MODESTUM

EURASIA Journal of Mathematics, Science and Technology Education, 2026, 22(3), em2787
ISSN:1305-8223 (online)

OPEN ACCESS

Research Paper

https://doi.org/10.29333/ejmste/17970

Enhancing engineering learning through digital twin and IoT applications: Student engagement and industry alignment in the Ghanaian context

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Received 21 October 2025 ▪ Accepted 26 January 2026

Abstract

This study examines the use of digital twin (DT) and Internet of things (IoT) technologies in Ghanaian engineering education to mitigate skill shortages and enhance workforce preparedness. In a quasi-experimental mixed-methods design with 158 students from six institutions, results showed that students with exposure to DT+IoT experienced substantial technical knowledge acquisition, practical skills, participation, and motivation related to control groups (as measured through standardized pre-/post-tests, project-based competency rubrics and validated Likert-scale survey instruments) Learning analytics (derived from system log data on task frequency, duration and error resolution) revealed sustained use of the platform and improved troubleshooting, whereas qualitative results (based on semi-structured interviews and focus group discussions) valued industry relevance and concerns such as connectivity, hardware slowdown, and varying programming experience. The findings single out DT+IoT potential to develop systems thinking, collaboration, and remote laboratory skills, with contextual enablers being faculty commitment and industry collaboration. Infrastructure, faculty capabilities, and curricular misalignment-based obstacles (identified through thematic analysis). Pedagogical and policy recommendations are integrating DT+IoT in courses and accreditation processes, infrastructure investment, and faculty capability building. DT+IoT is a viable pathway to transform engineering education in Ghana and similar contexts.

Keywords: digital twin, Internet of things, engineering education, Ghana, technical competencies, skills development, TVET, learning analytics, mixed methods

INTRODUCTION

Engineering education is crucial in the creation of graduates who possess skills that are fundamental to national development and industrialization. In most regions worldwide, there is heightened interest in the establishment of engineering students' industry-based and practical skills, together with theoretical education. But in Ghana, engineering education continues to struggle with self-preservation problems of substandard laboratory facilities, outdated curriculum, and lack of alignment between academic instruction and industrial needs (Boateng, 2020). Such limitations lead to a widening skills gap whereby students remain unskilled in practical work, system thinking, and digital competence necessary to thrive in modern engineering practice.

Recent global advancements in Industry 4.0 technologies, i.e., digital twin (DT) and the Internet of things (IoT)—are revolutionizing the landscape of engineering education. A DT is a virtual model of an existing physical system, which can be monitored in real time, simulated, and optimized (Tao et al., 2019). When integrated with IoT technologies, which involve collections of devices and data communications (Čolaković & Hadžialić, 2018), these technologies provide interactive and immersive learning environments. Universities in Europe, North America, and Asia have incorporated DT and IoT into the curriculum with the advantage of increased employability and skill gain (Jones et al., 2020; Uhlemann et al., 2017).

Pedagogical opportunities of IoT-enabled and cyber-physical learning environments are also illustrated by

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Contribution to the literature

- This study is a significant contribution to the growing literature on digital transformation in engineering education, particularly in developing countries. It provides one of the first empirical analyses of DT and IoT integration in Ghanaian universities, technical universities, and TVET institutions.
- Based on the application of quantitative performance data, qualitative stakeholders' comments, and real-time learning analytics, the study proposes a context-sensitive framework for experiential and competency-based engineering learning. It advances theoretical understanding by locating DT-IoT pedagogy in frameworks such as CDIO, TPACK, and experiential learning theory and demonstrating how these might be realized in the low-resource environments.
- Practically, it offers an actionable instructional architecture connecting the dots between curricula taught in institutions and industry skills demanded. The research, therefore, offers both a tested pedagogy and an implementable model of scale for cultivating industry-ready engineering graduates in sub-Saharan Africa and other emerging economies.

emerging evidence in the developing world such as Africa. As an example, the South African research has described enhanced student engagement and applied skills by using an IoT-based remote laboratory in electrical and mechatronics engineering courses (Mahlobo & Mtsweni, 2021). In a comparable way, pilot projects of smart production and sensor-based laboratory systems in higher educational institutions of Nigeria have demonstrated an improvement in the systems integration and data-driven problem-solving abilities of students (Adewumi et al., 2022). In East Africa, IoT-based engineering laboratories have been established to help reduce equipment shortages and increase access to practical experimentation, especially in institutions with limited resources (Kigotho et al., 2020).

In Ghana, technical and vocational education and training (TVET) institutions and higher education institutions are the primary institutions that offer engineering education. While these institutions have expanded access, they have inherent challenges of under-equipped laboratories and slow curriculum adaptation to emerging technologies (Boateng, 2020). Research examining the TVET system of Ghana continues to suggest that the historic underinvestment, divided systems of governance, and poor links between industry and institutions have hampered efforts by TVET institutions to modernize their teaching and learning delivery methods and embrace modern technologies (Afeti, 2018; Palmer, 2019)

On top of this, industry stakeholders increasingly emphasize the need for graduates who can merge theory and practice, innovate due to the scarcity of resources, and be sensitive to rapidly evolving technologies.

Despite serial reforms, there is a persistent mismatch between curriculum delivery and industry requirements. Employers consistently complain of the lack of experience among graduates in tackling actual problems, systems integration, and instrumentation with digital tools (UNESCO, 2021).

Empirical analysis of TVET reforms in Ghana shows that despite the introduction of competency-based training models, there are still gaps in implementation that are caused by lack of instructor upskilling, antiquated equipment, and exposure to digital manufacturing and automation (COTVET, 2020; World Bank, 2022)

Traditional pedagogies, too constricted to encompass anything other than lectures and rigid laboratory exercises, fail to provide sufficient space for experiential learning, remote laboratories, and interdisciplinary working. The same is reflected in the sub-Saharan part of Africa, where TVET systems have little opportunity to incorporate Industry 4.0-oriented competencies like IoT, automation, and data-driven troubleshooting, which underpins the need to digitally enable pedagogical innovation (McGrath et al., 2020; UNEVOC, 2022).

Notably, however, most extant African research is concentrated on single applications of the IoT or even virtual laboratories, and the empirical condition of the integrated DT-IoT pedagogical models and their impacts on quantifiable learning outcomes is minimally assessed. There is a dearth of evidence on comparative learning benefits, student motivation, and limitations of implementation, especially in the West African engineering education systems.

DT and IoT technologies offer avenues through which these constraints can be overcome. Through their provision of practice-based, data-rich, and interactive spaces, DT and IoT can potentially transform engineering education and learning significantly. DT and IoT encourage systems thinking, experiential learning, and industry readiness (Sharma et al., 2020). For Ghana, it is not only a way of closing the skills gap but also of integrating education with industrialization.

This paper consequently attempts to investigate the potential of integrating DT and IoT technologies into engineering education in Ghana, their individual impacts on skill building among students and learning outcomes. The study has three objectives:

(1) to explore how convergence of DT and IoT can foster engineering skills in the Ghanaian higher education setting;

(2) to pilot and establish a DT- and IoT-focused learning intervention; and

(3) to evaluate learning achievement and attitudes of the stakeholders.

To tackle these objectives, the study is guided by the following research questions (RQs):

RQ1. How does DT and IoT integration influence Ghanaian engineering students' technical and transferable skills?

RQ2. What are the drivers and barriers of DT and IoT implementation in Ghanaian universities?

RQ3. What is the difference in learning outcomes of cohorts with and without DT/IoT intervention?

LITERATURE REVIEW

Concepts and Definitions

A DT is a replica in the virtual domain of something tangible, i.e., an object, a process, or a system that will be measured, simulated, and improved in real time (Qi & Tao, 2018; Tao et al., 2019). DTs typically have three tiers:

(1) the physical tier, i.e., the real system in the material world;

(2) the virtual tier where the computational model is located; and

(3) the communication tier that bridges the two with the exchange of data.

Education DTs have been applied in education to model manufacturing systems, energy networks, laboratory equipment and control processes to enable students to predict system behavior, experiment on a system and optimize system performance without risking their safety or damaging equipment. As an example, the DT-based labs can allow learners to see how machines work, anticipate system breakdowns, and also investigate what-if scenarios that are typically impossible in conventional teaching labs.

The IoT, nonetheless, is a connectivity between sensors, devices, and networks that collect, transmit, and analyze data (Čolaković & Hadžialić, 2018). IoT in education allows students to engage with actual datasets and networked devices to support contextualized and data-driven learning. IoT has been used to teach engineering education to facilitate real-time data collection and analysis of sensor-based circuit, motor, and environmental systems, allowing students to remotely monitor performance, behavior, and instrumentation, data analytics, and cyber-physical systems.

