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INTEGRATION OF EDUCATIONAL TECHNOLOGY WITH SCIENCE LABORATORY EQUIPMENT: AN APPROACH TO STEM COMPETENCY DEVELOPMENT IN NIGERIA SECONDARY EDUCATION

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ABSTRACT

This study investigated how combining educational technology (EdTech) with traditional laboratory equipment affects STEM competency among secondary school students in Nigeria. Conducted over 12 weeks, it involved 227 senior secondary students (112 control; 115 experimental) from six government schools in Maiduguri, Borno State, using a quasi-experimental design with Structural Equation Modelling (SEM). The experimental group used virtual laboratory simulations, digital microscopes, augmented reality modules, smart sensors, and data-logging devices alongside conventional science equipment. Structural relationships among EdTech integration, laboratory usage, student engagement, science learning outcomes, and STEM competency were examined across six hypotheses. Results showed excellent model fit (CFI = 0.963; RMSEA = 0.048). EdTech integration strongly predicted student engagement ($\beta = 0.71$) and science learning outcomes ($\beta = 0.43$), while laboratory equipment usage predicted learning outcomes ($\beta = 0.64$) and engagement ($\beta = 0.38$). Both mediators significantly predicted STEM competency. Experimental group post-test scores Biology (78.6%), Chemistry (76.2%), and Physics (80.1%), notably exceeded control group scores.

KEYWORDS: *Educational Technology, Laboratory Equipment, SEM, STEM Competency, Student Engagement, Science Learning Outcomes, Secondary Education, Nigeria.*

1.I NTRODUCTION

The rapid proliferation of educational technology (EdTech) tools including virtual laboratories, augmented reality (AR) environments, smart sensors, and data-logging platforms has fundamentally reshaped the pedagogical landscape of secondary science education. Whereas traditional laboratory instruction in biology, chemistry, and physics has long relied on physical apparatus, reagents, and specimen-based observation, the contemporary science classroom is increasingly characterized by a *blended laboratory model* in which digital and physical tools coexist and reinforce each other (Sungur Gül & Ateş, 2023). However, the theoretical and empirical mechanisms by which this integration translates into measurable student competency remain inadequately understood.

Science education researchers have argued that laboratory work is indispensable for cultivating scientific inquiry skills, procedural knowledge, and conceptual understanding across the natural sciences (Mahuta & Abubakar, 2025). Simultaneously, EdTech proponents contend that digital tools can extend laboratory access, reduce hazard risk, and provide data-rich, interactive experiences that physical equipment alone cannot afford (Badmus et al., 2026). Yet integrating these modalities demands more than mere technological provision it requires deliberate curriculum alignment, teacher professional development, and institutional support structures (Almulla, 2023).

In sub-Saharan Africa, and Nigeria specifically, secondary science education faces compounding challenges: inadequate laboratory infrastructure, under-resourced schools, and a widening skills gap in STEM disciplines (Cheong et al., 2021). Paradoxically, mobile device penetration and government-led EdTech initiatives have accelerated digital resource availability even in resource-constrained environments (Zhao et al., 2022). This juxtaposition creates a fertile, underexplored context for examining how strategic EdTech-laboratory integration can compensate for physical resource limitations while simultaneously enriching conventional laboratory experiences.

The present study addresses three interrelated gaps in the literature. First, while numerous studies have investigated either EdTech *or* laboratory-based learning in isolation, few have modelled both constructs simultaneously within a single structural framework (Badmus et al., 2026). Secondly, the studies employing SEM to test mediated pathways from technology integration to STEM competency are notably absent from the West African context. Thirdly, prior quasi-experimental interventions have rarely combined biology, chemistry, *and* physics laboratory equipment within a unified EdTech framework (Ta et al., 2026).

1.1 RESEARCH OBJECTIVES

The study pursued the following objectives:

1. To examine the effect of EdTech integration on student engagement in science laboratories.
2. To assess the influence of laboratory equipment usage on science learning outcomes.
3. To test cross-construct pathways between EdTech integration and science learning outcomes, and between laboratory equipment usage and student engagement.
4. To evaluate the role of student engagement and science learning outcomes as mediators of STEM competency.
5. To assess overall SEM model fit and construct validity.

