

AI Assisted Virtual Laboratories for Engineering without Borders: Quasi Experimental Evidence from Sustainable Agricultural Irrigation Education in Higher Education Contexts

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Abstract— Unequal access to physical laboratories in engineering education continues to limit equity, experimental repeatability, and students' engagement with real-world sustainability challenges, particularly in resource-constrained contexts. This study presents a quasi-experimental evaluation of AI assisted virtual laboratories with intelligent feedback as a pedagogical strategy to support Engineering without Borders principles in higher education. The intervention was implemented in a Physical Experimentation and Statistical Thinking course through an authentic challenge focused on designing a sustainable agricultural irrigation system using a Mariotte Bottle. A mixed-methods quasi-experimental design was conducted with 93 undergraduate engineering students, divided into a control group ($n = 47$) using traditional physical experimentation and an experimental group ($n = 46$) combining physical practice with AI assisted virtual laboratories. Data were collected using pre- and post-tests, validated Likert-type surveys ($\alpha > 0.85$), standardized rubrics, and qualitative reflections. Statistical analyses included independent-samples t-tests, one-way ANOVA, correlation analysis, effect sizes, and power analysis (> 0.80). Results revealed significantly higher conceptual learning gains, motivation, technological acceptance, and problem-solving consistency in the experimental group. The normalized learning gain reached $g = 0.67$ compared to $g = 0.34$ in the control group ($p < 0.05$). Qualitative findings showed deeper integration of the Sustainable Development Goals (SDGs), particularly SDGs 2, 4, 6, 9, 12, and 13. The findings indicate that AI assisted virtual laboratories can complement physical experimentation, offering an ethically grounded instructional approach with potential for application in similar higher education contexts.

Keywords— *AI Assisted Virtual Laboratories, Engineering Education, Quasi Experimental Design, Sustainable Engineering, Agricultural Irrigation, Engineering without Borders.*

I. INTRODUCTION

Unequal access to physical laboratories remains a persistent challenge in engineering education, particularly in higher education institutions facing economic, infrastructural, or geographic constraints [1]. This limitation directly affects equity, experimental repeatability, and students' opportunities to engage with authentic engineering problems connected to

sustainability and social impact [2]. Within the framework of Engineering without Borders, addressing these disparities is essential to ensure that engineering education responds effectively to real-world challenges across diverse contexts in the Americas. This study is situated within STEM education (Science, Technology, Engineering, and Mathematics), emphasizing methodological rigor through statistical analyses such as ANOVA (Analysis of Variance) and ANCOVA (Analysis of Covariance) for data comparison and validation.

Recent studies demonstrate that artificial intelligence enriches STEM education by providing immediate feedback, simulating complex scenarios, and enabling personalized learning experiences [3]–[6]. Nevertheless, much of the existing research has focused on theoretical instruction or computational modeling, offering limited empirical evidence of AI integration within authentic experimental practices and their explicit connection to the Sustainable Development Goals. In Latin American contexts, where infrastructure limitations are more pronounced, AI assisted virtual laboratories represent a particularly relevant strategy for advancing inclusive, innovative, and scalable engineering education [7].

Prior research has documented consistent progress in pedagogical innovation supported by digital technologies. Tec et al. demonstrated how mobile sensors foster active learning in differential equations [8]; Pérez et al. proposed a research model oriented toward prototype construction, strengthening technical and transversal skills [9]; and Nieto-Jalil et al. highlighted the role of Generative AI and experiential learning in solving complex problems and enhancing motivation [10]. These precedents support the hypothesis that AI-assisted virtual laboratories do not replace experimental practice but amplify and extend its accessibility, offering fertile ground for the pedagogical comparison presented here. Despite these advances, there remains a lack of quasi-experimental studies that examine the use of AI assisted virtual laboratories within authentic experimental settings, particularly those explicitly aligned with sustainability challenges and the Sustainable Development Goals. This gap is especially evident in higher education contexts in Latin America, where empirical evidence

is needed to support scalable and transferable educational interventions grounded in engineering practice.

In response to this challenge, the present study was guided by the following research question: Can AI-assisted virtual laboratories with intelligent feedback transform engineering education by improving conceptual learning, motivation, technological acceptance, and sustainability-oriented competencies while expanding equitable access to experimental learning environments?