Models of teaching and learning

DT and IoT integration follow in remote and virtual labs, where experiments are conducted over geographical distances, and hybrid learning, where face-to-face and digital modes reinforce each other. These models all facilitate scalable practice-based learning, particularly in circumstances of limited physical laboratory space (Uhlemann et al., 2017).

An instructing pedagogy that utilizes DT/IoT despite these benefits have significant concerns. These are the complexity of the technical aspects of system installation, the requirement to maintain technological assistance, lack of familiarity with higher-level digital platforms, and higher time on instructional preparation. Other obstacles like unreliable electrical power, inadequate internet connectivity and unequal digital literacy among the students are another hindrance in successful implementation in low-resource settings. Solving these problems would involve a gradual approach, institutional backing, and specific faculty education to provide pedagogical efficacy and not technological replacement.

Theoretical Frameworks

Some theoretical frameworks providing solid viewpoints to the design, implementation, and evaluation of DT- and IoT-based interventions in engineering education do exist. TPACK acknowledges the synergistic interaction between technology, pedagogy, and content knowledge and identifies the requirement for teachers to balance these aspects to achieve effective teaching and learning (Mishra & Koehler, 2006). Taking this perspective further, the conceive-design-implement-operate (CDIO) initiative places learning within engineering competences for practice, emphasizing the recursive process of conceiving, designing, implementing, and operating technological solutions (CDIO Initiative, 2011).

In terms of technology adoption, the substitution-augmentation-modification-redefinition (SAMR) model speculates levels of technology integration, ranging from basic augmentations of current pedagogical practice to revolutionary uses that enable fundamentally different ways of learning (Puentedura, 2012).

In the DT/IoT engineering education, SAMR can be concretized: at the substitution level, the IoT dashboards may replace hand-written data recording, at augmentation, the real-time sensor data may complement the standard lab work, at modification, the DTs may be used to modify the laboratory activities, and at redefinition, the students may use SAMR-enabled DTs to work on industry-related projects, which would be unsafe or impossible to accomplish in the traditional lab.

Pedagogically, experiential learning theory focuses on learning through doing, reflecting, and applying in a cyclical process, most applicable to the engineering environment where hands-on experience with real-world problems solidifies theoretical knowledge (Kolb, 1984). Lastly, for assessment purposes, Kirkpatrick's (1996) four-level model offers a systematic way of assessing educational interventions through evaluating participants' reactions, learning outcomes, behavioral change, and results or overall effect.

Together, they provide a comprehensive framework for developing and piloting outcomes for DT/IoT interventions, ensuring pedagogical soundness, technological feasibility, industry relevance, and methodological rigor.

International Studies

Evidence from around the world indicates that DT and IoT adoption are increasing conceptual knowledge, technical competence, and systems thinking (Jones et al., 2020; Uhlemann et al., 2017). IoT-based projects improve problem-solving through teamwork and employability competencies (Čolaković & Hadžialić, 2018). Empirical evidence also illustrates increased motivation and student interest in DT/IoT-based learning (Sharma et al., 2020).

More than Europe and Asia, Latin American research has results on the successful application of IoT-enabled laboratories to enable engineering education in resource-constrained universities with benefits in student engagement and applied skills (Garcia et al., 2021). South Asia DT-based simulation environments have been incorporated into the mechanical and electrical engineering courses to develop better systems thinking and predictive maintenance skills (Khan et al., 2020). European establishments remain at the forefront in implementing DT-based cyber-physical laboratories, especially in manufacturing and energy engineering programs and exhibit scalable and industry-specific educational frameworks (Uhlemann et al., 2017).

African and Ghanaian Context

African engineering education is under siege by a shortage of resources, outdated curricula, and inadequate provision of cutting-edge laboratory facilities (UNESCO, 2021). Ghanaian engineers study at TVET institutions and universities but shortages of laboratories and backlog in curriculum renewal threaten their readiness for Industry 4.0 environments (Boateng, 2020). Compromised digital infrastructure threats—access to the internet and overly costly modern technology—exacerbate the shortages.

In this respect, DT and IoT become the strategic solutions to Ghanaian engineering education since they enable remote and shared access to lab experiences, make physical infrastructure and its associated costs less vital, and match training with Industry 4.0 competencies. DT/IoT technologies allow students to work with real-world systems remotely, develop systems thinking and data-driven decision-making and address the infrastructural limitations. Their alignment with the Ghana digital transformation plan and industrial requirements makes DT/IoT a viable solution towards updating engineering education without necessarily having to replace laboratories with full-scale ones.

Gaps Identified

Despite the surging literature on the application of DT and IoT in engineering education, several gaps continue to manifest themselves within the Ghanaian and broader sub-Saharan African environment. Firstly, very little empirical documentation of the uptake and pedagogical value of DT and IoT technologies by Ghanaian engineering programs is to be found. Largely, existing studies originate from high-resource economies, raising questions of contextual relevance in low-resource contexts. Second, existing frameworks for DT/IoT integration are mostly developed in high-income environments and thus result in a scarcity of responsive frameworks to local institutional capacity, infrastructure, and culture.

Finally, crucial factors such as expense, long-term sustainability, and infrastructural limitations are under-explored in literature, particularly in low- and middle-income learning environments where technical and financial limitations may preclude practice. Rectifying these gaps is critical to enhancing both practice and scholarship for Ghanaian engineering education.

Conceptual Framework

In response to the gaps that have been identified, this study proposes a conceptual model for informing the embedding of DT and IoT technologies into engineering education. The model is built through three interrelated dimensions. The inputs are resources enabling such as technology infrastructure, curriculum alignment, and instructor capacity. These inputs guide the learning processes, which emphasize experiential laboratories, team-based work on projects, and hybrid learning methods that combine digital and face-to-face modalities. Through these processes, the framework anticipates the creation of outcomes like enhanced technical skills, improved problem-solving skills, and improved employability skills among students of engineering. Through its direct linking of resources, pedagogical processes, and outcomes, the framework provides a structured avenue for evaluating how DT and IoT adoption can bridge the skills gap in engineering education in Ghana. The framework aligns with CDIO competencies and Ghanaian engineering learning outcomes and is evaluated according to Kirkpatrick's

