ZAMBIA INFORMATION COMMUNICATION TECHNOLOGY (ICT) JOURNAL
Volume 9 (Issue 2) (2025) Pages 24-30

Impact of Low Laboratory Assessment Weight on AI and IoT Skills in Engineering Education in Zambia: A Case Study of Electrical and Electronics Department

Everisto Chilombo
Department of Engineering, Zambia University College of Technology
Ndola, Zambia
theresandaya@gmail.com

***Abstract*— Laboratory sessions in engineering education are very essential in giving students hands-on training to complement theoretical learning. Unfortunately, many Zambian universities attribute less than 10% of the overall course grades to practical work, leading to poor engagement and limited skill acquisition and transfer. This study investigates the impact of low laboratory weighting on student outcomes within Electrical and Electronics Engineering programs. Emphasis is placed on the increasing need for practical competence in implementing Artificial Intelligence (AI) and Internet of Things (IoT) systems, which are driving modern electrical engineering innovations. This paper analyses the engineering curriculum, case studies, and prototypes developed by final-year students, highlighting the consequences of minimal lab exposure leading to reduced innovation capacity and industry unpreparedness. A model is proposed that increases laboratory assessment weight to 30–50%, integrates interdisciplinary project-based learning, simulations, and aligns skill development with industry demands. The findings suggest that rebalancing theoretical components can significantly enhance students' technical proficiency, system-level thinking, and readiness for AI- and IoT-driven environments.**

Keywords*— Engineering education, laboratory assessment, artificial intelligence, Internet of Things, curriculum design, practical skills, industry readiness.

I. INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) and the Internet of Things (IoT) is reshaping the landscape of modern engineering, particularly under the broader industry 4.0 agenda [1]. These technologies are not only transforming industries but also redefining the skills required of future engineers. In the context of developing nations such as Zambia, where technological infrastructure is still maturing, the integration of AI and IoT into engineering education presents both a critical opportunity and a significant challenge [2] [3].
Laboratory-based learning plays a pivotal role in equipping engineering students with hands-on, practical experience, especially in domains like AI and IoT that are inherently application-driven [4] [5],. However, within many higher education institutions in Zambia, there exists a disproportionately low weighting of laboratory assessments in the overall grading systems [2] [6]. This has led to a diminished emphasis on practical skills, despite their increasing relevance in the global job market [7] [8] [3] .
This paper investigates the impact of low laboratory assessment weight on the development of AI and IoT competencies among undergraduate students in the Electrical and Electronics Engineering departments at selected Zambian universities. Using a case study approach, the research evaluates how assessment policies influence student engagement, practical exposure, and overall preparedness for AI and IoT applications in real-world scenarios.
The findings aim to highlight gaps in the current curriculum structure and propose strategic improvements to align engineering education with the demands of the Fourth Industrial Revolution (4IR), ensuring Zambian graduates are not left behind in the evolving technological landscape [9].

II. BACKGROUND

Students learn AI best by building, testing, and troubleshooting models, machine learning algorithms, deep learning, generative AI, and real-world use cases in Western and Asian universities [10] [11] [12]. If lab work (which promotes hands-on learning) is low-weighted, students prioritize exams and theory over practical AI skills. Indeed, [1]reports that "students involved in AI-assisted experiential learning exhibited a 50% increase in creative ability compared to those following traditional learning methods."
Laboratory education has long been recognized as a foundational component in science and engineering curricula, providing students with essential hands-on experience that reinforces theoretical understanding [14] [4]. In [1], it is pointed out that in the age of Industry 4.0 and the Internet of Things (IoT) [15], electrical engineers must possess a dynamic skill set that encompasses not only core theoretical knowledge but also adaptability and the ability to grapple with complex, real-world challenges [7] [16]. Numerous studies emphasize the importance of practical learning in fostering problem-solving, critical thinking, and system-level design skills [17] [18]—competencies that are vital for emerging fields such as machine learning in Artificial Intelligence (AI) and the Internet of Things (IoT) [18].

III. LITERATURE REVIEW

A. Laboratory Assessment and Skill Development

Several researchers have identified that undervaluing laboratory work—especially through low assessment weight—diminishes students' motivation and engagement with practical components of their coursework [19] [5] [2]. For instance, [17] argue that assessment policies heavily favouring theory led to passive learning and reduced experimental proficiency.

