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AI-Based Virtual Lab Assistants for Personalized Engineering Education

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Abstract

Advances in artificial intelligence now enable virtual assistants that enhance laboratory-based learning through conceptual diagnostics and adaptive support. This study presents an Artificial Intelligence–based Virtual Lab Assistant (AI-VLA) designed to improve learner readiness and performance in engineering laboratory environments. The system uses natural language understanding to conduct pre-lab conceptual assessments that identify gaps in understanding before students begin experimental work, and during laboratory activities it delivers context-aware guidance aligned with course outcomes to support procedural accuracy, error correction, and stronger integration of theory and practice. A design-based research methodology was adopted to iteratively refine the system and examine its practical value, with descriptive findings from a pilot implementation involving 120 undergraduate students indicating improvements in conceptual preparedness, procedural correctness, task completion, and learner confidence. Students engaging with the AI-VLA entered the laboratory better equipped, made fewer execution errors, and demonstrated deeper engagement with experimental activities. The framework incorporates responsible AI principles through data minimization, transparency, and fairness-aware mechanisms. Overall, the study illustrates how AI-driven virtual assistants can strengthen laboratory instruction by embedding real-time conceptual assessment and adaptive scaffolding into a learner-centered, outcome-oriented support ecosystem.

Keywords — Adaptive Feedback; Artificial Intelligence; Engineering Education; Natural Language Processing (NLP); Personalized Learning; Virtual Labs

***JETLP Category*—Research**

I. INTRODUCTION

Laboratory-based learning remains a cornerstone of engineering education, offering invaluable opportunities for students to translate theoretical concepts into hands-on problem-solving skills. Despite their strengths, traditional laboratory models struggle to provide individualized guidance and timely feedback—challenges highlighted in prior studies of computer laboratory environments (Munawar et al., 2018). These limitations create a natural opportunity for intelligent, technology-driven solutions such as Virtual Lab reducing manual workload for educators.

Assistants to complement conventional instruction, enhance accessibility, and deliver personalized learning experiences.

In response, this study proposes an AI-Based Virtual Lab Assistant (VLA) designed to offer adaptive, context-aware support. The system builds upon prior research in AI-assisted virtual and hybrid laboratories (Murali et al., 2024; Groenewald et al., 2024) by integrating curriculum-aligned pedagogy with automated dialogue and adaptive scaffolding. Unlike earlier rule-based assistants (Josphineleela et al., 2023), the proposed VLA leverages NLP, learning analytics, and feedback loops to align learner support with course outcomes, consistent with trends in AI-enabled personalized education (Liu et al., 2024).

Recent studies have reported improved engagement and conceptual understanding through AI-enhanced learning environments (Ayre et al., 2023; Glick et al., 2024). However, most existing systems exhibit limited adaptability and insufficient transparency—issues emphasized in AI ethics and educational technology literature (Pérez-Lizano-Sánchez et al., 2025). The proposed VLA addresses these gaps by embedding explainable AI strategies, adaptive feedback, and faculty oversight into its architecture. Through NLP-driven interaction, real-time analytics, and feedback loops supervised by instructors, the system dynamically aligns support with learner performance and intent. This design contributes to the broader goal of advancing AI-enabled personalized engineering education, where intelligent systems complement rather than replace human mentorship.

System Design

The architecture of the VLA integrates pedagogical adaptability with data-driven decision-making to support personalized laboratory instruction. The system follows a modular design comprising five interdependent layers: User Interface, Knowledge Base, AI Assistant Layer, Assessment Engine, Feedback and Training Loop. The system architecture of the AI based Virtual Lab Assistant is shown in Figure 1.

User Interface acts as a responsive web portal that facilitates real-time interaction and visual feedback. Faculty dashboards display analytics on learner progress, enabling targeted interventions (Ramasamy et al., 2024).

The Knowledge Base forms the cognitive foundation of the assistant, incorporating structured content such as laboratory manuals, algorithmic examples, and conceptual frameworks. This layer is continuously updated based on faculty input and learner interaction data to maintain curriculum - learning outcome alignment (Josphineleela et al., 2023).

At the system core, the AI Assistant Layer employs NLP and dialogue management algorithms to interpret queries and generate pedagogically aligned responses. The model supports textual and multimodal inputs, allowing students to request clarifications, verify outputs, or explore concepts interactively (Liu et al., 2024).

The Assessment Engine functions as a formative analytics module that evaluates learner readiness through pre-lab diagnostics and contextual quizzes. It classifies learners into adaptive tiers based on response accuracy and time metrics, enabling feedback personalization (Elmesalawy et al., 2022). The assessment engine also determines each student's competency level in relation to the required learning objectives and enables to evaluate the attainment of the intended learning outcomes.

Finally, the Feedback and Training Loop captures instructor evaluations and learner behavior to refine future responses. This loop minimizes bias and ensures consistency across laboratory sessions.