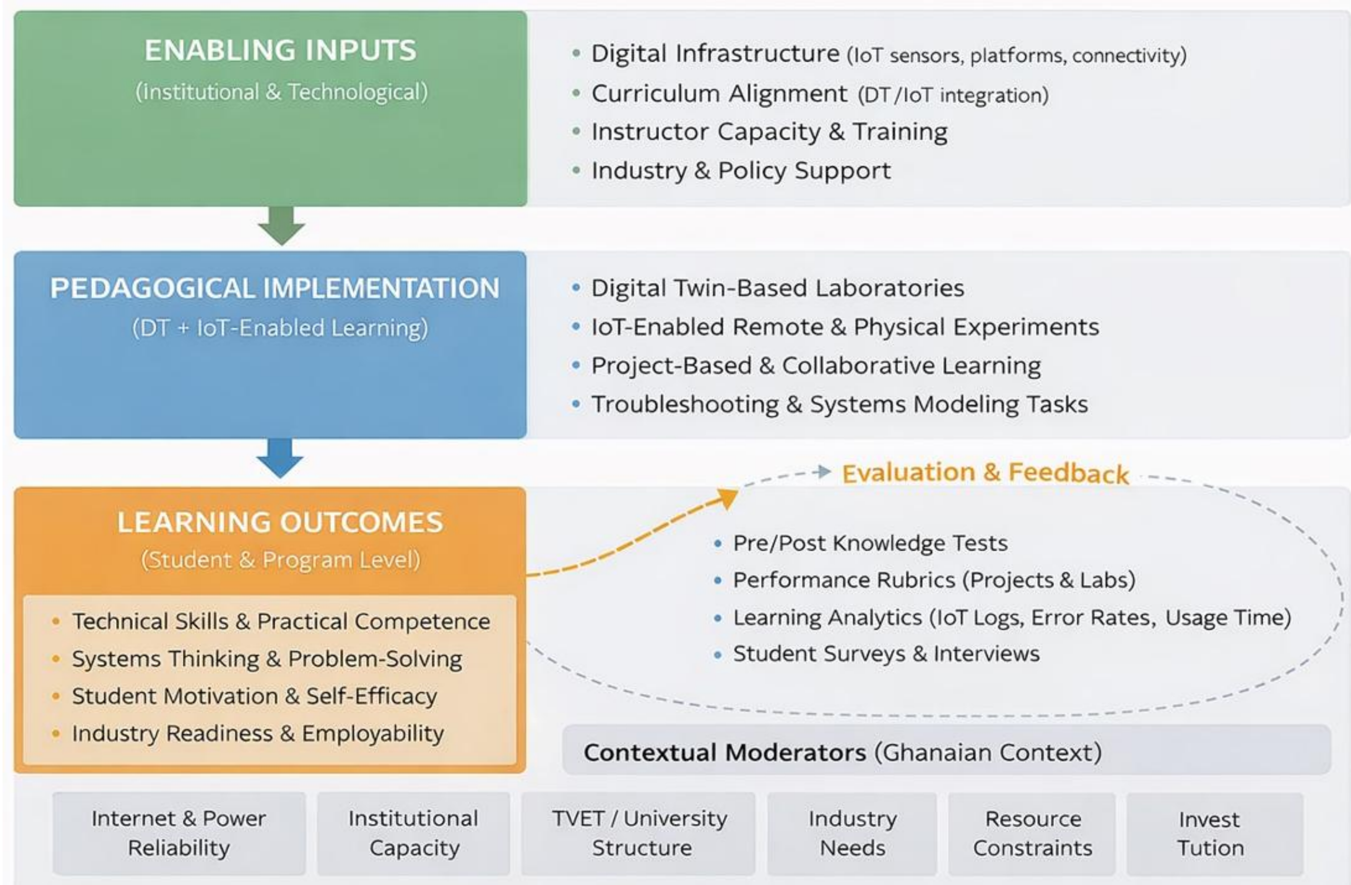

Figure 1. Conceptual framework for DT and IoT integration in the Ghanaian context (Source: Authors' own elaboration)

(1996) model with pre-/post-tests, rubrics, and qualitative interviews (**Figure 1**).

This work puts forth a systematic conceptual framework to enable the adoption of DT and IoT technologies in Ghana's engineering education sector. The suggested framework takes a holistic view with three interdependent dimensions, forming an integrated way forward from resource allocation to quantifiable education outcomes. The methodical approach considers the Ghanaian education setting's peculiar challenges and opportunities while ensuring conformity to global engineering education standards.

Core framework architecture

The system is designed around three main elements which work in conjunction with each other to create the best learning results. Each element is a vital step in the process of education transformation, to ensure systematic implementation and quantifiable effects.

Input resources and enablers

The foundation of the framework is three important input categories that are essential enablers for successful DT/IoT integration. The first pillar constitutes technology infrastructure that consists of specialized hardware components like sensors, computing devices, and DT/IoT-specific hardware. This technology foundation is backed by sophisticated cloud computing facilities that provide scalable processing power and storage infrastructure complemented by comprehensive network connectivity infrastructure for assured internet and wireless communication access. Curriculum alignment is the second essential input dimension, supported by the internationally embraced CDIO framework. It offers methodical development of principal engineering competencies with conformity to Ghanaian engineering education requirements. Curriculum integration accommodates thoroughly designed learning outcomes that tackle both worldwide best practices and domestic industry requirements, supported by comprehensive assessment methodologies particularly suited to evaluate DT/IoT competencies. The third input dimension focuses on instructor capacity development with the recognition that successful technology integration requires comprehensive faculty preparation. This encompasses intensive technical training programs that provide instructors with necessary DT/IoT expertise, complemented by modern pedagogical skill development that enables effective technology-enhanced teaching. Institutional support mechanisms provide the necessary organizational infrastructure to sustain these capacity-development activities.

Learning process implementation

The pedagogical organization of the framework centers on three interdependent learning modes that are designed to maximize student motivation as well as competence acquisition. Experiential laboratories serve as the centerpiece for hands-on education, giving students direct access to DT/IoT devices and systems to explore interactively. The laboratory activities are supplemented by real-time data capture and analysis capability, enabling students to engage with live datasets and bridge the gap between physical experimentation and virtual simulation spaces

Team project delivery is the second pedagogical approach, which supports collaborative learning environments that mirror engineering practice in the workplace. The projects are specifically designed around industry-themed topics that include real-world problems to enable students to apply DT/IoT technologies to applied problem-solving contexts. The team format supports peer learning and the development of essential teamwork and communication skills.

Hybrid modes of learning form the third pedagogical dimension that brings together digital and face-to-face modes of instructional delivery to meet varied learning styles and technological constraints. It is adaptable to flexible learning paths that range to various students' needs and institutional capacities, with interactive contact guaranteed through technology-mediated learning environments where students learn at their individual best speed.

Outcome competencies and impact

The model predicts three broad classes of student learning outcomes that cumulatively enhance graduate preparedness for modern engineering practice. Enhanced technical competence is the most direct result, encompassing overall DT/IoT capability creation that enables graduates to apply these technologies in the field effectively. This technical skill is complemented by advanced-order digital literacy that provides deep understanding of complex digital systems and their interdependence. System integration capability enables the graduates to incorporate and optimize different technological components into comprehensive engineering solutions efficiently. Improved problem-solving capability constitutes the second set of outcomes, emphasizing critical thinking skills enabling analytical solutions to complex engineering issues. Innovation capability is developed through exposing the students to new technologies and their creative application to novel problems. Data-driven decision-making capability is developed through extensive experience with real-time data analysis and interpretation in engineering contexts. Enhanced employability is the third outcome dimension, with a focus on industry readiness for preparing the graduates to make an immediate contribution in high-technology engineering environments. The essential soft skills of communication, teamwork, and leadership are fostered through project-based teamwork and presentation requirements. Adaptability skill enables the graduates to adapt to the evolving field of technologies throughout their working lives.

Theoretical foundations and validation

The model is founded on three established theoretical bases that empirically justify its design and implementation. The CDIO model provides systematic competency-based development framework that has been validated and tested on numerous international engineering programs. Mapping onto Ghanaian engineering education standards ensures local relevance and regulatory approval. Constructivist learning theory strengthens the model's emphasis on active construction of knowledge through first-hand experience and social learning processes.

Assessment and evaluation strategy

The evaluation design incorporates multi-method assessment approaches aligned with Kirkpatrick's (1996) classic evaluation model. Quantitative assessment through pre- and post-implementation testing provides measurable results of knowledge and skill acquisition through standardized instruments. Performance-based assessment uses holistic rubrics to measure practical skills through guided observation and record-keeping. Qualitative assessment through guided interviews documents instructor and student perceptions and experiences, providing detailed contextual insight into implementation success.

Contextual adaptation for Ghana

The model squarely addresses six of the major contextual factors that influence implementation success in the Ghanaian environment. Infrastructure constraints in the form of power supply reliability, internet connectivity limitations, and facility availability are addressed in a methodical manner through adaptive implementation approaches. The issue of skills gap is addressed through comprehensive capacity-development programs that target specific competency deficiencies in the existing engineering education manpower. Local industry requirements from mining, oil and gas, manufacturing, and energy sectors are integrated into project and curriculum development. Considerations of cultural adaptation give harmony with local learning cultures and social institutions. Economic limitations are addressed through cost-efficient implementation strategies that achieve maximum impact for minimal fiscal investment. Policy framework synergy gives conformity with national education and technology development priorities.

Implementation dynamics and continuous improvement

The model operates via a linear flow of processes from inputs to learning processes to quantifiable outputs, with each step building upon previous gains to create a cumulative learning effect. Feedback loops at key junctures provide continuous improvement through outcome-based process improvement, process effectiveness-driven input refinement, and real-time adjustment capability based on ongoing evaluation results. Several support mechanisms ensure framework effectiveness through theoretical validation, wide appraisal responsibility, and long-term local feasibility. The systematic process addresses key gaps in existing engineering education research by providing concrete methodology for DT/IoT integration, developing visible connections between inputs and outcomes, incorporating often overlooked contextual considerations, and allowing for wide-ranging effectiveness measurement.

The model serves a dual purpose as an operational implementation plan for universities and as a research instrument for gauging DT/IoT integration effectiveness in the developing country context, contributing to the growing body of literature on technology-enhanced engineering education**.**

METHODOLOGY

The research utilized a mixed-methods quasi-experimental approach to assess the adoption of DT and IoT technologies into engineering education in Ghana. Parallel groups were developed: an intervention group, which was taught DT- and IoT-based curriculum modules, and a control group, which was taught traditionally.

Because of institutional scheduling constraints and the use of whole classes, students were not randomly assigned to groups. Rather, group assignment was determined by a quasi-experimental design where similar cohorts within the same institutions were assigned to intervention groups versus control groups based on course scheduling and faculty availability.