In [20], it is stated that several decades ago, engineering educational laboratories were characterized by low laboratory instruction hours (or credit), decreased presence of faculty members, lack of students' interest, inadequate resources, disparity between laboratories and real-life situations, and almost no recognition of the efforts of faculty members participating in its instruction [10]; most of these characteristics are still true today in Zambia [21] [8] [16] [22].

B. AI and IoT in Engineering Education

Artificial Intelligence (AI) is not purely theoretical [10] [7]; it relies heavily on data handling, coding and model training, experimentation and iteration (using MATLAB machine learning tools for instance), and hardware and sensor integration (especially for IoT–AI systems). Studies by [18] and more recent work in IoT/AI-oriented laboratories [11] [4] [3] [22] suggest that experiential learning, especially through open-ended lab projects, significantly improves students' ability to implement intelligent systems and IoT prototypes.

In [19], experiential learning is described as providing a solid platform for stimulating the learners' intuitiveness to be more systematic and inquiry-based with a specific end in mind. Thus, it provides opportunities for the learners to be more engaging intellectually, creative, and taking initiative while making decisions and being accountable for the outcomes attained at the end of the exercise [23] [12] [2] [24].

However, curriculum audits in many sub-Saharan African institutions reveal a gap between theory-heavy programs and the practical demands of the digital economy [7] [16]. For example, in Zambia, university programs in electrical engineering often allocate less than 10% of course marks to lab work, despite the industry demand for hands-on AI and IoT knowledge [25] [26].

IV. BEST PRACTICES FROM INTERNATIONAL MODELS

Globally, engineering education is evolving toward more integrated and practice-oriented approaches, with notable frameworks such as the CDIO Initiative (Conceive–Design–Implement–Operate), Project-Based Learning (PBL), and Competency-Based Assessment (CBA) gaining traction [27, 28].

The CDIO framework, adopted by leading institutions in Sweden, Singapore, and Canada, emphasizes an engineering lifecycle approach where students move beyond isolated theoretical exercises to conceiving, designing, implementing, and operating real-world systems. This approach ensures that laboratory work is embedded into authentic engineering contexts, fostering both technical and professional competencies [27] [29] [7]. As [28] explain: "Within the CDIO program, we have identified an underlying critical need—to educate students who are able to Conceive–Design–Implement–Operate complex value-added engineering products, processes and systems in a modern, team-based environment."

This framework emphasizes active, experiential learning through design-build projects, integrating teamwork, communication, and professional skills alongside technical foundations [27] [6] [30]. It provides a structured way to align laboratory work, project-based learning, and assessment with professional engineering practice.

In parallel, [6] highlight the complementary role of project-based learning (PBL) in developing essential professional competencies. They argue: "Project-based learning is designed to challenge students with complex tasks based on real-world problems that require students to work in teams to design solutions. This approach helps students develop not only technical knowledge, but also communication skills, teamwork, and self-directed learning ability". Their conclusion are echoed by more recent PBL studies in IoT education and robotics-oriented curricula [31] [12] [32].

Project-Based Learning (PBL), which aligns closely with CDIO principles, engages students in extended, interdisciplinary projects that replicate industry challenges [6] [23] [26]. In PBL-based AI/IoT modules, students may be tasked to design an IoT-enabled energy monitoring system, train AI models for predictive maintenance, and integrate hardware–software components [18] [23] [26]. Studies have shown that such projects enhance self-directed learning, teamwork, and problem-solving skills, while also improving retention of theoretical concepts [6] [26] [30]. As [6] observe, "students who participate in project-based learning are generally motivated by it and demonstrate better teamwork and communication skills."

Competency-Based Assessment (CBA) shifts the focus from time-based academic achievement to the demonstration of mastery in defined learning outcomes. In engineering education, this often includes evaluating students' ability to apply knowledge in realistic scenarios—such as debugging an embedded AI system or optimizing IoT network performance—rather than merely recalling facts in written exams [29] [30] [33]. CBA frameworks in Germany, Finland, and Singapore allocate significant weight to practical and project-based components (30–50% of total course marks), ensuring that assessment mirrors the skills required in industry.

When combined, CDIO, PBL, and CBA create a reinforcing cycle: CDIO provides the structural roadmap for engineering practice, PBL delivers the experiential learning environment, and CBA ensures that assessment reflects actual competencies [27] [15] [30]. The synergy of these approaches has been linked to higher employability rates, stronger innovation capacity, and improved graduate readiness for emerging fields like AI and IoT [34].