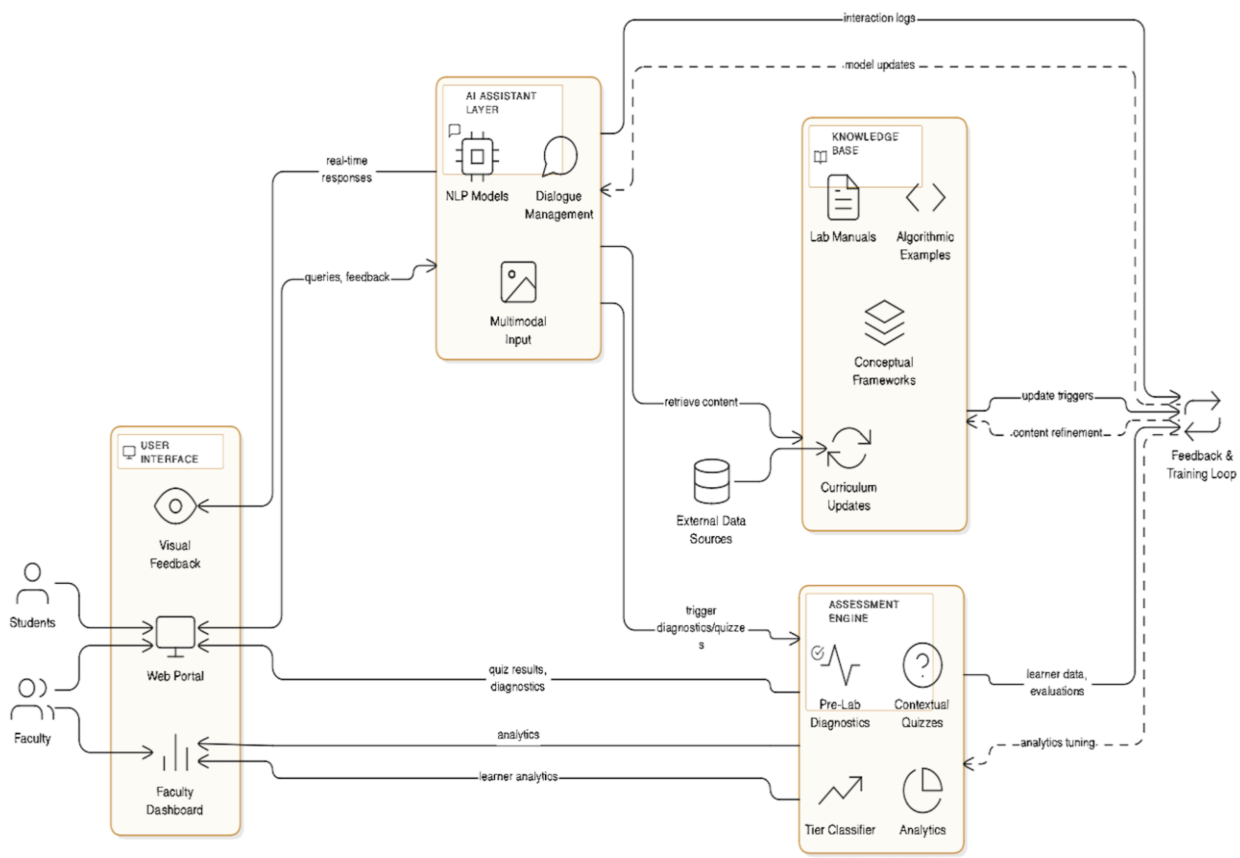

Figure 1. *System Architecture of the AI-Based Virtual Lab Assistant*

The overall design emphasizes **scalability**, **explainability**, and **ethical compliance**. Explainable AI mechanisms allow students to trace reasoning paths within the assistant's feedback, fostering transparency and trust (Groenewald et al., 2024, Pérez-Lizano-Sánchez et al., 2025).

Methodology

The evaluation of the Virtual Lab Assistant (VLA) followed a structured pre-test/post-test design integrated within a six-week laboratory module involving 120 undergraduate computer science students. The study was conducted across three laboratory courses: Compiler Design, Database Management Systems (DBMS), and Operating Systems (OS).

Participants and learning context

Students used the VLA during scheduled lab hours to seek conceptual clarifications, request adaptive hints, and verify logic or code output. Three faculty members monitored the sessions and provided conventional support when required. All interactions with the VLA were logged for analysis.

Assessment instruments

Learner performance was measured using two parallel assessment instruments (pre-test and post-test instruments) to measure conceptual, procedural, and application-level performance, consistent with methodologies from prior learning impact evaluations (Liu et al., 2024; Zhang et al., 2025).