This study employed a quasi-experimental design involving 93 undergraduate students enrolled in the Physical Experimentation and Statistical Thinking course, who were divided into an experimental group ($n = 46$) and a control group ($n = 47$). Both groups conducted the Mariotte Bottle experiment; however, the experimental group complemented physical experimentation with AI-assisted virtual laboratories providing intelligent feedback, parametric simulations, and advanced visualizations. The Mariotte Bottle was selected as the experimental system due to its metrological traceability, well-defined physical variables, and suitability for controlled analysis of hydrostatic pressure stability and flow rate in sustainable irrigation contexts. The Mariotte Bottle experiment consists of a simple yet powerful physical setup used to maintain constant hydrostatic pressure and flow rate, enabling precise analysis of liquid discharge. It typically employs a sealed container with a vertical air tube that stabilizes pressure as the water level decreases, making it ideal for studying Bernoulli's principle, fluid flow, and pressure equilibrium in irrigation contexts. The purpose of this work is to analyze the effect of AI-assisted virtual laboratories on conceptual understanding, motivation, and the development of technical and transversal competencies. Results between groups are compared using statistical analyses and pedagogical visualizations. Finally, we discuss the potential of this strategy as a replicable, scalable, and ethically grounded model aligned with both the SDGs and the Tec21 Model, which promotes active, interdisciplinary, and challenge-based learning.

We formulated three testable hypotheses: H1: The hybrid group will achieve higher normalized gains in key concepts, H2: The hybrid group will exhibit higher levels of motivation and technological acceptance (TAM/UTAUT). H3: The hybrid group will demonstrate more explicit integration of SDGs in products and reflections.

The main contributions of this work are: (1) To demonstrate the impact of AI-driven intelligent feedback on conceptual learning gains in experimental engineering practices, (2) To analyze the influence of virtual laboratories on students' motivation, engagement, and technological perception, (3) To explore the explicit integration of the SDGs into the educational process, incorporating ethical and social dimensions and (4) To propose a replicable and scalable intervention model that complements rather than replaces physical practice in STEM education

II. STUDY DESIGN

This study employed a quasi-experimental design with parallel groups to compare the pedagogical impact of AI-assisted virtual laboratories against a traditional experimental

approach. The intervention was conducted in the Physical Experimentation and Statistical Thinking course at Tecnológico de Monterrey, under the Tec21 Model, which emphasizes active, interdisciplinary, and challenge-based learning aligned with the Sustainable Development Goals (SDGs).

A. Population and Study Structure: Ninety-three undergraduate students were divided into two groups. The experimental group ($n = 46$) performed the Mariotte Bottle experiment complemented with AI-assisted virtual laboratories that provided intelligent feedback, parameter variation, scenario simulations, and advanced visualizations. The virtual laboratory was implemented using a custom simulation environment developed in MATLAB App Designer and complemented with ChatGPT-based feedback modules integrated through a web interface. Students accessed the platform using personal laptops and institutional computers during class sessions in the traditional laboratory setting, alternating between physical experimentation and digital simulation. The AI feedback module generated context-sensitive prompts offering suggestions for data correction, parameter adjustments, and error interpretation. The AI-assisted feedback system followed a hybrid architecture combining rule-based validation with Generative AI support. First, MATLAB App Designer processed experimental variables such as flow rate stability, hydrostatic pressure consistency, and discharge behavior using predefined physical thresholds. Subsequently, the ChatGPT-based module generated adaptive textual feedback, including conceptual explanations, error interpretation, parameter adjustment suggestions, and reflective prompts aligned with the learning objectives. This integration pipeline allowed students to iteratively compare physical and simulated scenarios while receiving immediate formative guidance during experimentation. The control group ($n = 47$) conducted the same experiment and produced traditional technical reports without AI mediation. Both groups shared the same challenge, schedule, content, equipment, and evaluation criteria, with AI integration being the only deliberate difference.

B. Methodological Phases: The intervention was structured into three pedagogical phases designed to ensure equity and isolate AI as the central variable [11].

Phase 1 – Conceptual Foundation: All students reviewed fluid flow, hydrostatics, Bernoulli's equation, and basic statistics. The experimental group additionally used interactive virtual simulations to reinforce prior knowledge and interdisciplinary connections.