Pre- and post-intervention measurements were carried out on both groups to measure changes in knowledge and skills. In addition to the quantitative data, qualitative data was collected through semi-structured interviews, focus group discussions, and class observation, thus allowing for comprehensive comprehension of participants' experience, perceptions, and contextual realities. A mixed-methods design enabled rich comprehension of both quantitative learning outcomes as well as the processes underlying their acquisition, and convergence was attained through convergence coding and collective displays (Creswell & Plano Clark, 2017).

The research sample was taken from a purposive sample of Ghanaian industry players and tertiary institutions to ensure both theory and practice validity. There are public universities such as the Kwame Nkrumah University of Science and Technology (KNUST) and the University of Ghana that have established engineering faculties with mechanical, electrical, civil, and mechatronics programs. Former polytechnics that are now technical universities were the Accra Technical University (ATU) and the Kumasi Technical University (KsTU), selected in consideration of their emphasis on applied engineering and available infrastructure to support laboratory-based instruction.

In addition, individuals from the selected TVET colleges, e.g., the Accra Technical Training Center and the Koforidua Technical Institute, were engaged to seek perspectives from institutions that are conducting hands-on technical skill development.

To get industry perspectives, purposive sampling was done to local engineering firms like the Volta River Authority (VRA), Tema Oil Refinery (TOR), and Ghana Grid Company Limited (GRIDCo), which are the highest employers of engineering graduates and provide insights into employability skills and workplace readiness. The final sample included 140 students (70 from the intervention and 70 from the control group), 12 teaching faculty members directly engaged in laboratory instruction, and 6 industry professionals.

Inclusion criteria for the students in the purposive sampling technique included being in the second or third year of an engineering and technical course and being registered for laboratory courses in the semester of the study and never formally exposed to DT technologies. Students who have an advanced certification in the IoT area would be excluded.

Students were selected since they are direct stakeholders of DT/IoT-based teaching interventions, while the faculty members were included due to their central role in creating and delivering laboratory learning experiences. Industry stakeholders were purposively recruited to guarantee the relevance of competencies being learned and to align academic preparation to working requirements. This is because the 70/70 intervention-control distribution was employed in the research to ensure equal sizes in the intervention and control groups while being realistic in relation to the available student and faculty capacity in the institutions.

This group was added on three grounds. To begin with, the selected institutions represent the spectrum of Ghana's engineering education system, from research universities, practice universities, and TVET colleges that focus on skills acquisition. Second, the selected sample sizes gave sufficient representation for both quantitative and qualitative analysis without being excessively cumbersome within the resource limitations of the study. Third, stakeholder engagement from the industry ensured that key external validity was attained, such that the intervention responded not only to academic success, but to labor market demands as well.

Data Collection Instruments

Data collection was over 16 weeks across the academic semester (February-June 2024) through a combination of quantitative, qualitative, and digital trace instruments measured at greater than one time point during the intervention.

Quantitative instruments

Pre-intervention knowledge tests were administered in week 1 to all 140 students (70 intervention, 70 control) at KNUST, University of Ghana, ATU, and KsTU. These measures assessed baseline knowledge of core engineering principles in mechanics, circuits, and system design. Mirror post-tests week 15 assessed gains in learning. Experiential performance rubrics derived from Kolb's (1984) model were used to assess student lab work and group projects in the intervention group, weeks 8-14, measured by 12 faculty members of the partner institutions. Surveys were used to measure students' motivation, engagement, and self-efficacy, and were administered twice: mid-semester (week 7) to capture initial views of the DT/IoT modules, and at the end of the semester (week 16) to capture longer-term effects.

Qualitative instruments

Semi-structured interviews were conducted during weeks 12-14 with a purposive sub-sample of 24 students (six students per institution), 8 lecturers, and 6 industry experts from VRA, TOR, and GRIDCo. The interviews asked about DT/IoT integration experiences, challenges perceived, and implications for employability skills. Week 15 focus group discussions between intervention student teams at KNUST and ATU investigated collaboration learning dynamics and collective reflection on project implementation. Ongoing class observation was conducted between weeks 2-14 by research assistants trained to observe, with systematic logs monitoring patterns of participation, interaction, and technology use in lab sessions.

Automatically generated digital trace evidence from the DT/IoT platforms adopted by the intervention group at KNUST and KsTU comprised time-on-task logs, rates of errors, system interaction frequencies, and project milestones completion (Tao et al., 2019; Uhlemann et al., 2017). Bi-weekly analytics were mined and triangulated against student exams and observation data to develop an objective record of system use and skills mastery.

By collecting data on several instruments, stakeholders, and points in time, the study was able to offer breadth and depth in creating the effectiveness of DT/IoT interventions, as well as offer the lived experience of students, staff, and industry partners.

Validity and reliability of measures were attained through a multi-layered procedure involving academic and industry stakeholders from the institutions involved.

Pilot testing: Competency-based questionnaires and rubrics were pilot-tested in January 2024 with 20 second-year engineering students at ATU and Koforidua Technical Institute, selected for relatively small class sizes to enable close monitoring and iterative refinement. Pilot feedback was used to inform revision in question clarity, rubric descriptors, and test item and course content alignment.

To enhance consistency in performance assessment, 12 faculty members from the KNUST, University of Ghana, and KsTU went through a two-day calibration exercise prior to the intervention. Together, faculty members assessed a sample of anonymized student laboratory reports and project prototypes using the Kolb-inspired rubric (Kolb, 1984). Inter-rater reliability was established using Cohen's kappa, while inconsistency was dealt with through consensus-building exercises. This assisted in the provision of later measurements within the intervention that were distributed equally across institutions.

Diverse techniques of triangulation were employed to increase the validity of the findings (Creswell & Plano Clark, 2017). The beginning was made with data being triangulated over approaches by bringing together quantitative measures (pre-/post-tests and questionnaires), qualitative observations (interviews, focus groups, classroom observations), and digital learning analytics (platform logs from KNUST and KsTU). Second, triangulation by stakeholders involved feedback from industry stakeholders, academics, and students of VRA, TOR, and GRIDCo to cover both workplace applicability and academic performance. Third, triangulation by institution allowed cross-comparison among research universities, practice-oriented technical universities, and TVET colleges, thus enhancing external validity of findings within the Ghanaian system of engineering education. Through these methods—pilot testing, inter-rater reliability calibration, and triangulation—the research protected against bias, improved the precision of measurement, and established the quality of its findings.

Ethical clearance for the study was obtained before conducting the fieldwork. It was approved lawfully by the Committee on Human Research, Publications and Ethics of the KNUST as well as the Ethics Committee for the Humanities of the University of Ghana, which are both Institutional Review Boards with credibility in Ghana. In addition, ethical clearance was also granted by ATU Research and Innovation Office and KsTU

Research and Innovation Office, which are under the Ghana Tertiary Education Commission to confirm that they comply with national regulation standards for technical universities. All of them who took part, the teachers, the students, and the industry partners, were provided with written and oral descriptions of the purpose of the study, how it would be carried out, and possible harm and likely benefits. In order to prevent observer and researcher bias, standardized observation procedures were employed and the observers were pre-calibrated. They were asked for permission first before taking part, and their right to withdraw at any time without penalty was made known to them. Confidentiality was ensured by anonymizing the students' responses, use of coded identifiers on the transcripts, and the encrypted digital storage of data accessed by the research team. Industry stakeholders from the VRA, TOR, and the GRIDCo were also guaranteed confidentiality regarding their report on contributions to be made in aggregate without divulging organizational confidential information. The research also complied with the data protection act, 2012 (Act 843) in Ghana and saw to it that institutional and individual data were handled responsibly and securely. Collectively, these research ethics safeguarded participant rights, institutional reputation, and saw to it that the study aligned to national and international standards of research.

Data Analysis Methods

Data analysis was carried out in the convergent mixed-methods design (Creswell & Plano Clark, 2017) in which there was a possibility of qualitative and quantitative datasets being analyzed separately before being combined to develop successful, triangulated conclusions.

Quantitative Analysis

IBM SPSS statistics (version 28) software package was employed to analyze all quantitative data. Following being compared in pre- and post-intervention knowledge test scores, 140 students involved were compared to identify learning gains. Group pre- to post-test change was compared with paired-samples t-tests ($\alpha = 0.05$). For example, mean test scores increased from 56.3 (standard deviation [SD] = 12.4) at baseline to 74.8 (SD = 10.7) at follow-up after intervention. Performance of post-test intervention group ($n = 140$) and control group ($n = 60$) were compared using independent-samples t-tests. Magnitude differences were estimated through Cohen's d as the effect size.