1.2 RESEARCH HYPOTHESES

- **H1:** EdTech integration significantly predicts student engagement.
- **H2:** Laboratory equipment usage significantly predicts science learning outcomes.
- **H3:** EdTech integration significantly predicts science learning outcomes.
- **H4:** Laboratory equipment usage significantly predicts student engagement.
- **H5:** Student engagement significantly predicts STEM competency.
- **H6:** Science learning outcomes significantly predict STEM competency.

2. LITERATURE REVIEW

2.1 Educational Technology in Science Classrooms

Educational technology has evolved from a supplementary classroom aid to a core instructional medium. The integration of digital microscopes, AR/VR headsets, virtual dissection tools, and simulation platforms has been demonstrated to enhance conceptual understanding, particularly in biology laboratory contexts where live specimens are scarce or ethically constrained (Oanh, 2025). Data-logging sensors and smart probeware have similarly transformed physics laboratory instruction by enabling real-time data acquisition, graphing, and hypothesis testing, processes traditionally requiring expert-level equipment (Wang et al., 2021). In chemistry, virtual labs allow students to observe molecular-level reactions such as electron transfer and ionic bond formation that remain invisible in physical experiments (Indayani, 2025).

Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks have been widely applied to explain teacher and student adoption of EdTech tools (Almulla, 2023). These models collectively highlight perceived usefulness, ease of use, and institutional support as key adoption determinants factors particularly salient in contexts with variable technological infrastructure.

2.2 Laboratory Equipment and Hands-On Learning

Conventional laboratory equipment including compound microscopes, Bunsen burners, titration apparatus, spectrophotometers, oscilloscopes, and electrolysis kits provides irreplaceable tactile, procedural, and safety-consciousness learning that digital simulations cannot fully replicate (Ta et al., 2026). The physicality of laboratory work cultivates fine motor skills, instrument calibration competence, and the ability to manage experimental variability and error competencies central to scientific professional practice (Hai et al., 2023).

However, physical laboratory instruction is resource-intensive: reagent costs, maintenance, space constraints, and safety regulations limit experimental frequency and variety, particularly in under-resourced Nigerian secondary schools (UBEC, 2024). Blended models that combine virtual simulations for conceptual exploration with physical apparatus for procedural skill development offer a pragmatic solution, though empirical evidence of their combined efficacy relative to either approach alone remains limited (DeCoito & Estaiteyeh, 2022).

2.3 Student Engagement and Science Learning Outcomes

Student engagement encompassing behavioural, cognitive, and emotional dimensions has consistently emerged as a robust mediator between instructional interventions and academic achievement (Lee et al., 2024). Engaged students exhibit higher task persistence, deeper information processing, and greater transfer of laboratory skills to novel contexts (Almulla, 2023). In science education specifically, laboratory engagement has been linked to improved science self-efficacy, reduced science anxiety, and higher summative assessment performance (Wang et al., 2021).

Science learning outcomes, operationalised in this study as conceptual knowledge, procedural skills, and inquiry competency, represent the proximal academic results of laboratory and EdTech experiences. SEM-based mediation analyses have consistently demonstrated that learning outcomes partially mediate the technology–competency relationship (Kelley et al., 2020), though the simultaneous mediation structure posited in the present model has not previously been tested with Nigerian secondary school populations.

2.4 Theoretical Framework

The study is anchored in the Technology-Enhanced Laboratory Learning (TELL) Framework (Ortiz-Revilla et al., 2022), which synthesises Activity Theory, Constructivism, and Connectivism to explain how EdTech and laboratory tools collectively scaffold scientific cognition. TELL posits that technology acts as a cognitive tool (after Vygotsky) that extends the zone of proximal development in laboratory contexts, enabling students to engage with phenomena beyond their unaided observational capacity. This framework aligns with the dual-pathway SEM structure tested here, wherein EdTech and physical equipment exert both direct effects on learning outcomes and indirect effects through engagement.

