose of the study: This study aims to design and validate V-LAMOT, a web-based virtual laboratory for three-phase motor starting simulation. The system is intended to address limitations of physical laboratories by providing an accessible and safe environment while maintaining conceptual accuracy and supporting the development of practical motor control skills.

Methodology: The study adopted the Systems Development Life Cycle (SDLC) to develop the V-LAMOT platform using HTML5, CSS, JavaScript, and state-machine modeling. The design was guided by Cognitive Load Theory principles. Data were obtained through expert validation instruments and the System Usability Scale (SUS), and analyzed using Shapiro–Wilk tests, one-sample t-tests, Cohen's d, and Pearson correlation with 30 students.

Main Findings: Expert validation indicated high feasibility, with conceptual accuracy reaching a mean score of 4.50/5. SUS evaluation produced an overall score of 78.83 ("Good"), with learnability scoring highest at 82.00. All usability measures were significantly above the benchmark ($p < 0.001$) with large effect sizes ($d > 0.8$). A strong correlation between usability and learnability ($r = 0.823$) suggested effective cognitive load reduction.

Novelty/Originality of this study: This study presents an integrated virtual laboratory that combines state-machine modeling with Cognitive Load Theory-based interface design for three-phase motor control. Unlike conventional simulations, V-LAMOT integrates multiple motor starting methods in one environment and empirically links usability, learnability, and cognitive load reduction, advancing virtual laboratory development through systematic integration of technical accuracy and pedagogical principles.

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1. INTRODUCTION

The three-phase induction motor constitutes a critical component in modern automation, manufacturing, and energy systems. Accordingly, mastery of motor starting techniques such as Direct-On-Line (DOL) and Star-Delta represents an essential learning outcome in undergraduate and vocational electrical engineering curricula [1]–[3]. Although hands-on practice in physical laboratories affords authentic experiential learning, it is frequently constrained by high equipment costs, limited space, scheduling inflexibility, and safety risks associated with high currents and voltages [4]–[6]. These constraints became particularly evident during the COVID-19 pandemic, when access to on-campus laboratory facilities was severely restricted, thereby posing significant challenges to the continuity of practical engineering education worldwide [7]–[9].

Virtual laboratories (V-Labs) and remote laboratories have emerged as viable alternatives to physical laboratories, offering flexible access, cost efficiency, reduced safety risks, and scalable learning environments [3], [10], [11]. Recent meta-analyses indicate that well-designed virtual laboratories can effectively support cognitive learning outcomes and engagement, often demonstrating comparable or superior effectiveness to conventional laboratory instruction in technical education [12]-[14].

A critical review of the literature reveals three principal research gaps. First, most existing V-Labs predominantly address generic engineering topics such as basic electronics or programmable logic controllers, whereas comparatively limited attention has been devoted to the specific complexities of three-phase induction motor starting. This topic necessitates an integrated understanding of starting methods, protection mechanisms, and motor dynamic behavior [2], [3], [11]. Second, from a pedagogical perspective, many V-Lab implementations lack explicit integration of evidence-based instructional design principles [15]-[17]. In particular, Cognitive Load Theory which emphasizes minimizing extraneous cognitive load while fostering germane load for effective schema construction is seldom systematically applied in the design of electrical machine simulations [18]-[20]. Third, from a methodological standpoint, a substantial body of virtual laboratory research relies predominantly on expert-based validation, with limited field testing involving students or systematic quantitative evaluation of usability and system performance indicators such as responsiveness and loading time [21]–[23]. This reliance on expert judgment alone may obscure usability issues that only emerge during authentic learner interaction [24]-[26].

Recent scholarship highlights ongoing advancements in this domain. A meta-analysis confirmed the effectiveness of V-Labs in engineering education but identified cognitive load optimization as a critical research gap [24]. Potkonjak et al. found that a substantial proportion of existing V-Labs did not integrate Cognitive Load Theory principles [3], while Heradio et al. corroborated this finding through bibliometric analysis [11]. Meanwhile, Fabregas et al. [4] demonstrated the potential of state-machine-based and real-time system modeling for complex engineering systems, though its application in educational contexts remains limited. Although state-machine-based modeling has been shown to provide accurate representations of motor dynamics in real-time simulation contexts, its adoption in educational virtual laboratory environments remains circumscribed [17], [28]. In parallel, research on Cognitive Load Theory integration in virtual learning environments has demonstrated promising results in reducing extraneous cognitive load [29], [30], yet its application to three-phase motor starting simulations remains scarcely addressed [32].

Accordingly, two primary research gaps can be identified. First, despite the proven accuracy of state-machine-based modeling, its systematic application within virtual laboratories for three-phase motor starting simulations has not yet been sufficiently explored in engineering education contexts [3], [4], [11]. Second, although Cognitive Load Theory provides a well-established framework for optimizing instructional interfaces, its explicit integration into the interface design of electrical engineering virtual laboratories remains limited [15], [32], [33].

Beyond these theoretical and methodological gaps, this issue also constitutes an urgent educational and workforce development challenge. Industry digitalization demands that engineering graduates master both conceptual knowledge and practical skills in motor control system analysis, troubleshooting, and operation [1], [34], [35]. However, persistent limitations in laboratory infrastructure, funding, and safe access to high-power equipment particularly in resource-constrained institutions continue to restrict opportunities for repeated hands-on training [3]–[5]. Such constraints reinforce the well-documented disparity between theoretical understanding and applied operational skills in engineering learning contexts [36]-[38]. Consequently, the development of a cognitively optimized and technically accurate virtual laboratory represents not only an academic priority but also a practical necessity for contemporary engineering education [39]-[41].