Phase 2 – Experimentation and Analysis: Both groups conducted the Mariotte Bottle experiment and collected flow and pressure data. The control group processed results manually with basic graphs, while the experimental group replicated scenarios with AI-assisted laboratories to validate data and generate advanced visualizations.

Phase 3 – Communication and Transfer: Both groups submitted technical reports. The control group followed a traditional format, whereas the experimental group incorporated AI-supported narratives, radar charts, heatmaps, and explicit reflections on sustainability and the SDGs.

This sequence ensured homogeneous conditions across content, timing, and assessments, with AI serving as the sole pedagogical differentiator.

C. Variables and Instruments

The study considered three main categories of variables: cognitive, affective, and technological. Cognitive variables focused on students' conceptual understanding of fluid mechanics and experimental reasoning related to sustainable irrigation systems. Affective variables addressed motivation, perceived engagement, and confidence in experimental decision-making. Technological variables examined students' perceptions of usability, clarity, and pedagogical value of the AI-assisted virtual laboratories.

Data were collected using multiple instruments to ensure triangulation and methodological robustness. Conceptual understanding was assessed through performance-based rubrics applied to experimental reports and design justifications. Motivation and engagement were measured using structured questionnaires with Likert-scale items ($\alpha > 0.85$), administered at the end of the intervention. Perceptions of the AI-assisted virtual laboratories were captured through a technology acceptance survey focusing on usability, feedback quality, and visualization effectiveness.

D. Statistical Analysis

Statistical analysis was conducted using a combination of descriptive and inferential techniques to examine differences between the experimental and control groups. Independent-samples t-tests were applied to compare post-test performance, normalized learning gains, and motivation between groups. One-way ANOVA was used to evaluate the effect of the intervention on learning gains and motivational outcomes. Pearson correlation analyses explored relationships between technological perception, motivation, and academic performance. Effect sizes (Cohen's d and partial η^2) and statistical power (> 0.80) were calculated to support the robustness and educational relevance of the findings.

E. Methodological Comparison Between Groups

To isolate the pedagogical effect of the intervention, both groups worked under equivalent conditions: the same challenge, content, schedule, physical instrumentation, and evaluation criteria. The only deliberate difference was the use of AI in the experimental group through virtual laboratories with intelligent feedback. This methodological decision guaranteed equity between groups and allowed observed differences to be attributed to the pedagogical approach implemented.

Table I summarizes the controlled conditions for both groups and highlights the only deliberate difference: the use of virtual laboratories with intelligent feedback in the experimental group, compared with the traditional approach of the control group. This methodological design made it possible to precisely isolate the impact of Generative AI-assisted virtual laboratories as the central pedagogical variable. By keeping the

physical experiment, resources, and evaluation criteria constant, it was ensured that the observed differences in learning gains, motivation, engagement, and ethical reflection linked to the SDGs were attributable to the use of AI in the experimental group.

TABLE I. METHODOLOGICAL COMPARISON BETWEEN GROUPS

Element	Experimental Group	Control Group
Physical experiment	Mariotte Bottle with AI-assisted validation	Mariotte Bottle with manual validation
Complementary simulation	Virtual laboratories with intelligent feedback	Not available
Visualization and simulation	Advanced graphs (radar, heatmaps); multiple scenarios	Traditional graphs (line, bar); single baseline scenario
Feedback	Immediate (AI) + formative (instructor)	Instructor-only feedback
Scientific narrative	AI-assisted explanations for assumptions, limitations, and knowledge transfer	Linear technical description of results
Ethical/SDG reflection	Explicit, guided reflection linked to SDGs (2, 4, 6, 9, 12, 13), assessed with rubric	Implicit reflection in reports, without specific rubric
Measured competencies	Experimental techniques, advanced analysis, scientific communication, critical thinking, motivation/autonomy, ethics and SDGs	Experimental techniques, basic analysis, academic writing, motivation, basic SDG scope

The following section presents quantitative and qualitative results with graphical visualizations comparing both groups in technical, motivational, and social competencies, demonstrating the potential of this approach as a replicable and scalable model for STEM education.