V. CURRICULUM REFORM AND EDUCATIONAL POLICY

Integrating CDIO, PBL, and CBA into AI/IoT-focused engineering curricula addresses a critical gap between academic instruction and industrial practice [28] [20]. Graduates emerge with not only the technical know-how to design and implement AI/IoT solutions but also the collaborative, evaluative, and operational skills required in

modern engineering careers. Such an approach directly aligns with UNESCO's vision of engineering education that is "sustainable, inclusive, and fit for the challenges of the 21st century."
Reform literature advocates for aligning curriculum design with industry needs, particularly in STEM fields [7]. According to the World Bank's higher education review [6] [9], African universities must revise outdated curricula and enhance lab infrastructure to improve graduate employability and technological innovation [4] [21] [16].

TABLE 1 Lab assessment weight in selected countries

Country	Assessment Weight (%)	Notes	Source / Reference
Germany	35–50%	Strong emphasis on applied engineering and practical labs in dual-study programs.	DAAD, TU Munich Curriculum Guides
Finland	30–40%	Competency-based education with lab-integrated coursework.	Finnish National Agency for Education
UK	25–40%	Labs contribute significantly to accredited BEng/MEng degrees.	QAA UK Engineering Benchmark Statements
Singapore	40–50%	Project-based, lab-intensive modules in AI, IoT, and electronics.	NUS/NTU Course Descriptors
India	30–40%	High lab weighting in IITs.	AICTE Model Curriculum (2021)
China	35–45%	Emphasis on innovation labs and applied learning in smart tech.	Tsinghua University & Ministry of Education
Zambia	<10%	Labs often under-emphasized; theory dominates assessment.	This Study; University Curriculum Reviews (2023)

VI. METHODOLOGY

This study adopted a quantitative approach to examine the impact of low laboratory assessment weight on engineering education in Zambia, with a focus on Electrical and Electronics departments. For qualitative study, results obtained from senior students' lab works and projects are examined.

A. Case Study Design

Four public universities in Zambia offering Electrical and Electronics Engineering programs were selected. Each institution was evaluated based on lab structure, assessment distribution, and the inclusion of AI/IoT components.

B. Data Collection Instruments

Two structured questionnaires were developed and distributed: one for lecturers and one for students. Additionally, academic course outlines and departmental syllabi were analysed to quantify lab-to-theory weight ratios, identify skill-based outcomes, and evaluate project components.
Purposive sampling was used to target lecturers and students in their final or penultimate year, who had completed most lab courses. A total of 379 students and 8 lecturers participated in the survey.

C. Data Analysis

Quantitative survey data were analysed using descriptive statistics and correlation analysis to determine the relationship between laboratory assessment weight and skill development in AI and IoT domains. Descriptive statistics involved calculating means, frequencies, and standard deviations of responses to understand general trends. For instance, 68% of students reported that lab sessions contributed less than 15% to their overall course grade, while over 70% expressed a desire for increased hands-on activities.
Pearson correlation analysis was conducted to assess the relationship between lab assessment weight and students' self-reported confidence in applying AI and IoT concepts. Inferential statistics analysis on "Do you feel your lab sessions prepare you for AI and IoT applications?" where lab weight <10% and the preparedness averaged responses in the Appendix are:

- No = 232 students
- Somewhat = 103 students
- Yes = 18 students (Total = 353 students).

Descriptive statistics: coding responses as No = 1, Somewhat = 3, Yes = 5, the weighted mean is

$$\bar{x} = \frac{232(1) + 103(3) + 18(5)}{353} \approx 1.79 \quad (1)$$

Standard deviation:

$$\bar{\sigma} = \frac{\sum f(x - \bar{x})^2}{n} \quad (2)$$

$$\bar{\sigma} = \frac{232(1 - 1.79)^2 + 103(3 - 1.79)^2 + 18(5 - 1.79)^2}{353} \approx 1.37$$

$$\sigma = \sqrt{1.37} \approx 1.17$$

Hence, mean = 1.79 and SD = 1.17.
Inferential Test (t-test & r): We test against neutral value $\mu = 3$.

$$t = \frac{\bar{x} - \mu}{\sigma/\sqrt{n}} \qquad (3)$$

$$t = \frac{1.73 - 3}{1.17/\sqrt{353}} = \frac{-1.21}{0.062} \approx -19.49$$

Effect size correlation r:

$$r = \sqrt{\frac{t^2}{t^2 + df}} \qquad (4)$$

$$r = \sqrt{\frac{(-19.49)^2}{(19.49)^2 + 352}} \approx 0.72$$

Interpretation: $t(352) = -19.49, p < 0.001, \quad r = 0.72$(large effect size). This means that students under <10% lab weighting are significantly underprepared for AI/IoT. The correlation $r$shows a very strong effect: the lower lab weight strongly predicts poorer preparedness.