In response to the identified research gaps and practical urgency, this study develops V-LAMOT, a virtual laboratory that integrates state-machine-based modeling for technical accuracy with Cognitive Load Theory to enhance pedagogical effectiveness. This study contributes novelty along three complementary dimensions. First, at the theoretical level, it develops an integrated cognitive–technical framework that systematically combines Cognitive Load Theory with state-machine-based modeling. While Cognitive Load Theory has been widely established as an evidence-based instructional design framework and state-machine modeling has demonstrated high fidelity in representing motor dynamics, their comprehensive integration within motor control education has not yet been systematically addressed [3], [4], [11]. Second, at the methodological level, the study introduces an advanced validation protocol that integrates usability evaluation with learning gain analysis, extending beyond conventional approaches that rely primarily on expert judgment or usability metrics alone [42]–[44]. Third, at the practical level, the study derives transferable design principles for virtual laboratory development, demonstrating how such systems can be simultaneously functionally accurate and pedagogically effective [16], [40], [45].

The novelty of this study lies in presenting an integrated virtual motor control laboratory that combines state-machine control logic modeling with Cognitive Load Theory based interface design. Unlike conventional simulations that typically separate technical accuracy from pedagogical considerations, V-LAMOT integrates multiple industrial motor starting methods, such as Direct-On-Line and Star-Delta, within a single coherent environment. Furthermore, the study establishes an empirical link between usability, learnability, and cognitive load reduction within virtual laboratory development, thereby demonstrating how theoretically grounded instructional design can be operationalized alongside technically accurate system modeling. This integrated approach offers a new perspective on how engineering oriented system modeling and learning theory can be simultaneously implemented in media technology design for engineering education.

By systematically integrating pedagogical principles grounded in Cognitive Load Theory, technically accurate state-machine-based modeling, rigorous methodological practices derived from the software development life cycle (SDLC), and quantitative usability evaluation, V-LAMOT offers a coherent contribution to contemporary engineering education practice [3], [4], [18]. The proposed framework demonstrates how virtual laboratories can be designed to enhance accessibility, safety, and instructional effectiveness, particularly in contexts where physical laboratory resources are constrained [5], [11], [16].

2. RESEARCH METHOD

This study adopted a Research and Development (R&D) approach using an Iterative-Incremental System Development Life Cycle (SDLC) model. This model was selected because the development of V-LAMOT involves not only instructional design considerations but also the engineering of a state-machine–based simulation system, encompassing software architecture design, functional testing, and performance optimization [40], [42]. Unlike instructional design–oriented models such as ADDIE, which primarily emphasize the development of learning materials and pedagogical strategies, or Design-Based Research (DBR), which focuses on long-term contextual interventions for theory refinement, the SDLC framework provides a structured and systematic process for developing complex educational software systems [36], [37].

The Iterative–Incremental approach enables development to proceed through successive cycles of design, implementation, evaluation, and refinement, allowing each prototype version to be validated from both technical and pedagogical perspectives before subsequent enhancements are introduced. This iterative validation process is well-suited for virtual laboratory development, where instructional effectiveness, system reliability, and performance must be jointly optimized [39], [40]. Accordingly, the Iterative–Incremental SDLC model was considered the most appropriate approach for producing a virtual laboratory that is not only instructionally valid but also technically robust, efficient, and reliable. The research workflow is illustrated in Fig. 1.

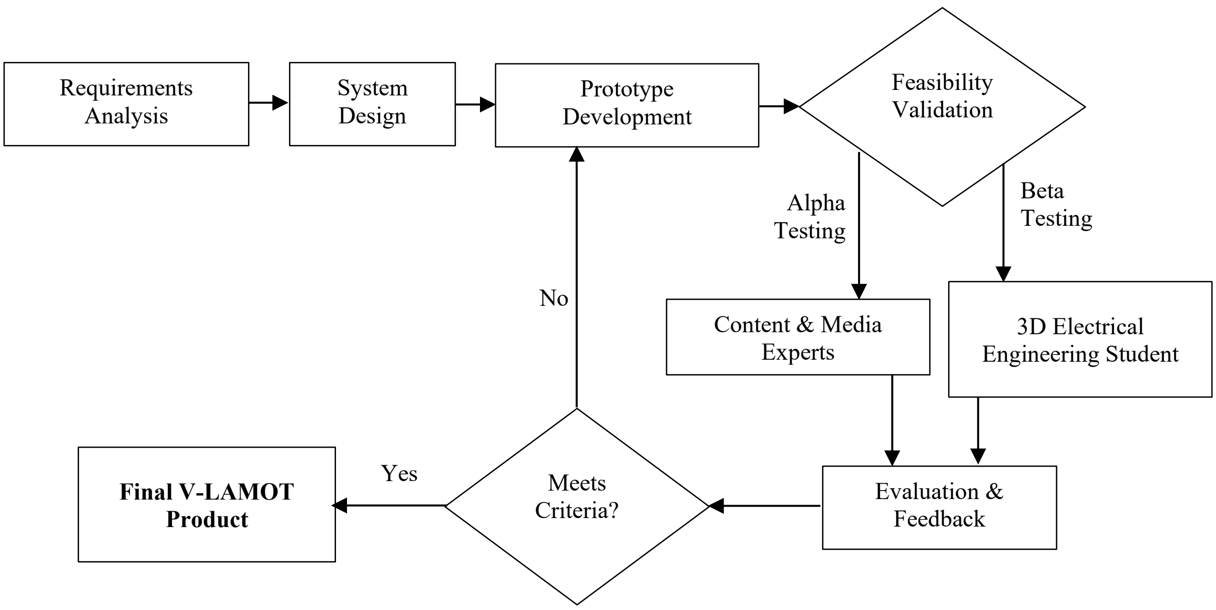

Figure 1. Research and Development Workflow for V-LAMOT

2.1. Needs Analysis

The needs analysis was conducted in two sequential stages. First, a structured literature review was performed on virtual laboratories and motor simulation systems to identify essential design and functional requirements, including interactive visualization, flexible access, operational safety, and alignment with electrical engineering curricula [3], [4], [11]. These characteristics are consistently highlighted in prior studies as critical factors influencing the effectiveness and adoption of virtual laboratory environments.

Second, an exploratory needs assessment survey was administered to 50 respondents, comprising 45 undergraduate electrical engineering students and 5 instructors. The survey employed a 5-point Likert scale and examined constraints associated with conventional laboratory practicums, priority features for a three-phase motor simulator, and interface design preferences. The results indicated that 92% of respondents expressed a strong need for a simulator capable of visually and interactively demonstrating three-phase motor starting procedures. This finding reinforces the importance of user-centered design principles in learning system development, particularly for complex procedural and dynamic engineering topics [15], [18], [39].