III. EVALUATION OF THE RESULTS

The educational impact was assessed through a mixed quantitative–qualitative approach integrating technical performance, conceptual understanding, motivation, engagement, technological perception, and alignment with the SDGs. This multidimensional approach allows the interpretation of results not only in terms of statistical significance, but also in relation to their educational relevance and potential implications for instructional practice in engineering education.

Data were collected through pre-, post-, and retention tests, validated Likert-type scales ($\alpha > 0.85$), standardized rubrics, and qualitative reflections, supported by comparative visualizations for pedagogical interpretation. The key results are presented below across five dimensions:

1. Conceptual Learning Gains (H1): Both groups completed diagnostic (pre-test) and outcome (post-test) assessments to measure conceptual understanding. Learning gains were computed using absolute differences and Hake's

normalized gain formula, $g = (\text{Post} - \text{Pre}) / (100 - \text{Pre})$, controlling for initial performance. Table II presents mean scores ($\pm$ SD) and normalized gains for each group. Results indicate that intelligent feedback in the AI-assisted virtual laboratories significantly improved concept consolidation and retention compared to traditional practice. Since both groups shared identical experiments, content, and evaluation criteria, the observed performance differences are associated with the AI-mediated pedagogical approach, supporting internal validity and instructional relevance..

TABLE II. PRE-TEST, POST-TEST, AND NORMALIZED GAIN RESULTS BY GROUP

Group	Pre-test (Mean $\pm$ SD)	Post-test (Mean $\pm$ SD)	g (Normalized Gain)
Experimental (n = 46)	41.2 $\pm$ 8.7	78.5 $\pm$ 9.3	0.67
Control (n = 47)	42.5 $\pm$ 9.1	65.8 $\pm$ 10.2	0.34

2. Motivation and Engagement (H2): Motivation and engagement are key drivers of active learning and persistence in STEM education. Both dimensions were evaluated through validated Likert-type scales ($\alpha > 0.85$) addressing intrinsic motivation, clarity, autonomy, and participation. Results revealed significant group differences: as shown in Figure 1, the control group showed a slight increase in motivation (median $\approx 3.2 - 3.5$), while the experimental group improved markedly ($\approx 3.3 - 4.3$). The lower response dispersion in the experimental group indicates a more stable and homogeneous commitment, attributed to the intelligent feedback provided by AI.

Figure 2 expands on this finding by presenting the post-test profile of transversal competencies. The experimental group not only maintained higher levels of motivation but also achieved higher scores in autonomy, conceptual clarity, and critical thinking, shaping a broader and more balanced profile. These results indicate that AI-assisted virtual laboratories go beyond motivational enhancement, contributing to the development of autonomy, conceptual clarity, and ethical reasoning, which are essential components of higher-order learning in engineering education.

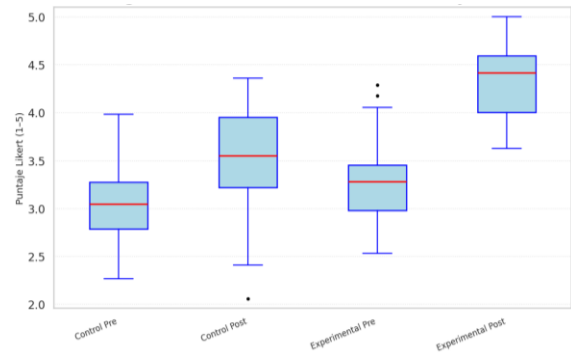


Fig. 1. Comparison of motivation levels between the control and experimental groups. The experimental group shows a higher central tendency and lower dispersion, suggesting a more stable motivational response associated with the use of AI-assisted intelligent feedback.

3. Technological Perception (H2): Technological acceptance is a critical factor in the adoption of educational innovations. According to the TAM/UTAUT model (Technology Acceptance Model / Unified Theory of Acceptance and Use of Technology), students' perceptions were evaluated across four main dimensions: perceived usefulness (PU), perceived ease of use (PEOU), attitude toward the tool (ATT), and behavioral intention for future use (BI).