Students who attended weekly lab sessions and engaged in open-ended projects scored significantly higher in a prototype challenge (average score: 82%) compared to those from departments with fewer lab hours (average score: 65%).

Qualitative data from open-ended questionnaire items and observational notes during prototype testing were coded thematically. Key themes included insufficient lab resources, lack of integration between theory and practice, and a strong student demand for more project-based learning. These qualitative insights helped contextualize the statistical findings and reinforce the conclusion that rebalancing lab weight is crucial for skill development.

Findings were triangulated across data sources to ensure consistency and reliability, thereby offering a holistic understanding of the impact of low laboratory weight on AI and IoT readiness in Zambia's engineering education system.

VII. RESULTS

The results from the survey and case study analysis revealed several key findings related to the assessment weight of laboratory sessions and the development of practical competencies in AI and IoT.

A. Survey Findings

A large majority of students (72%) and lecturers (83%) indicated that current lab assessments contribute inadequately to final grades, averaging only 10% or less. Students overwhelmingly reported that the low lab weight reduces their motivation to engage seriously in practical sessions. More than half (58%) of student respondents indicated they had skipped lab sessions due to perceived lack of academic value.

Lecturers echoed this concern, noting that reduced lab emphasis hinders students' ability to build foundational skills in embedded systems and hardware interfacing—skills critical for AI and IoT systems integration.

B. Correlation Results

Statistical analysis showed a moderate to strong positive correlation between lab weight and students' confidence in applying AI and IoT concepts.

1. **Lab Attendance vs. Confidence in Using Equipment:**
   Observed Trend: Students who attend lab sessions more frequently report higher confidence in handling equipment and software tools. Correlation Analysis: There appears to be a moderate positive correlation between attendance frequency and confidence ratings (scale of 1–5). Students who attend weekly labs commonly rate their confidence above 4. Those who attend rarely or sometimes rate their confidence between 2–3. Interpretation: More exposure to practical work strengthens technical competence, reinforcing hands-on learning.
2. **Lab Weight in Coursework vs. Desired International Standard:**
   Observed Trend: The majority of students feel that lab work holds less academic weight than it should. Correlation Analysis: A strong positive correlation exists between students' current lab weight (marks) and their ideal lab weighting to match international standards. If lab weight is below 10%, most students suggest increasing it above 30%. Where lab weight is between 10–20%, many recommend a small increase but still see room for growth.
   Interpretation: Students recognize the importance of lab work and want it to be better integrated into grading systems for educational impact.
3. **Lab Attendance vs. Preparedness for AI and IoT Applications:**
   Observed Trend: Frequent lab attendees generally feel more prepared for AI and IoT applications. Correlation Analysis: A weak-to-moderate positive correlation is observed. Students who report weekly lab attendance often agree or strongly agree that labs prepare them for AI/IoT. Those who attend sometimes/rarely show mixed confidence in AI/IoT readiness **Invalid source specified.**.
   Interpretation: While lab attendance helps students feel prepared, the content of lab sessions may not fully integrate AI and IoT, suggesting a gap in specialized training.
4. **Lab Equipment Availability vs. Student Satisfaction:** Observed Trend: Many students express dissatisfaction with lab equipment adequacy. Correlation Analysis: A strong negative correlation is found: when students rate lab equipment as insufficient, they also report low confidence in practical applications. Those who rate equipment as adequate tend to give higher confidence scores for lab work.
   Interpretation: Lack of modern equipment negatively impacts learning experiences and skill development.
5. **Group Size vs. Lab Efficiency:** Observed Trend: Larger lab groups lead to more complaints about insufficient hands-on experience.

Correlation Analysis: A moderate negative correlation suggests that large lab groups hinder efficiency. Students in large groups (>10 people) often struggle to fully participate in labs. Smaller groups (around 5 members) tend to report better learning experiences.

Interpretation: Reducing group sizes may improve student engagement and participation.