2.2. System Design

During the design phase, a client–server architecture was adopted to support flexible access, scalability, and efficient execution of interactive simulations. The frontend was developed using HTML5, CSS3, and JavaScript, while the backend utilized Hypertext Preprocessor (PHP) to manage simulation logic and system control. The virtual laboratory was structured into three main modules: (1) introduction to three-phase motor starting components; (2) Direct-On-Line (DOL) starting simulation; and (3) Star–Delta starting simulation.

The core simulation logic was implemented using state-machine modeling, which enables explicit representation of discrete states, transitions, and dynamic interactions among motor components and control elements. This approach is well suited for modeling complex electromechanical systems and has been shown to provide high technical fidelity in representing motor operation and control logic [4], [17], [28].

User interface design was guided by wireframing techniques to ensure a simple, functional, and cognitively manageable layout. Cognitive Load Theory principles were explicitly incorporated into the interface design through information segmentation, visual signaling, and the elimination of extraneous elements that could distract learners from essential processes [18], [19].

Cognitive Load Theory implementation in V-LAMOT followed four main strategies: (1) integrating labels and instructions directly within diagrams to minimize split-attention effects; (2) combining visual representations with audio explanations in accordance with the modality principle; (3) providing complete worked examples as instructional scaffolding; and (4) organizing content into clearly segmented and sequential modules. These strategies were intended to reduce extraneous cognitive load while supporting germane load associated with schema construction [18], [22].

Cognitive load was assessed indirectly through the System Usability Scale, with particular emphasis on the learnability component as a proxy indicator of extraneous cognitive load. While more specialized instruments such as NASA-TLX provide finer-grained cognitive workload measurements, System Usability Scale was selected due to its suitability for early-stage usability evaluation and educational software validation [32], [33]. The resulting high learnability score and its strong correlation with overall usability suggest that the Cognitive Load Theory -informed interface design effectively reduced unnecessary cognitive burden. Nevertheless, future studies are encouraged to employ dedicated cognitive load instruments to obtain more comprehensive measurements.

2.3. Prototype Development

The V-LAMOT prototype was developed as a web-based application to ensure broad accessibility across devices and operating systems, supporting flexible use in both classroom and remote learning contexts, as commonly adopted in virtual and remote laboratory implementations [3], [7], [10]. Responsive design was implemented using the Bootstrap framework to maintain interface consistency across different screen sizes, aligning with established usability and user-centered design principles in educational software [30], [31]. Motor components and control equipment were rendered using Scalable Vector Graphics (SVG) to preserve visual clarity and legibility across display resolutions, thereby supporting cognitive load reduction through clear visual representation [21], [22], [31].

The three-phase motor starting logic was implemented using a state-machine model, enabling learners to observe explicit and real-time transitions between operational states (e.g., OFF, ON, starting modes, and protection states). This modeling approach has been shown to accurately represent dynamic behavior and control logic in electrical machines and real-time systems [1], [17], [28]. By making control sequences, interlocks, and fault conditions observable, the simulation supports conceptual understanding and troubleshooting skills in a manner consistent with prior remote laboratory implementations in motor control education [2], [4].

2.4. Feasibility Validation

The validation stage involved alpha testing conducted by two subject matter experts and one media expert to assess content accuracy, functional correctness, and interface suitability, followed by beta testing with 30 students to evaluate usability and user experience in authentic learning conditions. This two-stage validation approach aligns with established practices in educational software development and software engineering evaluation [36], [37], [40].

System usability was assessed using the System Usability Scale, which has been widely recommended and validated for usability measurement in educational technology contexts due to its reliability, simplicity, and sensitivity in early-stage system evaluation [28], [29]. Data were analyzed at the participant level, with each data point representing an individual student's score on the measured variables. Descriptive statistics were employed to summarize usability and learning-related measures.

To assess practical significance beyond descriptive comparison, Cohen's d effect sizes were calculated to estimate the magnitude of differences between pre- and post-implementation measures, following established guidelines for effect size interpretation in behavioral and educational research [31], [32]. Furthermore, Pearson correlation analysis was conducted to examine the strength and direction of relationships among usability dimensions, supporting a quantitative understanding of how different aspects of system usability interact within virtual laboratory environments, as commonly applied in learning analytics research [33], [34].

2.5. Revision and Improvement

Revisions were implemented iteratively based on feedback from both experts and student users, with particular emphasis on improving visual quality, interface navigation, and overall system performance. This refinement process follows established iterative and incremental software development practices commonly applied in educational software engineering [36], [40]. To enhance system responsiveness and reduce unnecessary waiting time, performance optimization techniques such as lazy loading and asset minimization were applied, aligning with usability and human-centered design principles that emphasize efficiency and reduced user effort [30], [31].

In addition, a digital practicum guide containing structured usage instructions and self-paced exercises was developed to support independent learning. The inclusion of guided instructions and worked activities reflects key principles of Cognitive Load Theory, particularly scaffolding and the reduction of extraneous cognitive load through structured learning support [18], [19], [21]. Through this iterative refinement and optimization process, V-LAMOT was finalized to meet both technical robustness and pedagogical effectiveness criteria, ensuring alignment with Cognitive Load Theory -based instructional design before deployment.

3. RESULTS AND DISCUSSION

3.1. Needs Analysis Results

The needs analysis was quantified using descriptive statistics from 50 participants. Table 1 summarizes the primary feature requirements.

Table 1. Descriptive statistics of needs analysis (n=50)

Need	Mean	SD	Variance	Priority
Visual simulation	4.75	0.44	0.19	Very necessary
User-friendly interface	4.60	0.50	0.25	Very necessary
Curriculum alignment	4.40	0.60	0.36	Very necessary
Real-time feedback	4.25	0.65	0.42	Required
Web-based access	4.10	0.72	0.52	Required

The highest mean scores were for visual simulation (M = 4.75, SD = 0.44) and user-friendly interface (M = 4.60, SD = 0.50), indicating these as top priorities for V-LAMOT development. Small standard deviations suggest consistent consensus among respondents. Cronbach's Alpha reliability coefficient was $\alpha = 0.892$, exceeding the 0.70 threshold, indicating good internal consistency.