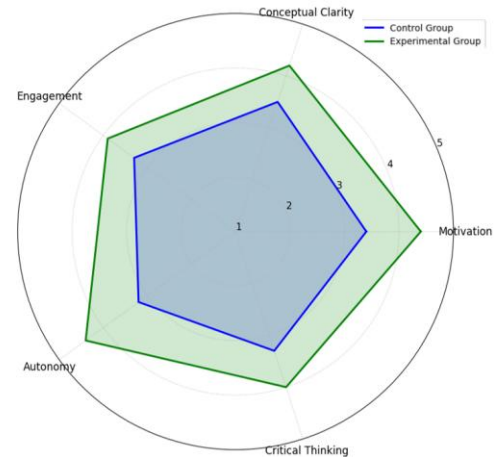


Fig. 2. Expanded profile of transversal competencies in the experimental group. Higher levels of motivation, autonomy, and critical thinking indicate a more balanced competency profile associated with the use of virtual laboratories with intelligent feedback.

These dimensions were measured using validated Likert-type scales ($\alpha \geq 0.85$), in order to analyze how AI mediation in virtual laboratories was received by students and how these perceptions were related to their academic performance.

Figure 3 shows a clear difference between groups. The control group maintained moderate scores ($\approx 3.5 - 3.6$ across all dimensions), while the experimental group achieved significantly higher values, particularly in PU (4.5 ± 0.4) and BI (4.6 ± 0.4). This indicates that students who worked with intelligent feedback not only perceived AI as useful and accessible but also expressed a strong intention to continue using it in the future.

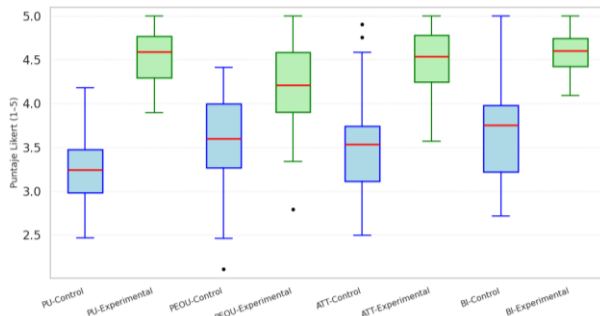


Fig. 3. Technological perception of AI in virtual laboratories. The experimental group reported higher perceived usefulness, ease of use, engagement, and behavioral intention, indicating a positive acceptance of AI-supported experimental activities.

Beyond averages, the correlational analysis made it possible to explore the relationship between technological perception and academic performance. Figure 4 shows that perceived usefulness (PU) and behavioral intention (BI) exhibited the strongest correlations with normalized learning gain ($r = 0.62$, $p < 0.01$) and with motivation ($r = 0.60$, $p < 0.01$). In turn, perceived ease of use (PEOU) was primarily associated with motivation ($r = 0.55$, $p < 0.01$), suggesting that when students perceive the technology as accessible, their willingness to engage with learning increases.

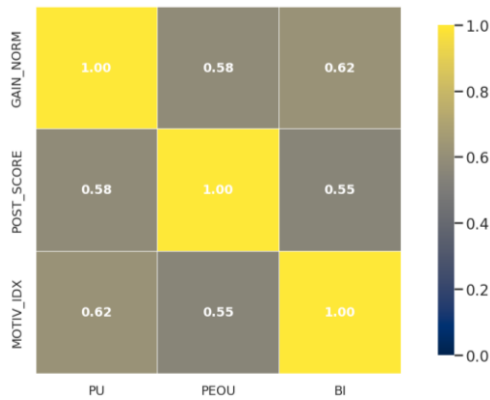


Fig. 4. Correlations between technological perception and academic performance. Perceived usefulness (PU) and behavioral intention (BI) exhibit the strongest associations with learning gains and motivation, suggesting a close relationship between technological acceptance and learning outcomes.

Taken together, these findings indicate that AI-assisted virtual laboratories were positively accepted by students, not only as functional tools, but as meaningful components of the learning process. The results suggest potential for continued educational integration in similar higher education contexts.

4. Transversal Competencies and SDG Integration (H3):

The qualitative analysis of student reflections made it possible to evaluate the degree of alignment with the SDGs, as well as the integration of transversal competencies into the learning process. For this purpose, the written productions were subjected to a thematic coding process, in which two independent researchers classified the references into categories associated with sustainability, ethics, and innovation. Inter-coder reliability reached a Kappa index of 0.87, ensuring consistency in data classification.