Overall Summary: Higher lab attendance correlates with better confidence in equipment use. Students overwhelmingly wish for higher lab weight in grading. AI and IoT preparedness are positively impacted by labs, but gaps remain. Poor lab equipment availability lowers students' confidence. Large lab groups negatively affect student participation and engagement.

VIII. DISCUSSION

These findings reinforce the argument that increasing laboratory weight within engineering courses significantly enhances students' readiness to engage with emerging technologies. By reallocating marks to include lab performance and embedding project-based tasks within AI and IoT modules, institutions can produce more industry-ready graduates.

Moreover, the positive correlation between lab exposure and prototype success suggests that competency in modern engineering domains cannot be developed through theory alone. Institutions must prioritize hands-on learning and update pedagogical strategies to include real-world problem-solving.

These insights can inform policy and curriculum decisions, pushing for a balanced, practice-oriented engineering education that aligns with Zambia's national goals for innovation and technological development.

IX. PROPOSED MODEL FOR ENHANCING LAB-BASED LEARNING

Based on the findings, we propose a model aimed at improving practical skills acquisition and aligning academic outcomes with industry expectations in AI and IoT domains. The model incorporates the following components:

1. **Balanced Assessment Structure:** The proposed model advocates for a 40:60 practical-to-theory assessment ratio in core technical courses. This reallocation ensures that laboratory work is weighted sufficiently to motivate participation and skill development, while still maintaining theoretical rigor.
2. **Integrated Project-Based Learning:** Each semester, students engage in interdisciplinary projects that require the application of both theoretical knowledge and practical skills. These projects are open-ended, allowing students to explore and innovate around real-world problems using AI and IoT tools such as microcontrollers, cloud platforms, and machine learning APIs.
3. **Lab Infrastructure and Resource Planning:** To support expanded lab activity, the model recommends phased investment in essential lab resources. This includes low-cost development kits (e.g., Arduino, Raspberry Pi), simulation software, and modular lab stations. Equipment-sharing strategies and mobile lab kits can optimize utilization. AI tools should also be made an essential part of research and program writing.
4. **Faculty and Peer Mentorship:** Lecturers receive training in project-based pedagogy and are encouraged to co-develop lab activities with industry partners. Additionally, senior students with demonstrated expertise can act as peer mentors, promoting collaborative learning and easing instructor burden.
5. **Continuous Curriculum Feedback Loop:** A digital feedback system is introduced to collect real-time student input on lab experiences. Data collected is analysed annually and fed into curriculum development workshops to ensure responsiveness to student needs and technological advancements, including the use of AI tools to achieve a prototype.
6. **Industry Partnership Integration:** The model emphasizes collaboration with local industries to co-develop lab challenges, provide guest lectures, and offer internship pathways. This connection ensures that academic content stays relevant and provides students with a clearer understanding of workplace expectations.
7. **Feasibility and Scalability:** The model is designed for gradual rollout, starting with revised assessments and pilot project courses. As resources grow, infrastructure and mentorship expand. The modular framework allows adaptation across disciplines, with industry and alumni networks supporting sustainability.

X. RECOMMENDATIONS

The study recommends increasing the laboratory-to-theory ratio to 30–40% in engineering courses so that practical competencies receive proper academic weight. Interdisciplinary, real-world projects should be integrated across semesters to promote creativity, teamwork, and hands-on use of AI/IoT technologies. AI tools (such as ChatGPT) should be used in labs to streamline coding tasks and focus student effort on problem-solving and innovation.

Pilot implementations in selected universities are advised to test the model before nationwide rollout. Broader policy dialogue involving universities, industry partners, and government bodies such as the Ministry of Higher Education (MoHE) and the Higher Education Authority (HEA) is essential for curriculum reform aligned with the Zambia Qualifications Framework (ZQF) and international engineering standards.

Specific curriculum improvements include:

i) Replacing "Introduction to IT" with microcontrollers and Python/C/C++.

ii) Phasing out outdated 8085/8086 processors in favour of modern platforms (Arduino, ESP32, STM, Raspberry Pi).

iii) Integrating AI tools into teaching and lab work.

iv) Making electronics and power electronics more hands-on.

Government support is recommended in the form of increased funding for lab infrastructure (equipment, virtual labs, training tools), aligned with national development plans such as the 7th National Development Plan (7NDP).

Programmes under the Teaching Council of Zambia should upskill lecturers in practical and project-based teaching methods, especially in AI and IoT. Industry partnerships are encouraged for co-developing lab modules, sponsoring equipment, and providing internship pathways.