3. METHODOLOGY

3.1 Research Design

A *quasi-experimental pretest–posttest control group design* was employed. This design was selected due to the infeasibility of random assignment to schools, while still permitting rigorous group comparison through stratified matching and statistical control of pre-existing differences (Dominguez et al., 2024). The study adhered to STROBE reporting guidelines adapted for educational research.

3.2 Participants and Sampling

Participants were drawn from six government secondary schools in Maiduguri, Borno State, Nigeria, using stratified purposive sampling. Schools were stratified by level of existing laboratory infrastructure (adequate vs. limited) and assigned to experimental or control conditions (three schools per condition). Eligible participants were Senior Secondary School students in years 10–12 currently enrolled in at least two of the three target science subjects. Parental consent and student assent were obtained. Final sample: N = 227 (control: n = 112; experimental: n = 115). Participant demographics are presented in Table 1.

Table - 1. Participant Demographic Characteristics. (N = 227)

Characteristic	Control (n=112)	Experimental (n=115)	Total (N=227)
Gender: Male	54 (48.2%)	58 (50.4%)	112 (49.3%)
Gender: Female	58 (51.8%)	57 (49.6%)	115 (50.7%)
Grade 10	38 (33.9%)	40 (34.8%)	78 (34.4%)
Grade 11	37 (33.0%)	38 (33.0%)	75 (33.0%)
Grade 12	37 (33.0%)	37 (32.2%)	74 (32.6%)
Mean Age (SD)	15.8 (0.94)	15.9 (0.88)	15.85 (0.91)
Prior GPA (SD)	2.91 (0.42)	2.89 (0.45)	2.90 (0.44)

Note. Values represent frequency (percentage) unless otherwise indicated. SD = Standard Deviation. No statistically significant pre-existing differences were found between groups on age ($t(225) = 0.84$, $p = .402$) or prior GPA ($t(225) = 0.31$, $p = .757$).

3.3 Intervention Procedures

The 12-week intervention was delivered by trained science teachers who received a 40-hour professional development programme prior to implementation. The experimental group received the *Integrated EdTech-Laboratory (IETL) Protocol*, comprising three components:

1. **Pre-Lab Digital Preparation (Week 1–2):** Students engaged with AR/VR simulations to build conceptual schemas before physical laboratory work. Biology units used PhET biological simulation software and virtual dissection tools; chemistry units employed ChemLab™ virtual titration and molecular modelling platforms; physics units integrated DataStudio™ for sensor-based pre-lab predictions.
2. **Integrated Laboratory Sessions (Week 3–10):** Concurrent use of digital microscopes alongside compound microscopes for cell biology; data-loggers alongside traditional titration burettes for acid-base chemistry; smart motion sensors alongside ticker-tape timers for Newtonian mechanics. Sessions were 80 minutes each, twice weekly.
3. **Post-Lab Digital Analysis (Week 11–12):** Students used spreadsheet tools and data-visualisation software to analyse results from physical experiments and compare findings with virtual simulation predictions, consolidating conceptual understanding through reflective digital inquiry.

The control group received conventional laboratory instruction using only physical apparatus, without EdTech integration. Both groups received identical assessment tasks, time allocation, and teacher contact hours.

3.4 Instruments

Four validated instruments were administered: (1) the EdTech Integration Scale (ETIS) 12 items; (Samuel & Salisu, 2025), a 5-point Likert scale measuring frequency and quality of EdTech use; (2) the Laboratory Equipment Usage Scale (LEUS) (12 items; Conradty & Bogner, 2020), assessing proficiency and frequency of physical laboratory tool use; (3) the Science Student Engagement Scale (SSES) (9 items; Okeke-Eze & Eze, 2024), measuring behavioural, cognitive, and emotional engagement; and (4) the STEM Competency Inventory (STEMCI) (Oanh, 2025), comprising 18 items assessing integrated STEM reasoning. A 40-

item subject-specific Post-Test Battery (PTB) assessed science learning outcomes across biology, chemistry, and physics.