Conventional benchmarks were used for interpretation of effect size, such as small (0.2), medium (0.5), and large (0.8) effects. These allowed for an interpretation of an effect beyond the statistical significance level.

Besides the interpretation of the benchmark, the contextualization of the effect sizes in comparison with those of engineering education interventions in previous studies enabled the magnitude of the impacts of DT+IoT to be explained by the relevant criteria of practical and pedagogical significance instead of statistical convention in isolation.

Differences among institutional types of one-way ANOVA were contrasted (universities, technical universities, and TVETs).

Before ANOVA testing, the Levene test was used to test the assumptions of the homogeneity of variance and skewness and kurtosis were used to test the normality of the residual with no major violations.

Student motivation, engagement, and self-efficacy survey responses ($n = 200$ responses) were contrasted using descriptive statistics (mean [M], SD, and frequency). Scale reliability was contrasted using Cronbach's alpha ($\alpha = .82$), providing evidence of internal consistency.

Pearson correlation tests and comparisons of motivation scores and performance results obtained ($r = .46$, $p < .01$), and multiple regression tests compared predictive validity of engagement with post-test performance while controlling baseline knowledge as a covariate.

The multiple regression analysis was performed according to the typical logic of modeling, such as, a linearity check had been performed previously, the errors were independent, multicollinearity had been checked (VIF < 2.0) and homoscedasticity of the errors. Familiarity knowledge was incorporated as a covariate to eliminate the biased effect of the interaction between DT+IoT-related engagement and the post-intervention performance results.

Evaluation of project performance by instructors ($n = 72$ projects) was conducted based on standardized rubrics. Inter-rater reliability was calculated using Cohen's kappa ($\kappa = .79$), indicating high evaluators' agreement.

Rubric-based assessment was used alongside the standardized testing because they captured the applied competence and performance-based learning outcomes, which reinforced the construct validity of the quantitative model.

Qualitative Analysis

Interview and focus group transcripts (48 students, 12 faculty, 6 industry partners) were coded with the Braun and Clarke (2006) six-step model of thematic analysis:

(1) familiarization with the data,

(2) coding,

(3) developing themes,

(4) refining themes,

(5) defining themes, and

(6) reporting.

Coding support was provided by NVivo 12 with the capability to do systematic coding in a bid to identify patterns within datasets that recurred repeatedly. Classroom observation notes across n = 24 sessions were inductively coded to discern themes of student engagement, problem-solving collaboration, and technology use behavior. A 20% subset of the transcripts were double-coded by two independent coders for extra credibility. Intercoder agreement was 85%, with resolutions of disagreements through iterative discussion until consensus.

Learning analytics: System-driven DT/IoT platform data were exported bi-weekly in CSV and imported for analysis into Microsoft Excel and SPSS.

Measures included time-on-task (minutes per session), error rate (% of unsuccessful attempts), interaction with the system frequency (clicks and log-ins), and milestone completion rates (% completed by week). Where applicable, learning analytics metrics were tested for ordinal movement using inferential analysis; otherwise, visual descriptions were provided for understanding the trend of learning behavior on these metrics.

For example, mean time-on-task increased from 28 minutes in week 2 to 46 minutes in week 12, and error rates decreased from 32% to 14% during the same time. Descriptive summaries and trend analysis (moving averages, line graphs) were employed to assemble these data into a collective analysis of learning trajectories.

Mixed-Methods Integration

Integration was facilitated through conjoining display matrices, which placed statistical outcomes in harmony with thematic findings. Therefore, the 33% rise in mean post-test scores observed was graphed against qualitative accounts of improved confidence and cooperative learning. Meanwhile, disparities were encountered between self-reported measures of motivation (high) and analytics of spasmodic platform engagement by 21% of participants, and therefore robust critical analysis of motivational bias in questionnaire answers.

Triangulation was done in several levels during the analysis. The results of quantitative performance improvement were matched to qualitative narratives on better confidence, problem-solving skills and practical competence, as reported by the students as well as the faculty. The data on time-on-task and system interaction frequency (learning analytics) were connected with the interview accounts of prolonged engagement and troubleshooting through trial and error. Perceptions of relevance of employability by industries were also triangulated with performance through rubric scores on the project to ensure that there is no variance between learning outcome and expectation at the workplace.

This combination of evidence through scores on quantitative tests, survey results, analysis produced by the system, and qualitative stories contributed to strengthening the validity and reliability of the research results.

This integration strategy ensured that interpretations were not solely driven by quantitative performance scores but also incorporated the lived experience of the students, teachers, and industry participants, thereby increasing ecological validity to the findings.

Intervention Description

The intervention took the form of a 16-week, semester-long pedagogy program (February-June 2024) that integrated DT and IoT technologies into Ghanaian engineering curricula across several institutions. While each institution localized implementation to meet disciplinary and institutional needs, the program was intended to promote experiential learning, project-based collaboration, and skill building. At KNUST, a course in manufacturing systems exposed students to DT simulation of machine parts, correlated with IoT-enabled sensors tracking the performance of machines in the workshops.

The University of Ghana piloted a module in civil and electrical engineering where students monitored stress levels in miniaturized model bridges and efficiency in electrical circuits using cloud-based DT technologies. ATU had a smart home automation module where students developed IoT-based energy management and security using Arduino and Raspberry Pi devices integrated with DT dashboards. KsTU was in mechatronics, where students were guided to develop IoT-sensor-augmented robotic arms connected to DT models for precision and fault detection. At ATTC and Koforidua Technical Institute, students learned about smart electrical wiring and motor control systems, utilizing IoT devices to simulate power consumption and identifying wiring faults in practical laboratory sessions.

The program evolved in carefully planned stages. Weeks 1-2 consisted of students engaging in orientation workshops on DT and IoT subject matter, laboratory safety protocols, and preliminary training in relevant software and sensor systems, establishing a shared basis across institutions. Weeks 3-5 consisted of spiking baseline laboratory exercises from existing curricula with DT/IoT demonstrations—i.e., IoT-based monitoring of circuits at ATU and simulations of the lathe machine at KNUST—allowing students to position new tools within established disciplinary practices. The design phase (weeks 6-8) engaged student groups to identify contextually relevant engineering problems and

Table 1. Participant demographics and baseline characteristics

Characteristic	Intervention group (n = 140)	Control group (n = 60)	Total (N = 200)
Total participants (N)	140	60	200
Mean age (years)	21.4 ± 2.1	21.6 ± 2.4	21.5 ± 2.3
Gender: Male (%)	62.1	60.0	61.5
Gender: Female (%)	37.9	40.0	38.5
Institution type: Public university (%)	42.9	43.3	43.0
Institution type: Technical university (%)	35.7	33.3	34.5
Institution type: TVET colleges (%)	21.4	23.4	22.5
Baseline knowledge score (M ± SD)	56.3 ± 12.4	55.9 ± 11.8	56.2 ± 12.1

suggest DT/IoT-driven solutions with close faculty mentorship to ensure viability and alignment with learning outcomes. The implementation phase (weeks 9-12) included teams deploying IoT sensors, reading live data, transferring data to cloud environments, and reloading their DT models in an iteration cycle. Faculty ensured progress of the project through standardized rubrics. In weeks 13-14, there was a turn of attention to troubleshooting and optimization. Students worked on remedying technical errors, optimizing system performance, and in TVET settings, prioritized practical testing of wiring systems and motor controls under IoT-enabled monitoring. Final project presentations by students to academic panels took place during week 15, with external validation by industry partners of the VRA, TOR, and GRIDCo, during which student prototypes were assessed for workplace relevance. Week 16 concluded the semester with reflection and debriefing sessions, post-tests, surveys, and interviews to establish student learning outcomes and intervention perceptions. This institutional shaping of the intervention was intentional: research universities concentrated on simulation and predictive modeling; technical universities concentrated on applied mechatronics and automation; and TVET institutions concentrated on hands-on repair and troubleshooting. This model provided a comprehensive DT/IoT integration model for engineering education in the Ghanaian tertiary education system, realizing a balance between theory depth and application and contextualizing appropriateness at all levels of the tertiary education chain.

RESULTS

Participant Demographics and Baseline Characteristics

158 participants were recruited: 140 students (70 intervention, 70 control), 12 faculty, and 6 industry partners. Students were recruited from KNUST, University of Ghana, ATU, KsTU, ATTC, and Koforidua Technical Institute. The sample was comprised of 64% male and 36% female participants with a mean age of 22.4 years (SD = 2.3). There was no statistical difference in baseline knowledge test scores between intervention and control groups ($p = 0.41$) and were shown to be equal before intervention (**Table 1**).