Regular audits of curriculum implementation and lab effectiveness will help maintain standards, focusing on student performance, equipment availability, and graduate employability.

The Engineering Institution of Zambia (EIZ) should contribute through industry–academia linkage, policy advocacy, and promoting recognition of AI/IoT lab competencies as essential engineering skills.

XI. STUDY LIMITATIONS

The study faced limited participation from the University of Zambia (UNZA) due to distance and communication challenges, reducing the intended sample size. Although the survey remains open for additional responses, current findings should be interpreted with awareness of this sampling constraint. Further participation is expected to strengthen the validity of the results.

XII. CONCLUSION

This study identified a major gap between theory-focused engineering curricula and the practical skills required for AI and IoT applications. Both quantitative and qualitative results show that low laboratory assessment weight reduces student motivation, hands-on competence, and industry readiness. A strong correlation $r$confirms that insufficient lab emphasis directly predicts poor AI/IoT preparedness [2] [23] [31]. Prototype-based learning demonstrated improved innovation and technical understanding.

The study further recommends that foundational courses such as Introduction to IT and Microprocessors be made fully hands-on using modern platforms like Arduino, ESP, and Raspberry Pi. Strengthening laboratory training will accelerate students' problem-solving ability, innovation capacity, and AI-driven engineering competence

REFERENCES

[1] A. Yeung, "“The Advancing Science by Enhancing Learning in the Laboratory (ASELL) Project: The first Australian multidisciplinary workshop," *Int. Journal of Innovation in Science and Mathematics Education,*, vol. 19, no. 2, p. pp. 51–72, 2011.

[2] L. M. K.-S. Huang, Introducing Machine Learning to First-year Undergraduate Engineering Students Through an Authentic and Active Learning Labware, vol. 66, 10.1109/FIE.2018.8659308, 2018/10/01, p. pp. 217–226.

[3] K. R. Banagar Amruta, "IoT based Smart Laboratory System," *International Journal of Engineering Research ,* vol. 9, no. 10.17577/IJERTV9IS010178, p. pp. 1934–1945, 2020/01/25.

[4] R. R. P. P. G. M V, "M-Learning Based Remote Laboratory for Electronics Experiments," *International Journal of Online and Biomedical Engineering (iJOE),* vol. 16, no. 10.3991/ijoe.v16i11.16177, p. pp. 45218–45232, 2020/11/13.

[5] B. N. Gussai Sheikheldin, "Engineering education, development and growth in Africa," *Scientific African,* vol. 6, no. e00200, pp. ISSN 2468-2276, 2019.

[6] J. M. a. D. Treagust, "Engineering education—Is problem-based or project-based learning the answer?," *Australasian Journal of Engineering Education,* vol. 3, no. 2, p. pp. 2–16, 2003.

[7] W. L. Jiaxing Li, "Effectiveness of virtual laboratory in engineering education: A meta-analysis," 30 12 2024. [Online]. Available: •https://doi.org/10.1371/journal.pone.0316269. [Accessed 11 12 2025].

[8] A. M. a. G. Phiri, "Challenges of engineering practical training in Zambia," *African J. Sci. Technol. Innovation Dev. ,* vol. 15, no. 4, p. pp. 512–522, 2023.

[9] W. Bank, "World Bank education overview," 2025.. [Online]. Available: https://www.worldbank.org/en/topic/tertiaryeducation..

[10] S. Papadakis, "The impact of AI and robotics on engineering education," *Comput. Appl. Eng. Educ.,* vol. 29, no. 3, p. pp. 628–640, 2021.

[11] L. G. a. S. Bogosyan, "Current trends in remote laboratories," *IEEE Trans. Educ.,* vol. 65, no. 2, p. pp. 135–143, May 2022..

[12] V. T. R. S. S. P. K. Sharma, Artificial Intelligence-Powered Assessment Framework for Skill-Oriented Engineering, vol. 17, 10.48550/arXiv.2509.25258, 2025/09/27, p. pp. 378–388.

[13] ,. E. Murniarti, "The synergy between artificial intelligence and experiential learning," *Frontiers in Education,* vol. 10, no. Article 1606044, 2025..

[14] L. D. F. a. A. J. Rosa, "The role of the laboratory in undergraduate engineering education," *Journal of Engineering Education,* p. pp. 121–130, Jan. 2005.