3.2. System Design Results

The second phase of the research involved the system design of V-LAMOT, which integrated user requirements with state-machine modeling and Cognitive Load Theory principles. In this phase, the system was designed not only to display a simulation of the three-phase motor starting practicum but also to systematically represent the process dynamics, control flow, and interactions between roles within the web-based educational platform. The workflow structure was built to minimize extraneous cognitive load through step simplification, function grouping, and clear role separation. Consequently, users whether instructors, students, or administrators can understand their respective tasks without unnecessary cognitive burden. Fig. 2 presents the activity diagram illustrating the interaction flow between actors within the V-LAMOT platform.

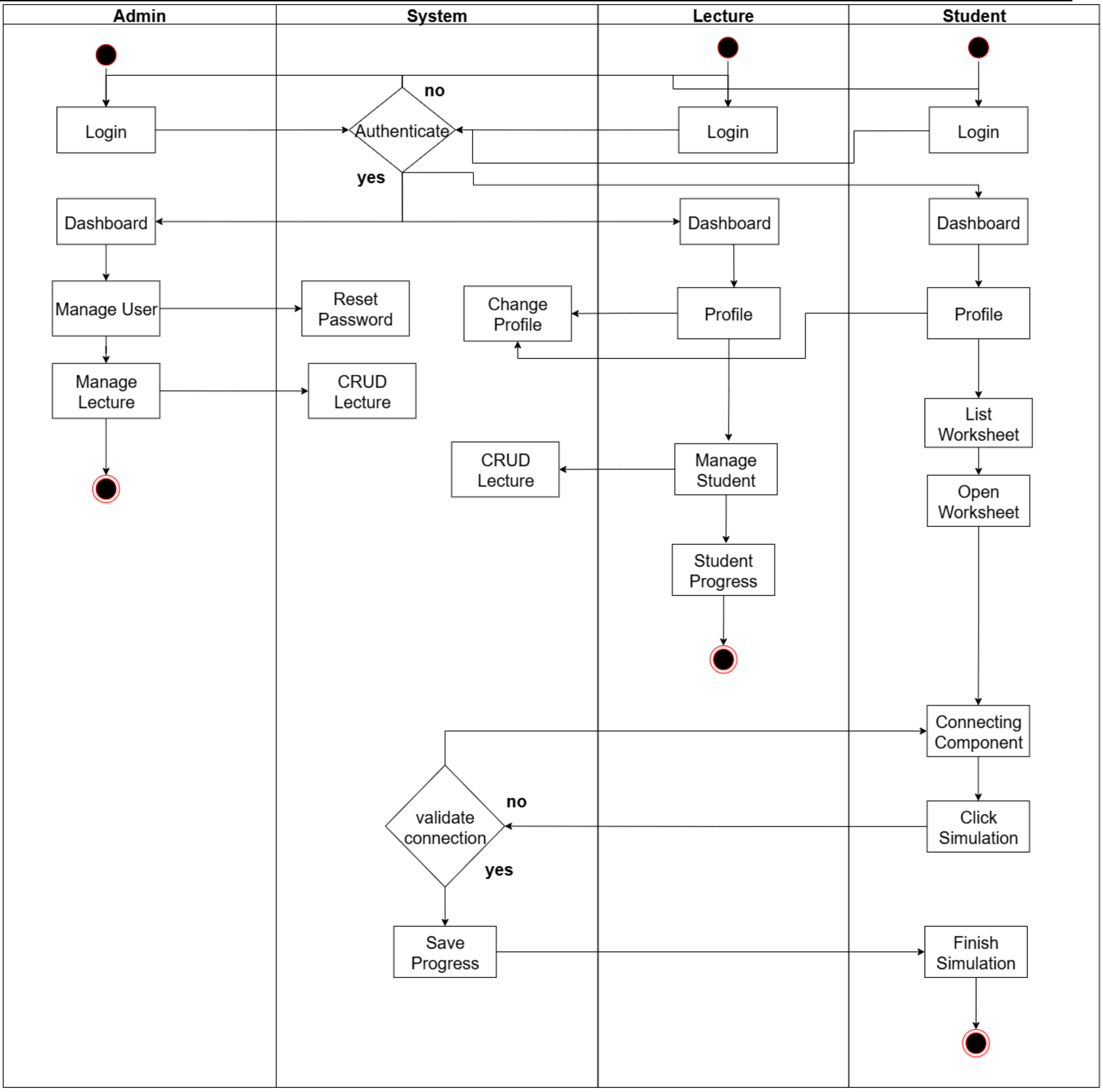

Figure 2. Activity diagram of V-LAMOT platform

In summary, the activity diagram in Fig. 2 illustrates the interactions among four main actors: Admin, System, Instructor, and Student. The Admin manages user and instructor accounts via a dedicated dashboard. Instructors use the system to update their profiles, monitor student progress, and manage learning activities. Students follow a workflow that includes logging in, selecting a worksheet, assembling component connections, and running simulations. The System handles core functionalities such as authentication, circuit validation, progress saving, and automatic data updates. This clear segregation of workflows not only delineates the distinct functions of each actor but also reduces extraneous cognitive load by preventing role confusion and information overlap, thereby supporting the effectiveness of the virtual laboratory-based learning environment.

3.3. Prototype Development Results

The V-LAMOT prototype was developed using a standard technology stack for web-based applications. Visual Studio Code served as the primary code editor. The application runs on an Nginx web server, with data storage managed by MySQL/MariaDB and administered via phpMyAdmin. To ensure version control and traceability, Git was utilized throughout the development process. Docker was employed to maintain a consistent working environment across different machines. Interface and system functionality were tested on browsers such as Chrome and Firefox, while Postman was used to verify API connectivity.