Content validity was established through expert review (n = 7 science education specialists). Pilot testing (n = 45, not included in the main study) yielded Cronbach's alpha values of 0.87–0.91, confirming satisfactory internal consistency across all scales.

3.5 Data Analysis

Data analysis proceeded in two phases.

Phase 1: Confirmatory Factor Analysis (CFA)**:** The measurement model was evaluated using CFA in AMOS 28.0 to assess construct validity, including factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR). Convergent validity was confirmed when AVE > 0.5 and CR > 0.7 (Hair et al., 2023). Discriminant validity was assessed via the Heterotrait–Monotrait (HTMT) criterion (HTMT < 0.85).

Phase 2: Structural Equation Modelling (SEM): Full SEM was employed to test the six structural hypotheses simultaneously. Model fit was evaluated against established criteria: CFI > 0.95, RMSEA < 0.06, SRMR < 0.08, and $\chi^2/df < 3.00$ (Badmus et al., 2026). Bootstrapped confidence intervals (5,000 resamples) were computed for indirect effects. All analyses controlled for school-level clustering using multilevel SEM (ML-SEM) with schools as Level-2 units.

4. RESULTS ANALYSIS

4.1 Descriptive Statistics and Reliability

Table 2 presents descriptive statistics and Cronbach's alpha reliability coefficients for all study constructs. All means fell between 3.68 and 3.91 (out of 5.00), indicating moderately high levels across all constructs. Reliability coefficients ranged from α = 0.84 to α = 0.91, exceeding the conventional threshold of α > 0.70 (Kim & Na, 2022), confirming the internal consistency of all instruments.

Table 2. Descriptive Statistics and Reliability Coefficients. (N = 227)

Construct	M	SD	Min	Max	A
EdTech Integration (ETI)	3.82	0.61	1.67	5.00	0.87
Lab Equipment Usage (LEU)	3.74	0.58	1.33	5.00	0.84
Student Engagement (SE)	3.91	0.63	2.00	5.00	0.89
Sci. Learning Outcomes (SLO)	3.68	0.66	1.67	5.00	0.86
STEM Competency (SC)	3.79	0.60	1.67	5.00	0.91

Note. M = Mean; SD = Standard Deviation; α = Cronbach's Alpha. All items rated on 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