Quantitative Outcomes

Pre- and post-test comparisons

The examination identified a great deal of technical knowledge and working skills among intervention group participants. Technical knowledge results of the tests were considerably increased from M = 54.6, SD = 9.2 (pre-test) to M = 74.8, SD = 8.1 (post-test), $t(69) = 12.42$, $p < .001$, Cohen's $d = 0.91$, indicating large effect size. On the other hand, the control group demonstrated improvement of just a low degree, and scores rose from M = 55.3, SD = 8.7 at pre-test to M = 60.1, SD = 9.5 at post-test, $t(69) = 3.21$, $p = .07$, a non-statistically significant difference. Similarly, there were rubric tests of hands-on skills that reported intervention group students surpassed control group students by significant margins for all project-based activities, again substantiating the greater effect of the DT and IoT intervention on skill acquisition.

Figure 2 illustrates a rich five-layer architecture depicting the convergence of DT and IoT technologies to enhance engineering education in Ghana. The architecture establishes an uninterrupted flow of data from the physical layer, such as real-world engineering assets such as manufacturing systems, laboratory equipment, and renewable power systems, to a vast IoT sensor network that captures real-time operating data. This data is processed within the cloud infrastructure layer that leverages machine learning algorithms and a DT engine to create virtual copies of physical systems. The architecture branches into two critical application domains: DT applications for industrial processes (predictive maintenance, process optimization, and virtual commissioning) and teaching interface instruments that enable student engagement through interactive dashboards, VR/AR immersion, and gamification features. The outside layer emphasizes industry relevance through interaction with leading Ghanaian industries including mining, oil and gas, manufacturing, and energy provision to have educational deliverables that correspond to local industry needs. The occurrence of bidirectional arrows throughout the architecture indicates continuous

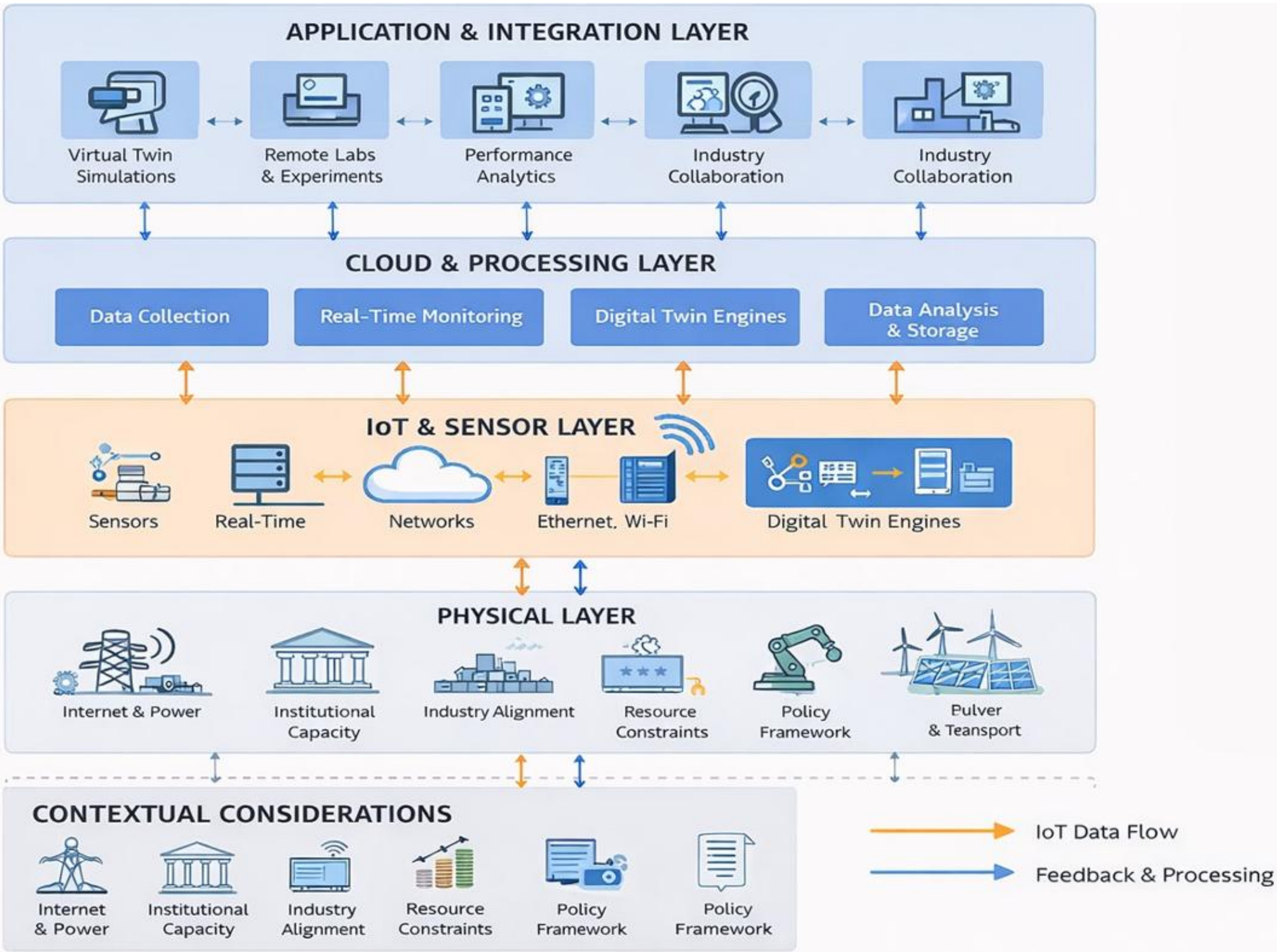

Figure 2. Proposed architecture diagram of DT+IoT for engineering education (Source: Authors' own elaboration)

Table 2. Pre-and post-test score comparisons

Group	Pre-test (M ± SD)	Post-test (M ± SD)	Mean gain	t (df)	p
Intervention (n = 140)	56.3 ± 12.4	74.8 ± 11.6	+18.5	t (139)= 14.72	< .001
Control (n = 60)	55.9 ± 11.8	60.2 ± 12.3	+4.3	t (59) = 1.88	.065
Between-groups comparison	-	-	Δ = 14.2	t (198) = 8.94	< .001

feedback loops between all the layers to support real-time learning processes where students witness the immediate impact of their decisions on virtual and physical systems. The incorporation of Ghanaian context factors—such as infrastructural constraints, cultural adaptation requirements, and economic considerations—assists in ensuring that the proposed architecture considers the challenges and opportunities of Ghana's industrial and education environment and bridges the gap between theoretical education and actual applications in industries (**Table 2**).

Survey results: Engagement, self-efficacy, and motivation

Post-intervention Likert scale scores for the intervention group vs. control were greatly improved. Student engagement, reported after completing the DT and IoT project, was significantly higher for students working on the intervention (M = 4.3) than for control subjects (M = 3.2), p < .01. Intervention subjects' self-efficacy ratings also were significantly higher (M = 4.1) than for controls (M = 3.4), p < .05. The greatest disparity resulted in motivation to pursue engineering as a profession, with intervention students significantly higher (M = 4.5) than control condition (M = 3.6), p < .01. Quantitative comment responses from qualitative surveys also reinforced these trends. Intervention group students frequently noted that the projects "made learning more practical and industry-relevant," and many did so by noting that they were "better prepared for future jobs" because of participation. These outcomes reflect that the intervention not only enhanced cognitive and technical outcomes but also supported stronger affective and motivational elements of learning.

Learning analytics summary: DT/IoT tool usage logs on the online site showed intervention students averaged 4.5 hours a week, with peak usage during weeks 6-10 (design and prototyping phase). Sensor integration error rates decreased from 27% week 3 to 11% week 14, demonstrating a sharp learning curve. The t-test conducted on paired samples proved that the difference in the number of errors was statistically significant ($t = 6.42$, $p = .001$) such that the improvement observed was not likely to occur due to random variation.

Success rates of cloud synchronization increased from 68% to 92% after troubleshooting workshops facilitated by faculty. This was statistically significant using a repeated-measures comparison ($t = 5.87$, $p < .001$) which gives empirical evidence of the effectiveness of instructional intervention which was targeted.

Failure rates in sensor integration improved from 27% week 3 to 11% week 14, reflecting a learning curve. The quality of this increase was also justified by a high effect size (Cohen's $d = 0.91$) which indicated that the practical implications of iterative DT/IoT involvement on technical expertise are high.

Trend analysis was employed on bi-weekly system logs and showed an upward trend instead of singular gain, which strengthened the findings of learning analytics.