System interaction analytics

Interaction logs were analyzed for frequency of queries, coding errors, and instructor interventions, following frameworks similar to those applied in remote chemistry and AI-enabled laboratory studies (Lizano-Sánchez et al., 2025; Pérez-Lizano-Sánchez et al., 2025).

Student perception and Usability measures

Learner perception was evaluated through Likert-scale ratings, consistent with usability research using SUS and trust/transparency measures (Glick et al., 2024).

Results Preparation & Statistical Rigor Plan

To strengthen methodological rigor, the study outlines a structured plan for quantitative analysis, acknowledging that full inferential testing will be conducted once complete data are available. Descriptive outcomes will be supplemented with inferential statistics to examine the significance and magnitude of learning gains. Planned analyses include paired-sample t-tests to compare pre- and post-test scores across conceptual, procedural, and application-level measures, accompanied by effect size calculations (e.g., Cohen's d) to quantify the strength of improvements (Liu et al., 2024; Zhang et al., 2025). Confidence intervals will be reported for major performance metrics to enhance interpretability, and reliability analyses—such as Cronbach's alpha—will be applied to assessment instruments to ensure internal consistency. Incorporating these statistical components in the full-scale evaluation aligns the study with expectations for empirical rigor and strengthens the robustness and validity of the resulting conclusions.

Ethical Oversight

All data collection followed institutional ethical guidelines, including anonymization, secure storage, and transparency in use. Participation was voluntary, and informed consent was obtained. Data usage adhered to guidelines for responsible AI in education (Pérez-Lizano-Sánchez et al., 2025; Abdullah et al., 2024).

Results and Discussion

Conceptual and Skill-Based Learning Gains

The distribution of conceptual gains across the three laboratory courses is summarized in Table 1, which highlights consistent improvements of 18–19% across domains. resulting in an overall mean learning gain of 19.3%.

Table 1: Domain-wise Conceptual gain

Laboratory Course	Pre-VLA Conceptual Score (%)	Post-VLA Conceptual Score (%)	Improvement (%)
Compiler Design	62	81	+19
DBMS	66	84	+18
Operating Systems	64	82	+18
Mean Improvement	—	—	**+19.3**

In addition to conceptual improvement, overall task performance strengthened significantly. The task completion rate rose from 67% (before VLA) to 88% (with VLA), demonstrating a 21% increase in successful experiment completion.

Automated log analysis further confirmed learning improvements at the technical level. The average number of coding and logic errors per submission decreased from 4.8 to 2.9, a 39% reduction, indicating more accurate application of concepts and procedures.

The skill-wise overall performance gains are summarised in *Table 2*, which presents improvements across conceptual understanding, procedural accuracy, and application-level reasoning. Students demonstrated notable progress across all dimensions, with post-test scores consistently higher than pre-test measures.

Table 2. Skill-wise Overall Performance Gain

Skill Dimension	Pre-test (%)	Post-test (%)	Improvement (%)
Conceptual Understanding	61.5	80.2	+18.7
Procedural Accuracy	64.8	83.6	+18.8
Application Skills	63.2	83.4	+20.2

Collectively, these results demonstrate that the VLA meaningfully strengthens conceptual mastery, enhances procedural accuracy, and supports more effective application-level problem-solving.

Learner Autonomy and Behavioral Shifts

Interaction analytics indicated clear and meaningful shifts in learner autonomy. Self-guided attempts increased by 26%, demonstrating a greater willingness among students to explore solutions independently. In parallel, hint requests decreased by 18%, suggesting reduced reliance on external prompts as the VLA provided targeted scaffolding and conceptual reinforcement.

Learners also displayed stronger intrinsic motivation, reflected in a 31% increase in voluntary re-attempts of lab tasks. These patterns align with established models of self-regulated learning, indicating that the VLA effectively cultivates proactive and reflective engagement during laboratory activities.

Overall system engagement remained high, with students initiating an average of 3.6 queries per session and achieving a 94% experiment completion rate. Together, these behavioral indicators confirm that the VLA not only enhances performance but also promotes sustained engagement and independent learning.

Instructor Support Load and Teaching Efficiency

System logs revealed that the VLA effectively absorbed routine, first-line support during laboratory sessions. Repetitive student queries to instructors decreased by 28%, and the system maintained an average 2.3-second error detection latency with consistent accuracy in identifying common conceptual and procedural mistakes. Correspondingly, instructor intervention data showed a reduction from 14 to 9 interventions per session, indicating a 35% decrease in routine instructional load. This shift enabled faculty to redirect their efforts toward deeper conceptual explanations and higher-order problem-solving guidance, thereby improving the overall quality of instructional interactions.

System Usability, Trust and Student Perception

Usability and perception measures, gathered through an adapted System Usability Scale (SUS) and an explainability-focused questionnaire, demonstrated strong positive acceptance of the VLA. The overall SUS score increased from 78 to 89, indicating a marked improvement in perceived system quality. Trust in AI-generated feedback rose by 22%, and perceived clarity of feedback improved by 17%, reflecting the effectiveness of the VLA's explainable-AI features and transparent reasoning cues.