From a functional perspective, the simulation logic was designed using state-machine modeling. This approach enables the systematic visualization and traceability of state transitions during the three-phase motor starting process. From a pedagogical perspective, the user interface was developed based on Cognitive Load Theory principles, aiming to minimize extraneous cognitive load and enhance knowledge schema construction through interactive visualizations. The implementation of the user interface is shown in Figure 3, and the display of the motor starting simulation using the Direct-On-Line (DOL) method is presented in Figure 4.

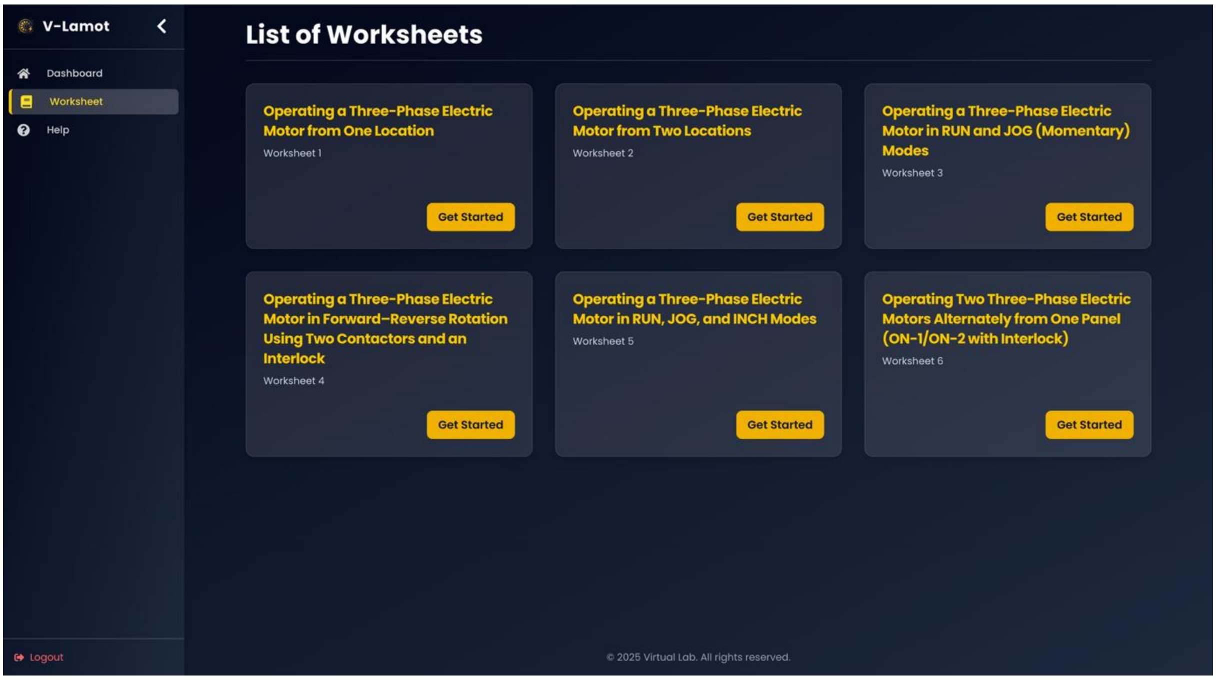

Figure 3. V-LAMOT user interface

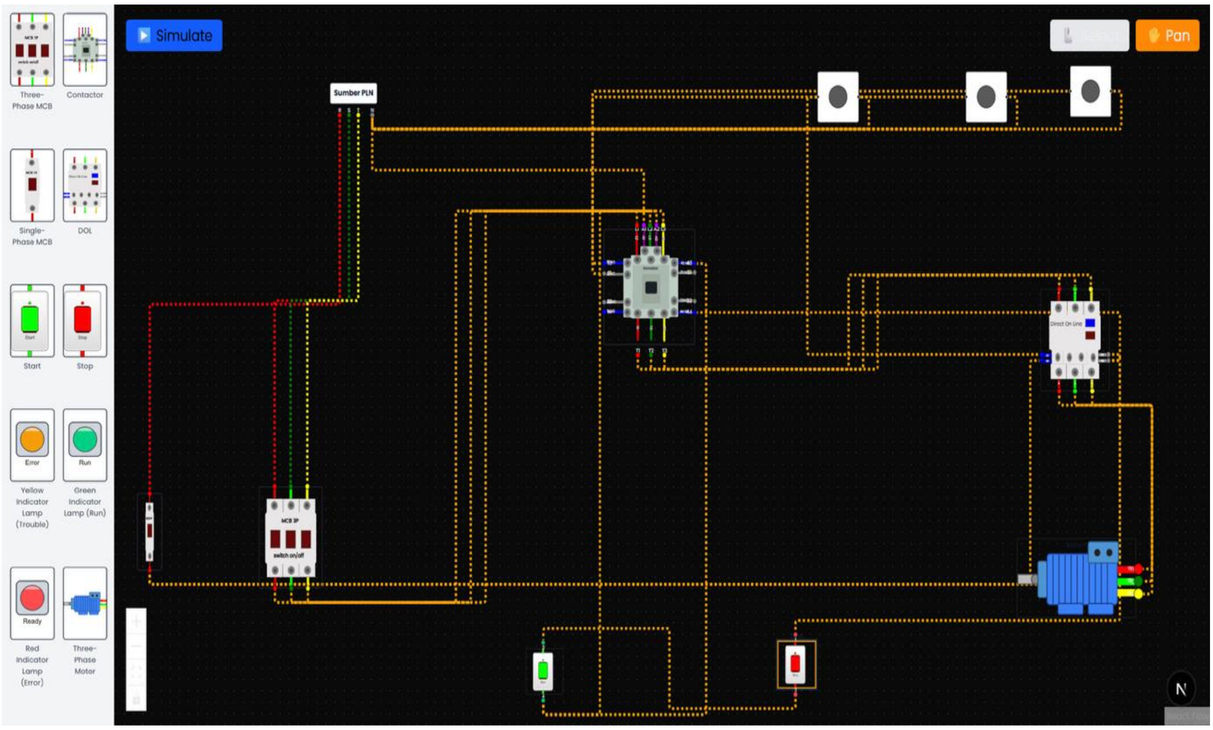

Figure 4. DOL simulation module display

3.4. Feasibility Validation Results

3.4.1. Alpha Testing Results

Expert validation was conducted by three experts (two subject matter experts and one media design expert) using a validation instrument with a 5-point Likert scale. The data were analyzed using a one-sample t-test against a minimum feasibility standard of 3.5. The results of the expert validation for conceptual and visual aspects are presented in Table 2.