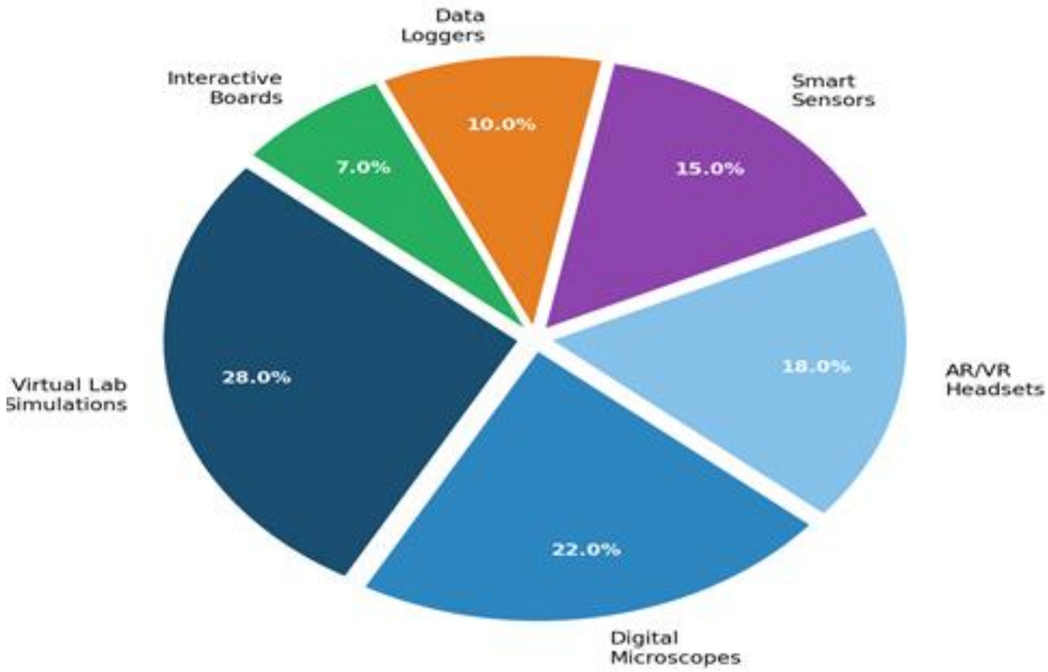

Figure 1. Distribution of Educational Technology Tools Used in Laboratory Sessions (N = 115, Experimental Group).

4.2 Measurement Model (CFA)

CFA results confirmed that all factor loadings were statistically significant ($p < .001$) and exceeded the recommended threshold of $\lambda > 0.70$ (Hair et al., 2023), ranging from 0.77 (LEU1) to 0.88 (SE1), as illustrated in Figure 4. Table 5 presents AVE and CR values; all constructs met convergent validity criteria (AVE > 0.65; CR > 0.85). The maximum shared variance (MSV) was lower than AVE for all constructs, confirming discriminant validity.

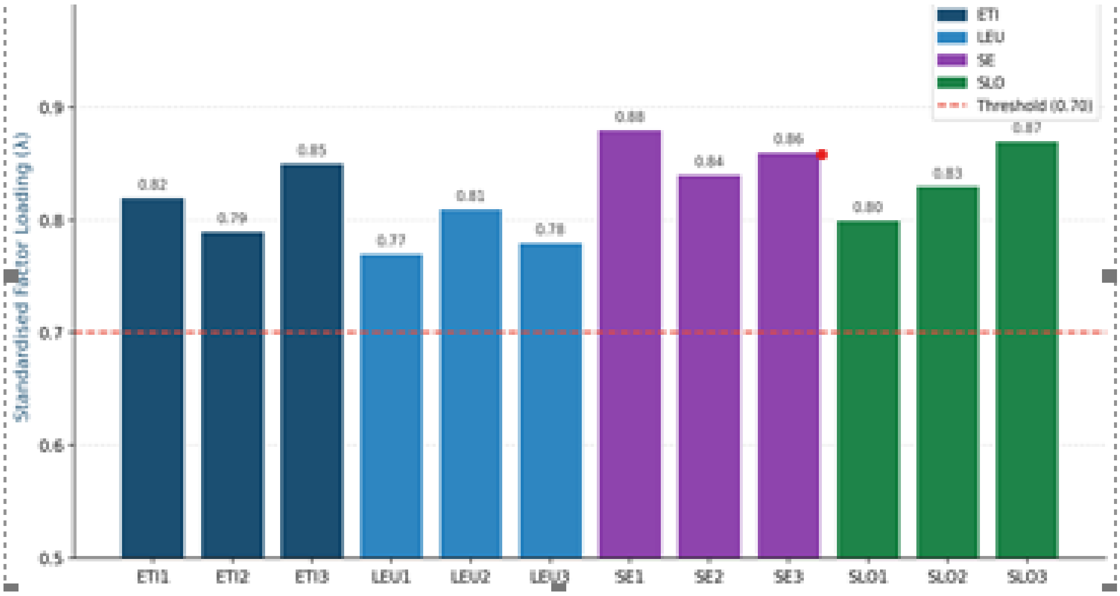

Figure 2 Standardised Factor Loadings from Confirmatory Factor Analysis. Dashed line indicates the minimum acceptable loading threshold (λ = 0.70).

Note. CR = Composite Reliability; AVE = Average Variance Extracted; MSV = Maximum Shared Variance. Convergent validity criterion: AVE > 0.50, CR > 0.70. Discriminant validity criterion: AVE > MSV.