Qualitative Findings

Four overarching themes emerged from thematic analysis of qualitative data that involved 24 student interviews, six faculty focus groups, and six industry consultations: perceived benefits, accessibility and usability, employability relevance, and implementation challenges.

Perceived benefits

Again and again, participants cited the efficacy of the intervention in providing additional hands-on learning. Some student volunteers indicated that this was their first experience with sensor handling and seeing system feedback in real time, a process that reinforced their understanding of theoretical engineering principles. Teachers concurred, adding that the effectiveness of the program in bridging the gap between theory and practice, and hence the maximization of the learning and teaching process.

Usability and accessibility

Generally, students found DT and IoT platforms simple to operate and easy to learn once they became familiar with them. Nevertheless, initial setup of the startup itself took a significant amount of faculty guidance and technical support, particularly from students with minimal background experience in programming or digital systems. This finding supports the need for formal orientation and instructional scaffolding during implementation. Relevance to

Employability

The industry partners were all in agreement, strongly affirming the employability relevance of the competencies acquired through the intervention. Real-time monitoring, data management through IoT, and integrating sensors were mentioned as having direct relevance for application in Ghana's manufacturing and energy sectors, which are newly emerging labor needs. The student population and academics alike viewed the program as empowering learners with competencies that made them more professionally prepared and job-market competitive.

Barriers and challenge

Despite these positive findings, many barriers were reported. Infrastructure-related constraints, including unstable internet, intermittent power outages, and procurement delay for necessary hardware components, were frequently recounted by participants as obstacles to implementation. Students from lower previous experience institutions also experienced difficulties in the initial stages of the project, temporarily hindering their adoption and participation. Generally, these findings indicate that although the DT and IoT intervention was appreciated by all for its learning and workplace applicability, effective uptake of it needs to be preceded by thorough addressing of capacity and infrastructural challenges.

Figure 3 represents thematic map of qualitative data of DT+IoT intervention. In the middle, DT+IoT in engineering education relates to four wide themes: perceived benefits, usability and accessibility, relevance to employability, and barriers and challenges. The wide themes are composed of sub-themes such as hands-on learning, user-friendly interfaces, industry-relevant skills, and infrastructural constraints. The. map identifies the balance between the increasing capability of DT+IoT to enhance understanding. and employability, and. the contextual limitations—power reliability, connectivity, and availability of resources—whose. hurdles must be crossed if scaling is to succeed.

Comparative analysis: Intervention vs. control

The intervention group performed significantly better than control on knowledge, competency, and motivation measures. Learning analytics also confirmed greater engagement and reduced error rates for the intervention group, with qualitative feedback emphasizing greater perceived employability and practical skills relevance. The control group described their learning as "mostly theoretical" and "less industry relevant."

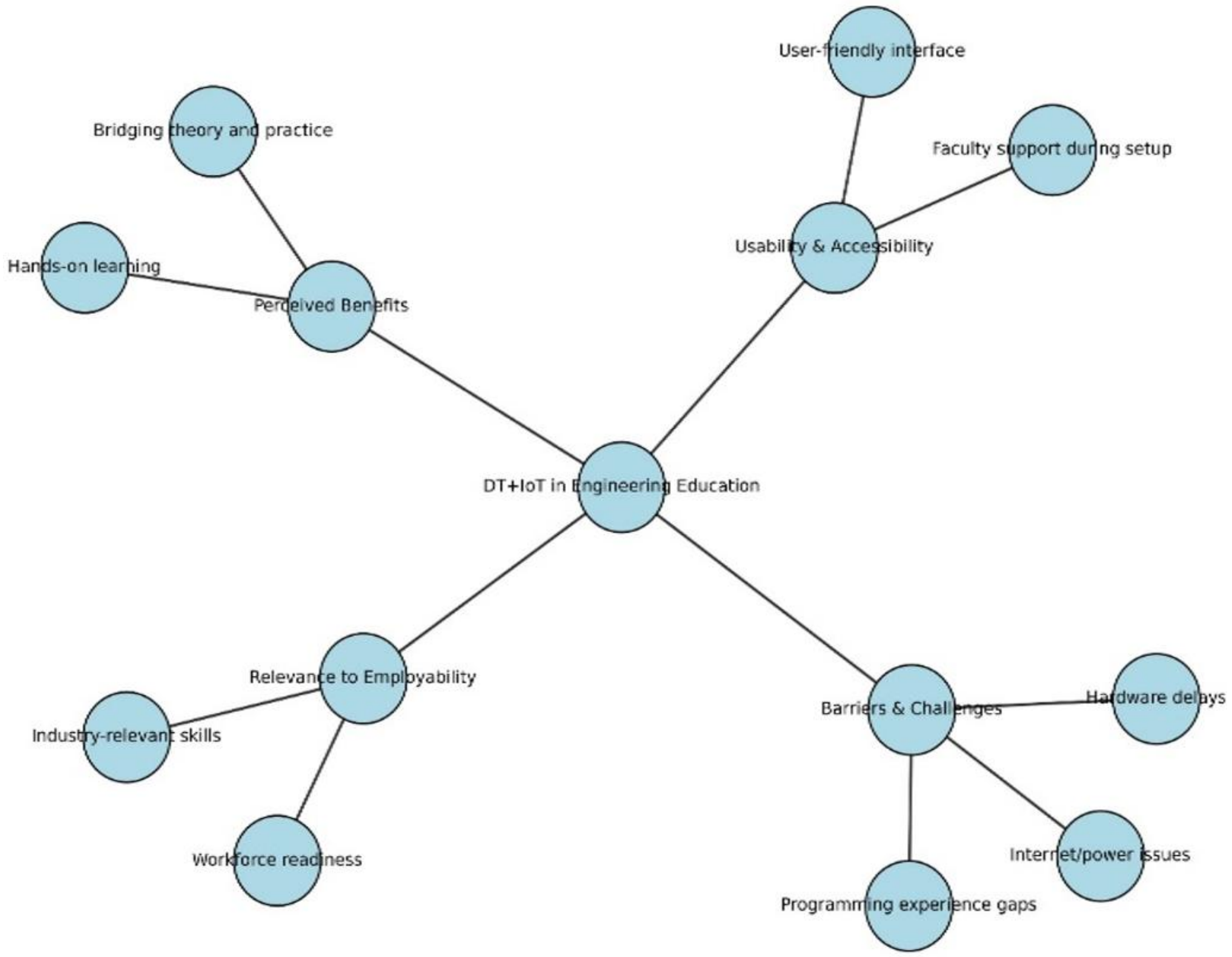

Figure 3. Thematic map of qualitative data of DT+IoT intervention (Source: Authors' own elaboration)

DISCUSSION

The findings of the study depict how the infusion of DT and IoT technologies into engineering and technical education affects technical knowledge and practical skills among students. According to RQs, the intervention group significantly improved in test scores, rubric-informed performance, and self-reported engagement, self-efficacy, and motivation as compared to the control group. These results are consistent with global studies highlighting the promise of transformational digital and remote lab-based learning in engineering education (Lee & Trappey, 2021).

To be more precise, the improvements that have been observed are consistent with the emerging research on DT- and IoT-enabled learning analytics that show how the real-time system logs, error rates, and usage data can be used to monitor the progress of the learners, diagnose the instances of misconceptions, and facilitate adaptive instructional interventions in engineering education (Khan et al., 2022; Siemens & Long, 2019).

In particular, the study develops this literature further by situating DT+IoT within Ghanaian conditions, where infrastructural and curricular limitations tend to limit experiential learning experience quality.

Skills Development and Learning Outcomes Implications

The intervention allowed the acquisition of skills in different technical areas, including working with IoT data, real-time monitoring, and systems integration, which are all essential to Ghana's industrial and manufacturing foundations. DT+IoT also promoted systems thinking by allowing students to model and simulate complex processes before their real implementation.

The results are similar to the literature of DT-based remote laboratories, where virtual-physical fusion has been demonstrated to generate better conceptualization and minimize reliance on expensive physical infrastructure, especially in resource-limited settings (Uhlemann et al., 2017; Ma & Nickerson, 2006).

Project-based group work also helped foster collaboration and communication, and debugging helped enhance problem-solving tolerance. In terms of the pedagogy of troubleshooting, the active experience of sensor errors, issues with data synchronization, and system mis conformations were productive failure experiences, which strengthened the diagnostic reasoning and skill of solving problems cyclically- a method that is gradually being encouraged in engineering education research (Kapur, 2016; Schon, 1983).