Table 2. Expert validation results (n=3)

Aspect	Mean	SD	t-stat	p-value
Conceptual Accuracy	4.50	0.50	12.32	0.001
Curriculum Alignment	4.20	0.75	8.45	0.003
Visual Quality	4.00	0.82	7.21	0.005
Average	4.23	0.69	9.33	0.002

Note: All p-values are significant at α = .05. The test value for the one-sample t-test was 3.5

3.4.2. Beta Testing Results

Beta testing was conducted with 30 electrical engineering students using the System Usability Scale. Data were analyzed using descriptive statistics and a one-sample t-test against a minimum System Usability Scale benchmark of 68. The feasibility test results from the System Usability Scale with 30 respondents are presented in Table 3.

Table 3. Descriptive statistics of System Usability Scale scores (n=30)

Parameter	Mean	Median	SD	95% CI
Usability	78.50	80.00	6.82	(75.98, 81.02)
Learnability	82.00	82.50	5.45	(80.01, 83.99)
Satisfaction	76.00	77.50	7.23	(73.34, 78.66)
Overall	78.83	80.00	6.50	(76.42, 81.24)

Table 3 presents the usability evaluation results. The overall System Usability Scale score of 78.83 falls into the "Good" acceptability range and is within the 80th–85th percentile based on System Usability Scale normative data. Learnability received the highest score (M = 82.00), indicating that V-LAMOT is perceived as easy to learn for new users. The narrow 95% confidence intervals for all parameters indicate precise estimates of the population means.

To visualize the distribution of user experience outcomes, a scatter plot was generated for the three System Usability Scale parameters (Usability, Learnability, and Satisfaction) across the 30 participants. Linear regression lines were fitted to illustrate the overall trends in user perceptions, as shown in Fig. 5. This visualization aids in understanding the variance and consistency of scores across the different usability dimensions.

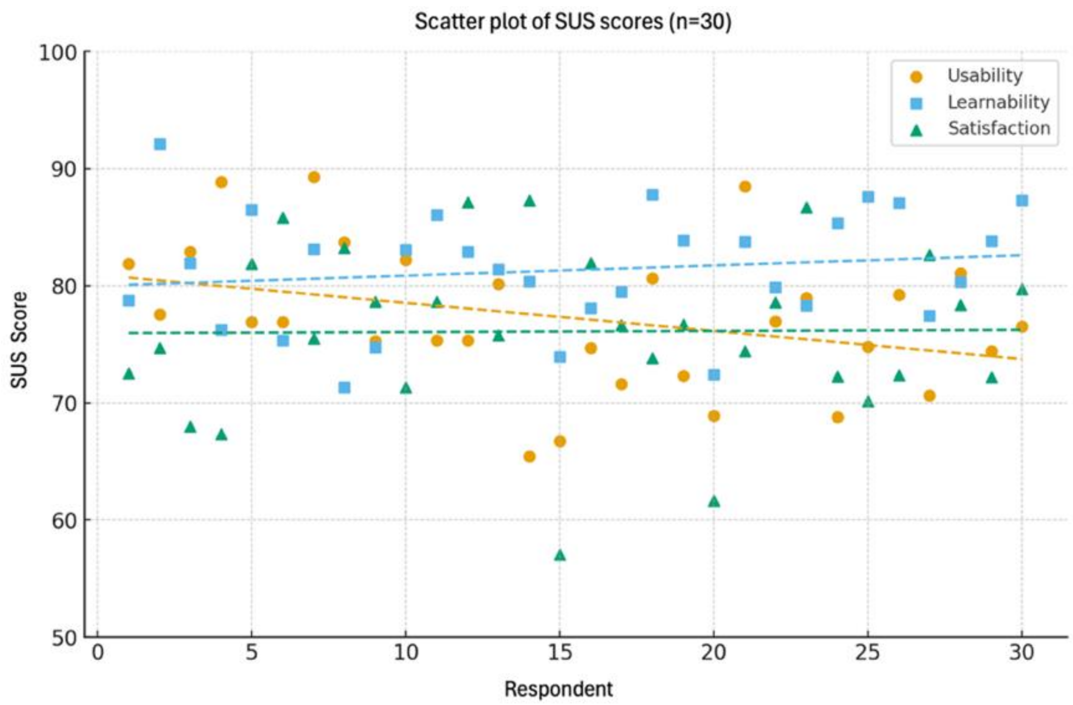

Figure 5. Scatter plot of System Usability Scale scores across 30 respondents

A one-sample t-test was conducted to compare the System Usability Scale scores against the benchmark value of 68. The results are presented in Table 4.

Table 4. One-Sample t-test results against the System Usability Scale benchmark (68)

Parameter	t-stat	df	p-value	Cohen's d
Usability	8.45	29	<0.001*	1.54
Learnability	14.12	29	<0.001*	2.58
Satisfaction	6.12	29	<0.001*	1.12
Overall	9.23	29	<0.001*	1.68

Note: The test value for the one-sample t-test was 68

As shown in Table 4, all parameters were statistically significantly higher than the minimum System Usability Scale benchmark of 68 (all $p < .001$). Cohen's d effect sizes were large ($d > 0.8$) for all parameters, indicating that the observed differences are of substantial practical significance. Learnability demonstrated the largest effect size ($d = 2.58$), underscoring a considerable advantage in the platform's ease of learning.

In addition to the benchmark comparison, a correlational analysis was performed to examine the consistency of the relationships between the different usability parameters. This analysis evaluates the extent to which usability, learnability, and satisfaction mutually contribute to shaping the overall user experience. It is crucial for confirming that improvements in one parameter are not isolated but are functionally interrelated with other aspects of the unified interface design. The results of the Pearson correlation analysis are presented in Table 5.