[15] P. C. W. a. K. A. S. J. E. Froyd, "Five major shifts in 100 years of engineering education," *Proc. IEEE,* vol. 108, no. 4,, p. pp. 598–611, Apr. 2020.

[16] G. Mohamedbhai, "Engineering Education in Sub-Saharan Africa: Quest for Quality," *International Journal of African Higher Education,* vol. 2, no. 10.6017/ijahe.v2i1.9259, p. pp. e23491, 2016/03/19.

[17] S. Nikolic, "Decoding student satisfaction: How to manage and improve the laboratory experience," *IEEE Trans. Educ.,*, vol. 58, no. 3, p. pp. 151–158, Aug. 2015.

[18] U. F. O. N. a. G. U. M. L. O. Nweke, "Enhancing entrepreneurial skills through experiential learning in IoT, AI, and cybersecurity," *Education and Information Technologies, .,* 202.

[19] Y. Kong, "The Role of Experiential Learning on Students' Motivation," *International Journal of Educational Studies,* 2021.

[20] E. W. Ernst, "A New Role for the Undergraduate Engineering Laboratory," *IEEE Transactions on Education,* vol. 26, no. 3, p. 149–157, Aug. 1983.

[21] O. R. M. K. M. N. N. W. K. B. C. B. A. M. N. S. Siame John, A Review of Engineering Education in Zambia for the 21st Century: Historical, Current, vol. 15, 2016/04/22, p. pp. 512–522.

[22] M. Budhu, "Virtual Laboratories for Engineering Education," *Int Conf Eng Educ,* vol. 1, p. pp. 12451–12463, 2002/01/01.

[23] M. B. A. a. E. V. Quesada, "Predictable Influence of IoT (Internet of Things) in the Higher Education," *International Journal of Information and Education Technology,* vol. 7 , no. 12, p. pp. 118756–118771, 2021..

[24] H. Saul, "How AI and machine learning are revolutionizing the laboratory," vol. 152, pp. 1-2, October 1, 2025.

[25] L. G. a. S. Bogosyan, "Current trends in remote laboratories," *IEEE Trans. Educ,* vol. 65, no. 2, p. pp. 135–143, May 2022.

[26] T. S. O. a. J. A. Akinyemi, "Practical-based learning and employability of engineering graduates in Africa," *Int. J. Eng. Educ.,*, vol. 38, no. 5, p. pp. 1450–1460, 2022.

[27] J. M. S. Ö. a. D. R. B. E. F. Crawley, Rethinking Engineering Education: The CDIO Approach, New York, NY, USA: Springer , 2007.

[28] J. M. a. S. Ö. E. F. Crawley, Rethinking Engineering Education: The CDIO Approach, London, U.K.: Springer, 2014 .

[29] P. C. W. a. K. A. S. J. E. Froyd, " Five major shifts in 100 years of engineering education," *Proc. IEEE,* vol. 108, no. 4, p. pp. 598–611, Apr. 2020.

[30] R. M. F. a. R. Brent, "Active learning: An introduction," *ASME J. Eng. Educ,* Vols. 111, , no. 1, pp. pp. 010801-1–010801-17, 2023.

[31] J. Defranco, "A systematic literature review on Internet of things in education: Benefits and," *Journal of Computer Assisted Learning,* 2019.

[32] L. Y. Dr. Huiming Fan, "Digital Transformation of Engineering Education—The Practices in Chinese," in *2025 ASEE Annual conference&Exposition*, Montreal, QC, 22-25 June 2025.

[33] A. B. M. A.-H. a. S. A. D. A. A. D. A. K. D. B. K. Alqahtani, "Assessing the Impact of the Use of Generative AI in Developing and Using Assessment Grading Rubrics for Engineering Courses," *American Society for Engineering Education,* 2025.

[34] Y. Y. I. M. P. N. B. S. Veza Ibham, "Current Status Of Global Engineering Education: Mini Review," *Radial : Jurnal Ilmiah Sains dan Rekayasa,* vol. 1, no. 10.62024/radial.v1i2.8, 2023/09/30.

[36] ZESCO Limited, "Grid Reliability Report,," ZESCO Limited,, Lusaka, Zambia, 2020.

[37] W. E. Forum, "Future of Jobs Report 2023," WEF, , Geneva, Switzerland,, 2023..

[38] UNESCO, "Engineering for sustainable development: Delivering on the Sustainable," International Centre for Engineering Education, Paris, France,, 2021.