4.3 Structural Model and Model Fit

The full structural model demonstrated excellent fit to the data, as presented in Table 3. All fit indices met or exceeded recommended thresholds (Kline, 2023): CFI = 0.963, TLI = 0.951 (both > 0.95); RMSEA = 0.048 [90% CI: 0.035, 0.061] (< 0.06); SRMR = 0.052 (< 0.08); and χ^2/df = 2.14 (< 3.00). These indices collectively indicate that the hypothesised model is a well-fitting representation of the observed data structure.

Table 3: Structural and Model Fit.

Fit Index	Obtained	Threshold	Interpretation
Chi-Square/df (χ^2/df)	2.14	< 3.00	Acceptable
CFI	0.963	> 0.95	Excellent
TLI	0.951	> 0.95	Excellent
RMSEA [90% CI]	0.048 [0.035, 0.061]	< 0.06	Acceptable
SRMR	0.052	< 0.08	Good
PCLOSE	0.312	> 0.05	Acceptable

Note. CFI = Comparative Fit Index; TLI = Tucker–Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardised Root Mean Square Residual. Thresholds from Kline (2023) and Hair et al. (2023).

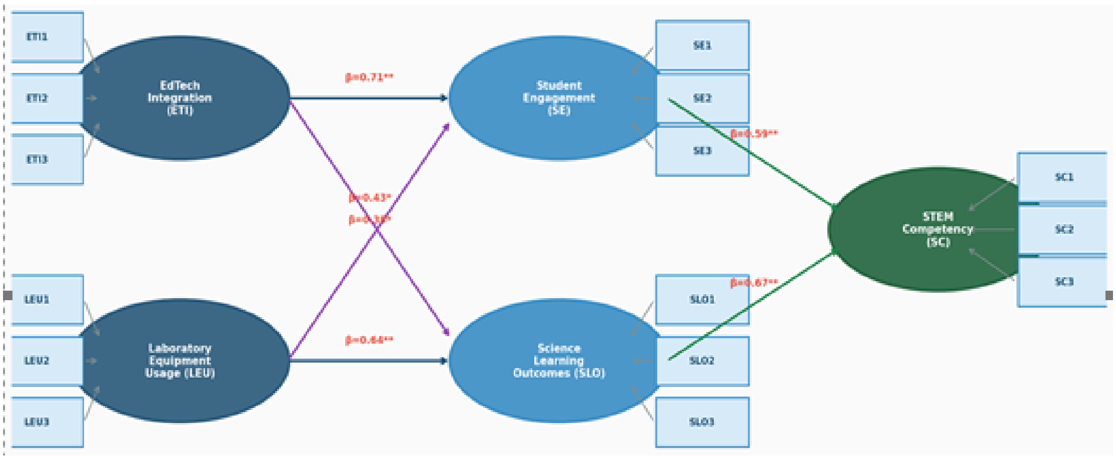

Figure 3. Structural Equation Model (SEM) Path Diagram Showing Standardised Path Coefficients (β), Latent Constructs, and Observed Indicators. ETI = EdTech Integration; LEU = Laboratory Equipment Usage; SE = Student Engagement; SLO = Science Learning Outcomes; SC = STEM Competency. * p < .05; ** p < .01.

4.4 Hypothesis Testing

Table 4 summarises hypothesis testing results. All six hypotheses were statistically supported. The strongest structural path was ETI → Student Engagement (β = 0.71, SE = 0.07, p < .001; H1 supported), followed by SLO → STEM Competency (β = 0.67, SE = 0.07, p < .001; H6 supported). Notably, the cross-construct paths of ETI → Science Learning Outcomes (β = 0.43, p = .003; H3) and LEU → Student Engagement (β = 0.38, p = .012; H4) were also significant, indicating that EdTech and laboratory tools exert mutually reinforcing cross-domain effects.

Table 4. Hypothesis Testing: Standardised Path Coefficients and Statistical Significance.