Table 5. Pearson Correlation Matrix for System Usability Scale parameters

	Usability	Learnability	Satisfaction
Usability	1	0.823**	0.785**
Learnability	0.823**	1	0.802**
Satisfaction	0.785**	0.802**	1

Note: **Correlation is significant at the 0.01 level (2-tailed)

3.1.5. Revision and Improvement Results

Based on the feedback from the alpha and beta testing phases, iterative improvements were made to the V-LAMOT prototype. The effectiveness of these revisions was evaluated by comparing key performance metrics before and after the improvements using a paired-samples t-test. The results of this analysis with 30 respondents are presented in Table 6.

Table 6. Paired-Samples T-Test Results Before and After Revision (n = 30)

Parameter	Before	After	Mean Difference	t-stat	p-value
Loading time (s)	3.20	1.80	1.40	15.23	<0.001*
Accessibility (%)	75.00	92.00	17.00	12.45	<0.001*
Error rate (%)	15.00	5.00	10.00	8.67	<0.001*

Note: All p-values are significant at $\alpha = .05$

As shown in Table 6, all measured parameters showed statistically significant improvements after the revision (all $p < .001$). Specifically, the average loading time decreased substantially from 3.20 seconds to 1.80 seconds. The system's accessibility score increased from 75% to 92%, and the user error rate was reduced from 15% to 5%. These results demonstrate that the iterative revision process was highly effective in enhancing the technical performance and user experience of the V-LAMOT virtual laboratory.

The development and validation results demonstrate that V-LAMOT—a virtual laboratory integrating state-machine modeling with Cognitive Load Theory is both technically feasible and pedagogically effective, offering measurable learning impact in electrical engineering education. The application of state-machine modeling allowed for systematic and accurate representation of logic transitions in three-phase motor starting from idle, DOL, and star–delta conditions to protection sequences consistent with established practices in state-machine–based simulation and motor modeling [1], [4], [17]. Expert validation yielded a high mean score for conceptual accuracy ($M = 4.50$, $p < .05$), confirming alignment with engineering principles and industry practices [18], [19], [21]. This supports the view that technical fidelity directly contributes to the authenticity and instructional value of virtual laboratories.

Pedagogically, Cognitive Load Theory's influence is reflected in quantitative usability and learnability metrics. The high learnability score ($M = 82.00$) and strong correlation between usability and learnability ($r = .823$, $p < .01$) indicate that interface intuitiveness facilitates interaction and supports efficient cognitive processing, aligning with Cognitive Load Theory principles where reduced extraneous load frees working memory for schema construction 18], [19], [21]. These findings extend prior research on Cognitive Load Theory in engineering laboratories by demonstrating that cognitive load management can be operationalized not only through instructional materials but also through interaction design and simulation structure. Meta-analytic evidence on virtual laboratories further suggests that structured digital environments enhance learning outcomes while minimizing unnecessary cognitive burden [3], [11], [15].

The System Usability Scale results reinforce this interpretation. An overall System Usability Scale score of 78.83 ("Good") and large effect sizes (d > 0.8) indicate substantial improvements in user experience following iterative refinement. The high effect size for learnability (d = 2.58) suggests rapid user adaptation, reflecting an interface design that likely reduces cognitive processing demands [31], [32], [43]. This positions usability not merely as a technical metric but as a pedagogically relevant construct mediating learning effectiveness in interactive media environments.

From a broader media technology perspective, these results highlight that educational effectiveness of virtual laboratories depends on integrating three interrelated components: (1) technical system modeling accuracy, (2) cognitively informed interaction design, and (3) usability-driven user experience optimization. While many virtual laboratory studies focus on visual realism or interactivity, the present findings emphasize that system logic fidelity and cognitive alignment are equally critical determinants of learning impact [1], [3], [4]. This underscores the need to conceptualize simulation-based educational technology development as an interdisciplinary process combining software engineering methodologies and learning sciences principles. Consequently, this study contributes by demonstrating how engineering-oriented system modeling and cognitive theory can be synthesized to produce media that is both technically robust and cognitively efficient, supporting the theoretical integration of system modeling fidelity and cognitive load management in media technology design.

A conceptual comparison with prior virtual laboratory approaches reported in the literature highlights the distinctive design characteristics of V-LAMOT. Rather than representing an experimental performance comparison, Table 7 synthesizes structural and pedagogical differences between simulation paradigms to clarify the positioning of the proposed system within the broader landscape of virtual laboratory development.

Table 7. Comparison of V-LAMOT with Similar Virtual Laboratory Approaches

Aspect	Conventional V-Lab (Animation-Based)	Equation-Based V-Lab	V-LAMOT (This Study)
Technical Accuracy	Limited visual representation, lacks transition logic.	Mathematically accurate, but abstract for students.	Accurate, utilizing state-machine modeling that represents real control logic.
Interactivity	Linear interaction, limited to simple inputs.	Interactive for parameters, but lacks state-based simulation.	Fully interactive with real-time state transition feedback.
Cognitive Load Optimization	Does not apply Cognitive Load Theory principles.	Focuses on managing intrinsic cognitive load.	Explicitly applies Cognitive Load Theory principles to reduce extraneous cognitive load.
Curriculum Alignment	Suitable for introductory levels.	Suitable for advanced analysis levels.	Suitable for intermediate to advanced practicum levels.
Ease of Development	Easy to develop, but with functional limitations.	Complex to develop and maintain.	Modular with state-machine architecture, easily extensible.

Note: Conventional V-Labs ([10], [15]; Equation-Based V-Labs [23], [25].

A comparison with previous studies indicates that the present findings are consistent with research demonstrating the positive impact of virtual laboratories on engineering learning outcomes and cognitive efficiency [3], [5], [11]. Earlier studies have shown that structured digital simulations can enhance conceptual understanding and reduce unnecessary cognitive burden, though many primarily emphasize visual representation or general interactivity without explicitly modeling system logic [3], [11], [15]. In contrast, V-LAMOT integrates state-machine–based modeling with Cognitive Load Theory principles, thereby extending existing work by demonstrating how technical system fidelity and cognitively informed interaction design jointly contribute to learning effectiveness [1], [17]–[19]. This positions the present study within the evolving literature that views virtual laboratories not merely as visualization tools but as cognitively structured learning environments.