The findings revealed clear contrasts between the groups. The control group made only brief and generic references to the SDGs, such as “this project can help the environment.” In contrast, the experimental group provided explicit and well-structured reflections, directly connecting the Mariotte Bottle experiment to global objectives—for instance, “this system contributes to SDG 6 by improving water efficiency and promoting responsible consumption (SDG 12).”

Figure 5 clearly illustrates this difference. The experimental group reached between 15 and 22 explicit mentions per SDG, in contrast to the 4 to 10 implicit mentions in the control group. This gap is particularly evident in SDG 4 (Quality Education) and SDG 6 (Clean Water and Sanitation), both directly linked to the Mariotte Bottle challenge. The experimental group also excelled in SDG 9 (Industry, Innovation, and Infrastructure), showing that AI helped students recognize the technological innovation component in their practice.

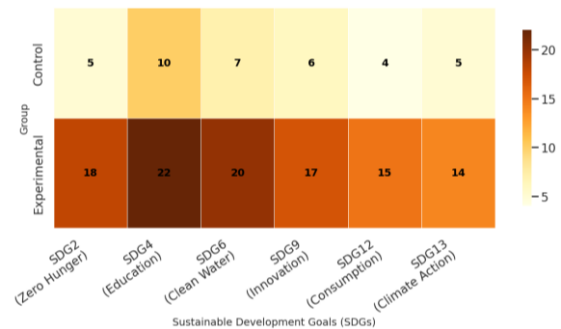


Fig. 5. Integration of Sustainable Development Goals (SDGs) in student reflections. The experimental group shows a higher frequency and explicitness of SDG references, indicating deeper engagement with sustainability and ethical dimensions within the experimental activity.

Beyond frequency, the quality of the reflections also differed between groups. In the control group, the mentions lacked critical depth, whereas in the experimental group interdisciplinary connections emerged, such as the relationship between water sustainability and food security (SDG 2), or between technological innovation and climate change mitigation (SDG 13). This demonstrates that AI mediation not only increased the frequency of SDG-related references, but also structured and deepened students’ ethical and social reasoning within an engineering context.

5. Final Statistical Integration. To consolidate the quantitative evidence of the intervention, inferential tests were applied to contrast the differences between groups and to explore the relationship between motivation, technological perception, and conceptual performance.

First, independent-samples t-tests confirmed highly significant differences between the experimental and control groups in normalized learning gains, post-test scores, and motivation. In all three cases, effect sizes were large ($d \approx 0.76$ – 0.82), demonstrating that AI mediation produced substantial and consistent improvements beyond sample variability (Table III). The experimental group significantly outperformed the control group in learning gains, final scores, and motivation, with large effect sizes, confirming the impact of intelligent feedback.

TABLA III. RESULTADOS DE T-TEST PARA MUESTRAS INDEPENDIENTES.

Variable	Control (M±SD)	Experimental (M ± SD)	t	df	p-value	Cohen's d
Normalized learning gain (g)	0.34 ± 0.11	0.67 ± 0.09	7.12	91	<0.001	0.82
Post-test score	65.8 ± 10.2	78.5 ± 9.3	5.84	91	<0.001	0.76
Motivation	3.5 ± 0.6	4.3 ± 0.5	6.23	91	<0.001	0.8

Likewise, the one-way ANOVA showed that the type of intervention explained between 17% and 21% of the variance in normalized learning gain, motivation, and perceived usefulness (PU). This finding highlights that AI mediation not only increased conceptual learning but also strengthened the perception of technology's usefulness as a pedagogical resource (Table IV).

TABLE IV. ONE-WAY ANOVA RESULTS

DEPENDENT VARIABLE	F	DF (1, 91)	P-VALUE	PARTIAL η^2
NORMALIZED LEARNING GAIN	21.6	(1, 91)	<0.001	0.19
MOTIVATION	18.3	(1, 91)	<0.001	0.17
PERCEIVED USEFULNESS (PU)	24.1	(1, 91)	<0.001	0.21

Regarding the reliability of the instruments, Cronbach's α values ranged from 0.87 to 0.91, ensuring the internal consistency of the motivation, engagement, and technological perception scales. This level of reliability supports the robustness of the results obtained from the administered questionnaires (Table V).