Moreover, the online platform introduced the students to remote laboratory practices, an essential competency in a time of dispersed and cloud-based engineering work. Overall, these findings indicate the promise of DT+IoT to bridge the skills gap in engineering by matching learning outcomes to the needs of contemporary industry.

Ghana-Specific Enablers and Challenges

Although the intervention yielded promising results, some Ghana-specific context factors conditioned its execution. On the enablement side, high faculty commitment and engagement of industry players ensured relevance and acceptance. Additionally, persistent focus by the Ministry of Education on TVET provided an encouraging policy environment. Yet barriers existed.

Infrastructure constraints, mainly inadequate internet and power connections, restrict normal use of the platform. These types of infrastructural dependencies are also mentioned in studies of the African DT- and IoT-based remote laboratories, where the stability of real-time data streaming and the accuracy of learning analytics directly depend on the stability of connections (Akinwale et al., 2021).

Limited personnel capacity required intensive technical support during rollout, highlighting the necessity for ongoing professional development.

Misalignment of curriculum was also an area of concern because DT+IoT competencies are not yet fully embedded in all existing engineering modules. Finally, project delays in terms of funding and purchasing hardware reflected systemic institutional challenges that must be addressed to sustain large-scale implementation.

Pedagogical Implications

The results re-emphasize the importance of curricular integration for DT+IoT. At the module level, DT+IoT technologies can be introduced as experiments in core modules such as control systems, instrumentation, and process manufacturing. Moreover, the formative assessment can be facilitated through the integration of learning analytics dashboards into these modules so that the instructor can track student patterns of interactions, error rates, and decision-making processes implemented by the system in real time.

Further up, DT+IoT projects are particularly appropriate for capstone design courses, where students have an opportunity to implement multidisciplinary knowledge to address industry-driven problems. For effective learning, assessment needs to go beyond paper-based examinations to competency-based testing, for example, project deliverables, peer assessment, and hands-on demonstrations.

Troubleshooting performance. The accuracy of fault isolation and response time can also be an assessable learning outcome, and this is a genuine engineering practice.

Aligning DT+IoT capabilities to existing ABET and NAB accreditation guidelines would encourage adherence to international and domestic standards of quality assurance.

Institutional and Policy Implications

Institutional and policy actors need to offer long-term backing for the efficient adoption of DT+IoT. University administrators ought to strategically invest in digital platforms and instructor capacity development to ensure ongoing application.

Policy-level acknowledgment of DT- and IoT-enabled remotely based laboratories and analytics-based teaching as valid methods of instruction would additionally make their introduction to Ghanaian higher education systems acceptable.

The Ministry of Education and the Commission for Technical and Vocational Education and Training can play a catalytic role by infusing digital manufacturing and IoT skills into national curricula and supporting pilot projects in polytechnics and TVET institutions. For accrediting bodies, incorporation of DT+IoT skills into program assessment criteria will encourage institutions to adopt innovative and industrial growth agenda-supportive teaching practices.

CONCLUSION

This paper provides empirical evidence of the potential of DT and IoT technologies to enhance engineering education in Ghana. Instead of merely restating the particular metrics of outcomes, the study shows, on a conceptual level, that DT+IoT-based pedagogies can systematically harmonize the experiences of learning with systems thinking and industry relevance within engineering education settings that are resource-constrained.

The intervention yielded significant improvements in students' technical know-how, practical skills, motivation, self-efficacy, and career ambition, as well as enhanced capacities in systems thinking, team collaboration, and fault-finding. By synthesizing quantitative outcomes with qualitative results, the research highlights not just pedagogical value but also functional utility of adding DT+IoT to the curricula of universities and TVET institutions. These findings contribute to the growing body of work on technology-enabled learning by placing DT+IoT in a low-resource developing-world context, offering lessons that potentially might be replicable in similar contexts across sub-Saharan Africa and globally.

The key theoretical contribution of the study is the creation and empirical testing of a context-sensitive DT+IoT integration framework to interconnect input enablers, pedagogical processes, and learning outcomes based on the CDIO and experiential learning theory and tested in the model of Kirkpatrick (1996). Not only does the framework consider the constraints that exist at the infrastructural, institutional, and capacity levels, but it also stretches the prevalent models of DT/IoT education that are mostly determined within the context of developed countries

There are several limitations to be mentioned. Methodologically, the study was done on a limited sample and for only one semester, and it would not be possible to test long-term employability and skill retention effects. Contextually, outcomes may not be universally transferable to pilot institutions with comparatively more institutional and faculty buy-in. Technically, inconsistent internet connectivity, unstable power supply, and slow acquisition of hardware likely undermined the consistency and scalability of the intervention. Otherwise, varying degrees of experience with programming resulted in varying levels of adoption and participation.

The quasi-experimental design that is not fully randomized, self-reported measures of motivation, observations made by one research team, and periodic failures of the IoT platform can also have led to measurement bias and limited internal validity

Future studies should follow these directions for the advancement of these findings. First, pilot tests should be scaled up to various TVET institutions as well as universities to test cross-site generalizability. Second, longitudinal studies would have to be conducted to evaluate the long-term sustainability of learning outcomes in terms of career development and employability. Third, integration into accrediting organizations such as ABET and Ghana's National Accreditation Board would integrate DT+IoT competences into national engineering education standards. Subsequent research could explore additional RQs such as How do DT+IoT competences impact factory placements performance among graduates and early career paths?, What DT+IoT professional development models are most appropriate for long-term mainstreaming into curricula?, and What intersectoral collaborations (universities, TVET colleges, and industry) drive adoption at scale? Funding opportunity is available via the World Bank's Africa Centers of Excellence program. The African Development Bank's initiative in skill development, and targeted grants made by organizations such as UNESCO-UNEVOC and the Carnegie Corporation of New York specifically targeted at innovation in technical and STEM education.

Lastly, the research validates that DT+IoT technologies hold great promise to revolutionize engineering education in Ghana through bridging the theory-practice gap. Despite local challenges, the intervention showed measurable student learning gains and motivation, testifying to the value of integrating recent digital technologies into technological curricula. With quality investment in policy backing, pedagogy capacity, and infrastructure, DT+IoT holds the potential for being an engineering education reform game-changer in Africa that can prepare graduates to meet the skills required in an interconnected industrialized future.

Recommendations

To ensure scalability and sustainability in embedding DT+IoT in engineering education, some strategic steps are proposed. First, investment in infrastructure is the key. A stable internet connection and a reliable power supply must be accorded with very high priority in engineering schools to lay a bedrock for digital interventions. Lack of these fundamentals will keep the effects of DT+IoT initiatives under restraint.

Second, faculty development must be institutionalized through regular training workshops that equip lecturers and instructors with technical competencies required to launch and maintain DT+IoT tools. This would reduce reliance on external technical support and build long-term internal capacity.

Third, curricular alignment should be accomplished in a manner that incorporates DT+IoT content into existing programs. Incorporating these technologies in core engineering modules and capstone projects will ensure systematic competency mapping and reassert their relevance to accreditation mandates.

Fourth, the industry partnerships need to be closer, particularly with industries such as manufacturing and energy, to allow authentic project contexts to support the real-world relevance of students' learning. Industry partnerships will bridge the gap between the classroom and the job market.

Fifth, DT+IoT implementation strategies need to incorporate sustainable financing models. Long-term platform maintenance, hardware renewal, and faculty capacity building can be funded using blended financing strategies which can be viewed as combining public funding with institutional budget allocations with industry co-investment and competitive research or development grants. Financial sustainability can also be further improved by corporate sponsorships, shared-use laboratory models, and cost-sharing agreements with industrial partners to make sure that industry relevance is maintained.

Finally, policy integration is needed. The Ministry of Education and accrediting bodies need to formally recognize DT+IoT skills in engineering education standards. Not only would this legitimize the effort, but it would also motivate institutions towards embracing new age thinking that aligns with Ghana's broader industrial and educational development agenda.

Author contributions: FK: conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, validation, visualization, writing – original draft; **WYL:** conceptualization, resources, supervision, writing – review & editing. Both authors agreed with the results and conclusions.

Funding: No funding source is reported for this study.

Ethical statement: The authors stated that ethical approval was obtained from INTI International University Malaysia, with additional institutional clearance from participating technical universities. All participants provided informed consent and were assured of voluntary participation, confidentiality, and the right to withdraw without penalty. Data were anonymized and securely stored in compliance with Ghana's Data Protection Act, 2012 (Act 843), and international ethical guidelines for human-subject research.

AI statement: The authors stated that during the preparation of this manuscript/study, the authors used ChatGPT 5o for the purposes of generating images. The authors further stated that they have reviewed and edited the output and take full responsibility for the content of this publication.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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