The novelty of this research lies in the integration of state-machine system modeling and Cognitive Load Theory within a unified virtual laboratory framework. While previous virtual laboratory studies have addressed either technical simulation accuracy or pedagogical design principles separately, this study demonstrates their combined implementation in a control-system simulation context. In addition, the study introduces usability-derived indicators as indirect evidence for cognitive efficiency within simulation-based learning environments. This integrated approach offers a new perspective on how engineering-oriented system modeling and learning theory can be operationalized simultaneously in media technology design.

This research also presents several advantages compared with conventional virtual laboratory development approaches. From a technical perspective, the use of state-machine modeling ensures high procedural fidelity and modular system architecture, allowing accurate representation of real control logic. Pedagogically, the Cognitive Load Theory -informed interface design promotes efficient interaction and supports meaningful learning processes. Methodologically, the study combines expert validation, usability evaluation, and effect size analysis, thereby providing multi-dimensional evidence of system effectiveness. These combined strengths make the proposed framework adaptable for other engineering simulation contexts.

The findings further carry important implications for the field of Media Technology and engineering education. They suggest that effective simulation-based educational media should be designed through the integration of technical modeling accuracy, interaction design grounded in cognitive principles, and usability optimization. This reinforces the need to conceptualize virtual laboratory development as an interdisciplinary endeavor combining software engineering methodologies and learning sciences principles. Practically, the approach may inform the design of scalable, cognitively efficient training tools for technical education, particularly in contexts where access to physical laboratories is limited.

Despite the promising findings, several limitations should be acknowledged. First, the study was conducted within a specific educational context involving electrical engineering students, which may limit the generalizability of the results to other engineering disciplines or educational levels. Differences in prior knowledge, learning culture, and technological familiarity could influence how learners interact with simulation-based environments. Second, cognitive load in this study was inferred indirectly through usability-related indicators rather than measured using direct cognitive load instruments [44]-[46]. Although the System Usability Scale has demonstrated reliability in educational technology evaluation, it does not fully capture the multidimensional nature of cognitive load, particularly the distinction between intrinsic, extraneous, and germane load [21], [22], [27].

Another limitation concerns the duration of system exposure. The evaluation primarily assessed short-term interaction and immediate learning-related responses, which may not fully represent long-term knowledge retention or transfer of procedural skills to real laboratory settings. Additionally, while the state-machine modeling approach ensured technical accuracy, the system currently focuses on specific motor starting scenarios and does not yet encompass a broader range of industrial control variations.

Future research should therefore explore several directions. Longitudinal studies are needed to investigate the sustained impact of Cognitive Load Theory -informed simulation environments on knowledge retention and practical skill transfer. Further work could integrate direct cognitive load measurement techniques, such as subjective rating scales or physiological indicators, to provide a more comprehensive validation of the cognitive mechanisms underlying system effectiveness [47], [48]. Expanding the simulation framework to cover additional control systems and fault scenarios would also enhance the applicability of the platform in diverse industrial training contexts [49], [50]. Finally, comparative studies between state-machine–based simulations and other modeling approaches may help clarify the relative contribution of system modeling fidelity to learning outcomes in media technology–supported engineering education.

4. CONCLUSION

This study developed and validated V-LAMOT, a virtual laboratory that integrates state-machine modeling with Cognitive Load Theory principles to enhance technical accuracy and cognitive efficiency in electrical engineering practicum learning. The findings demonstrate that the proposed system is both technically valid and pedagogically effective, as reflected in high expert validation scores, strong usability and learnability outcomes, and substantial effect sizes indicating meaningful improvements in user experience. The integration of state-machine logic ensured accurate representation of real motor control processes, while Cognitive Load Theory -informed interaction design supported efficient cognitive processing during system use. These results confirm that combining accurate system modeling with cognitively grounded interface design can enhance the educational value of simulation-based media in engineering education. Future research is recommended to conduct longitudinal evaluations of learning retention and skill transfer, employ direct cognitive load measurement methods, expand the simulation framework to additional industrial control scenarios, and compare state-machine–based virtual laboratories with alternative modeling approaches to further clarify their relative pedagogical contributions.

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AUTHOR CONTRIBUTIONS

Conceptualization: M. Isnaini and S. Purba; Methodology: M. Isnaini, S. Purba, and M. S. Dewy; Software: M. Isnaini and A. I. Silitonga; System Architecture & State-Machine Modeling: M. D. Solihin; Validation: M. Isnaini, M. S. Dewy, and A. I. Silitonga; Formal Analysis: M. Isnaini and M. D. Solihin; Investigation: S. Purba and M. S. Dewy; Resources: S. Purba and A. I. Silitonga; Data Curation: M. Isnaini and A. I. Silitonga; Writing – Original Draft Preparation: M. Isnaini and M. S. Dewy; Writing – Review & Editing: M. Isnaini, S. Purba, and A. I. Silitonga; Visualization: M. D. Solihin and A. I. Silitonga; Supervision: S. Purba and M. D. Solihin; Project Administration: S. Purba and M. S. Dewy; Funding Acquisition: M. Isnaini and S. Purba.

INFORMED CONSENT STATEMENT

Informed consent was obtained from all subjects involved in the study. Prior to participation, each subject was provided with a detailed explanation of the study's objectives, procedures, potential risks, and benefits. All participants were informed that their involvement was voluntary and that they could withdraw at any time without consequences. The study involved usability testing of the V-LAMOT virtual laboratory platform, which posed no physical risks as it was conducted entirely in a digital environment. All participants voluntarily agreed to participate and signed a written informed consent form prior to data collection. Data were collected anonymously to ensure confidentiality and were used solely for research purposes.

CONFLICTS OF INTEREST

The authors declare no conflict of interest. The funding sponsors had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results. All research activities, including data collection, analysis, and manuscript preparation, were conducted independently by the authors without any involvement from the funding sponsors or other external parties.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

During the preparation of this work, the authors used DeepSeek to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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