Finally, the correlational analyses allowed the integration of the evaluated dimensions. Significant correlations were found between motivation, perceived usefulness (PU), and behavioral intention (BI) with both normalized learning gain and post-test scores. In particular, PU and BI stood out as the strongest predictors, showing that technological acceptance and the willingness to continue using AI were determining factors in achieving deeper learning (Table VI).

TABLE V. RELIABILITY OF THE APPLIED INSTRUMENTS

INSTRUMENT	CRONBACH'S α
MOTIVATION SCALE	0.87
ENGAGEMENT SCALE	0.89
TECHNOLOGICAL PERCEPTION SCALE	0.91

TABLE VI. CORRELATIONS BETWEEN PERCEPTION, MOTIVATION, AND PERFORMANCE

Variable	Normalized Learning Gain	Post-test (r)
Motivation	0.61	0.55

Perceived usefulness	0.62	0.58
Behavioral intention (BI)	0.6	0.57

Taken together, these statistical tests reinforce the conclusion that virtual laboratories with intelligent feedback generate not only statistically significant improvements, but also pedagogically meaningful effects relevant to instructional design and learning evaluation in engineering education.

IV. DISCUSSION

The results indicate that integrating virtual laboratories with AI-mediated intelligent feedback can substantially enhance engineering education at the university level. In this study, intelligent feedback was generated through a hybrid system that combined rule-based error detection (derived from predefined thresholds in MATLAB scripts) with a Generative AI assistant capable of producing adaptive textual feedback. This mechanism analyzed student input—such as flow rate, pressure stability, and calculated efficiency—and returned explanations, conceptual hints, and validation prompts in real time, fostering self-regulated learning and conceptual reinforcement. Significant differences in conceptual learning, motivation, and technological acceptance reveal not only quantitative improvements but also a qualitative shift in the learning experience.

Consistent with prior research on interactive digital environments [1], [2], this study shows that AI mediation addresses several limitations of physical laboratories by providing immediate feedback, opportunities for personalization, and improved scalability. This directly addresses a central challenge in STEM education: combining technical rigor with accessibility and social relevance. A key finding is AI's ability to highlight the ethical and social dimensions of learning. While the control group made only tangential references to the SDGs, the experimental group explicitly integrated sustainability, ethics, and innovation, aligning outcomes with the 2030 Agenda [3], [4]. This suggests that AI-mediated scaffolding can support the explicit articulation of ethical and social considerations within technically grounded engineering activities.

Motivation emerged as a key mediating factor. As reported in prior studies on digital engagement [5], it is closely associated with both academic performance and learning persistence. Our results show that intelligent feedback strengthens and stabilizes motivation, fostering a more inclusive learning environment. Despite being implemented in a specific instructional context, the evidence suggests that this approach has potential for adaptation in comparable engineering education settings. From a scalability perspective, the proposed intervention has potential for adaptation across diverse higher education institutions, particularly in contexts with limited access to advanced laboratory infrastructure. Because the approach combines low-cost physical experimentation with AI-assisted virtual support, it may be implemented progressively using commonly available computational resources. Furthermore, the modular structure of the intelligent feedback system facilitates its adaptation to other STEM disciplines, sustainability-oriented challenges, and interdisciplinary engineering environments throughout Latin

America and similar educational contexts. Overall, AI-assisted virtual laboratories function as a strategic complement to physical experimentation, expanding access, enhancing learning processes, and supporting the integration of technical, ethical, and sustainability-oriented competencies.

V. CONCLUSION

This study showed that integrating virtual laboratories with AI-mediated intelligent feedback is associated with improvements in conceptual understanding, motivation, engagement, and transversal competencies in engineering education. Results showed significant gains in conceptual understanding, motivation, and technological acceptance, confirming that AI integration strengthens both learning outcomes and inclusivity in the classroom. Beyond technical performance, the intervention connected experimental practice with the SDGs, emphasizing ethical, social, and innovative dimensions aligned with the 2030 Agenda.