Student satisfaction ratings further supported these findings. On a 1–5 Likert scale, learners rated the VLA highly for Ease of Use (4.6), Feedback Clarity (4.4), Conceptual Support (4.5), and Overall Satisfaction (4.7). Notably, 85% of students reported that the adaptive hinting mechanism enhanced their confidence and supported independent problem-solving. Collectively, these results indicate that the VLA is not only technically effective but also well-received as a user-friendly, trustworthy, and pedagogically supportive learning companion.

Time Efficiency and Workflow Improvements

Time-on-task analysis showed that the VLA contributed to more efficient laboratory workflows. The average time required to complete a lab experiment decreased from 52 minutes to 41 minutes, reflecting a 21% improvement in completion time. This reduction indicates that students were able to identify errors more quickly, navigate procedures more efficiently, and complete tasks with fewer delays.

Overall impact summary and discussion

The study confirms the pedagogical value of integrating intelligent virtual assistants into laboratory teaching. Across learning, behavioral, perceptual, and time-efficiency dimensions, the VLA consistently enhanced laboratory instruction quality. Students demonstrated stronger conceptual foundations, higher autonomy, improved satisfaction, and greater efficiency, while faculty experienced reduced repetitive load. These combined effects position the VLA as an effective AI-assisted learning tool capable of supporting scalable, outcome-driven engineering education.

Table 3: Summary of Results

Metric	Baseline	With VLA	Improvement
Conceptual Understanding (%)	64%	83.3%	+19.3%
Task Completion Rate (%)	67%	88%	+21%
Instructor Interventions (count)	14	9	−35%
Errors per Submission	4.8	2.9	−39%
Self-Guided Attempts (%)	—	—	+26%
Voluntary Re-attempts (%)	—	—	+31%
Usability Score (SUS)	78	89	+14.1%
Trust/Transparency (%)	—	—	+22%

As summarized in Table 3, the 19.3% improvement in conceptual understanding across Compiler Design, DBMS, and Operating Systems strongly correlates with the 21% increase in task completion rates. Students entered each lab session with better pre-lab readiness due to the VLA's adaptive conceptual checks, which reduced misconceptions before hands-on work began. This improved clarity, reduced coding and logic errors by 39%, shortened lab completion times by 21%, and increased voluntary re-attempts by 31%, indicating deeper engagement. These results together show that enhanced conceptual grounding not only improves accuracy but also promotes a growth-oriented approach to laboratory work. Greater autonomy is evident from fewer instructor interventions which is about 35% reduction and more self-guided attempts contributed directly to higher satisfaction. This positive experience was further supported by improved usability scores from 78 to 89 and increased trust perceptions. Overall, the results reflect a positive cycle in which better conceptual grounding enhances performance, which in turn boosts satisfaction and encourages deeper engagement with the VLA. This cycle reflects the success of the VLA as a human–AI collaborative ecosystem, where cognitive gains (mastery), behavioral gains (task completion, autonomy), and affective gains (satisfaction) mutually amplify one another.

Conclusion

The Virtual Lab Assistant developed in this study demonstrates the expanding potential of AI to strengthen laboratory-based engineering education. Through NLP-driven interaction, adaptive assessment, and real-time analytics, the system bridges conceptual understanding with procedural execution. Its five-layer architecture delivers integrated, personalized support that enhances conceptual clarity, improves task accuracy, and reduces coding and logical errors. Evidence from the six-week evaluation reinforces these contributions: students showed substantial gains in conceptual mastery (+19.3%), task completion accuracy (+21%), and application-level reasoning (+20.2%), alongside higher autonomy, engagement, and intrinsic motivation. Instructor load decreased by 35%, and usability and trust ratings indicated strong acceptance. These outcomes position the VLA as a scalable human–AI collaborative ecosystem that supports learner-centered, outcome-driven pedagogy, strengthened by explainable AI features and fairness-aware mechanisms. While the results validate the system's effectiveness, they also highlight opportunities for future work, including incorporating multimodal inputs (voice, diagrams, code visualizations), examining long-term retention and metacognitive development, expanding deployments across additional engineering domains, and advancing privacy-preserving adaptation strategies such as federated learning. **Future full-scale evaluations will incorporate a structured methodological and statistical-rigor plan, including preregistered hypotheses, power analysis, reliability checks, and inferential testing (e.g., paired-sample t-tests, effect sizes, and confidence intervals) to ensure robust, generalizable conclusions.** Overall, the study provides a strong foundation for responsible, personalized AI integration in laboratory instruction and demonstrates its measurable cognitive, behavioral, and affective benefits.

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Author Biodata

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