Even after controlling for initial differences through ANCOVA, the observed effects remained statistically significant, supporting the consistency of the findings. Practically, two hybrid sessions with simulation–test–adjustment cycles are recommended to replicate this model, ensuring effective and ethical AI support. Overall, AI-assisted virtual laboratories complement rather than replace physical practice, democratizing access, amplifying learning, and offering a scalable, replicable model for sustainable STEM education.

Despite the promising findings, some limitations should be acknowledged. The quasi-experimental design did not include random assignment of participants, which may introduce potential selection bias despite the equivalence maintained between groups. Additionally, the intervention was implemented within a single institutional context, limiting broader generalizability. Future studies should explore longitudinal implementations, multi-institutional collaborations, and randomized designs to further validate the scalability and robustness of AI-assisted virtual laboratories in engineering education.

Future work may explore longitudinal implementations, cross-institutional contexts, and the refinement of AI feedback mechanisms to further examine their role in supporting learning processes in engineering education.

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REFERENCES

- [1] J. M. N. Jalil, E. R. Alvarez, I. R. K. García, and S. P. Almaguer, “Work in Progress: Design and Construction of Physics Laboratory Equipment and an Authentic Evaluation System as a Pedagogical Tool in the Integral Training of Engineering Students,” Proc. 2020 IEEE Global Engineering Education Conf. (EDUCON), Porto, Portugal, 2020, pp. 1471–1477, doi: 10.1109/EDUCON45650.2020.9125294.
- [2] W. K. Chiu, “Pedagogy of emerging technologies in chemical education during the era of digitalization and artificial intelligence: A systematic review,” Education Sciences, vol. 11, no. 11, p. 709, 2021.
- [3] H. Bazie et al., “The Effect of Virtual Laboratories on the Academic Achievement of Undergraduate Chemistry Students: Quasi-Experimental Study,” JMIR Formative Research, vol. 8, e64476, Nov. 2024.
- [4] R. Elmoazen et al., “Learning analytics in virtual laboratories: A systematic literature review of empirical research,” Smart Learning Environments, vol. 10, art. 23, 2023.
- [5] Deriba, F. G., Saqr, M., & Tukiainen, M. (2024, June). Assessment of accessibility in virtual laboratories: a systematic review. In Frontiers in Education (Vol. 9, p. 1351711). Frontiers Media SA.
- [6] Dodevska, M., Zdravetski, E., Chorbev, I., Kostoska, M., Branco, F., Coelho, P. J., ... & Lameski, P. (2025). Virtual reality as a learning tool: Evaluating the use and effectiveness of simulation laboratories in educational settings. Social Sciences & Humanities Open, 12, 101742.
- [7] R. Kaliisa et al., “Have Learning Analytics Dashboards Lived Up to the Hype? A Systematic Review of Impact on Students’ Achievement, Motivation, Participation and Attitude,” arXiv preprint arXiv:2312.12345, Dec. 2023.
- [8] A. I. T. Chim, J. M. Nieto-Jalil, D. S. Jimenez, and J. M. M. Huerta, “Breaking Barriers: Smartphone Sensors, Mobile Technology in Online Teaching of Differential Equations,” Proc. 2024 IEEE Global Engineering Education Conf. (EDUCON), Kos Island, Greece, 2024, pp. 1–6, doi: 10.1109/EDUCON60312.2024.10578693.
- [9] A. S. Perez, J. M. Nieto-Jalil, A. I. T. Chim, J. M. M. Huerta, and L. L. Cavazos, “Scientific Research Model Applied to Mathematical Modeling and Prototype Construction,” Proc. 2025 IEEE Global Engineering Education Conf. (EDUCON), London, United Kingdom, 2025, pp. 1–7, doi: 10.1109/EDUCON62633.2025.11016324.
- [10] J. M. Nieto-Jalil, A. I. Tec Chim, D. Seuret-Jimenez, and J. M. Martínez Huerta, “The impact of GPT, experiential learning, and reinforcement methods on complex problem solving,” Proc. 2025 IEEE Engineering Education World Conf. (EDUNINE), Montevideo, Uruguay, 2025, pp. 1–6, doi: 10.1109/EDUNINE62377.2025.10981377.
- [11] L. N. Gitlin, “Introducing a new intervention: An overview of research phases and common challenges,” The American Journal of Occupational Therapy, vol. 67, no. 2, pp. 177–184, 2013.