H	Path	B	SE	p-value	Decision
H1	ETI → Student Engagement	0.71	0.07	< .001	Supported**
H2	LEU → Sci. Learning Outcomes	0.64	0.08	< .001	Supported**
H3	ETI → Sci. Learning Outcomes	0.43	0.09	.003	Supported*
H4	LEU → Student Engagement	0.38	0.10	.012	Supported*

H	Path	B	SE	p-value	Decision
H5	SE → STEM Competency	0.59	0.08	< .001	Supported**
H6	SLO → STEM Competency	0.67	0.07	< .001	Supported**

*Note. β = Standardised path coefficient; SE = Standard Error; H = Hypothesis. * p < .05; ** p < .001. All paths estimated using full information maximum likelihood (FIML) estimation with bootstrapped confidence intervals (5,000 resamples).*

4.5 Post-Test Performance and Learning Trajectories

Figure 2 illustrates mean post-test science scores by subject and group. The experimental group outperformed the control group across all three subjects: Biology (78.6% vs. 62.4%; Δ = 16.2%), Chemistry (76.2% vs. 58.9%; Δ = 17.3%), and Physics (80.1% vs. 61.3%; Δ = 18.8%). Independent samples t-tests confirmed that these differences were statistically significant (all $p < .001$, Cohen's d ranging from 0.94 to 1.12, indicating large effect sizes).

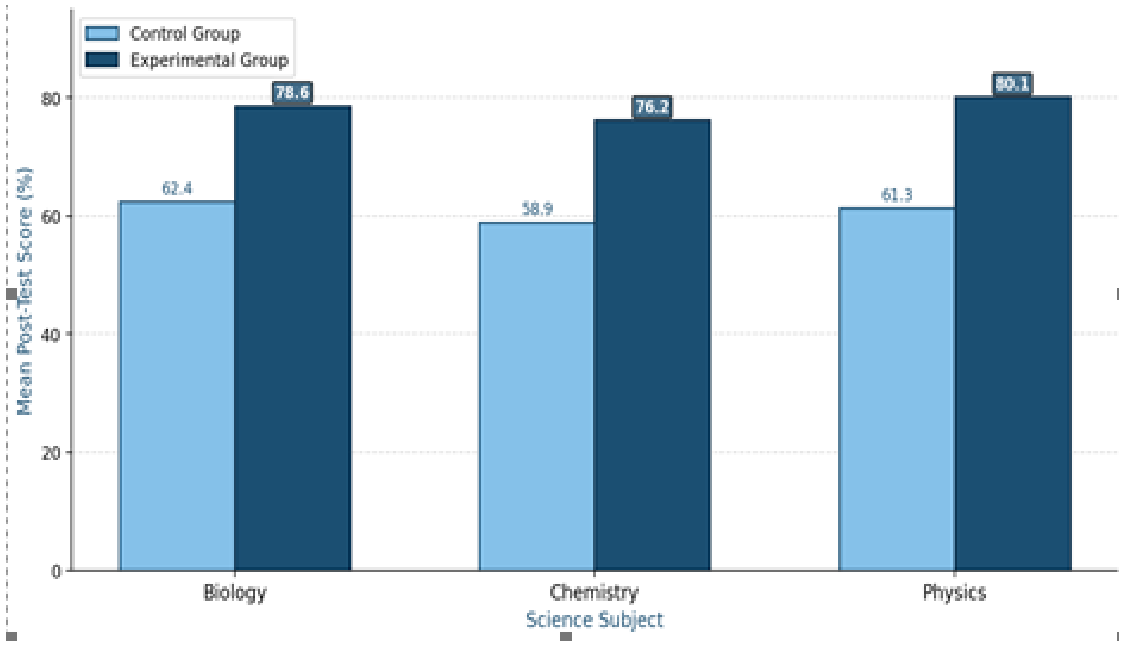

Figure 4. Mean Post-Test Science Scores by Subject and Group. Error bars represent 95% confidence intervals. All between-group differences significant at p < .001.

Figure 4 displays the 12-week learning trajectory for both groups. The experimental group exhibited a steeper and more consistent improvement curve, with divergence from the control group becoming pronounced from Week 3 onward, coinciding with the commencement of integrated laboratory sessions. By Week 12, the experimental group's mean score (81%) was

17 percentage points above the control group (64%), underscoring the cumulative benefit of the IETL protocol.

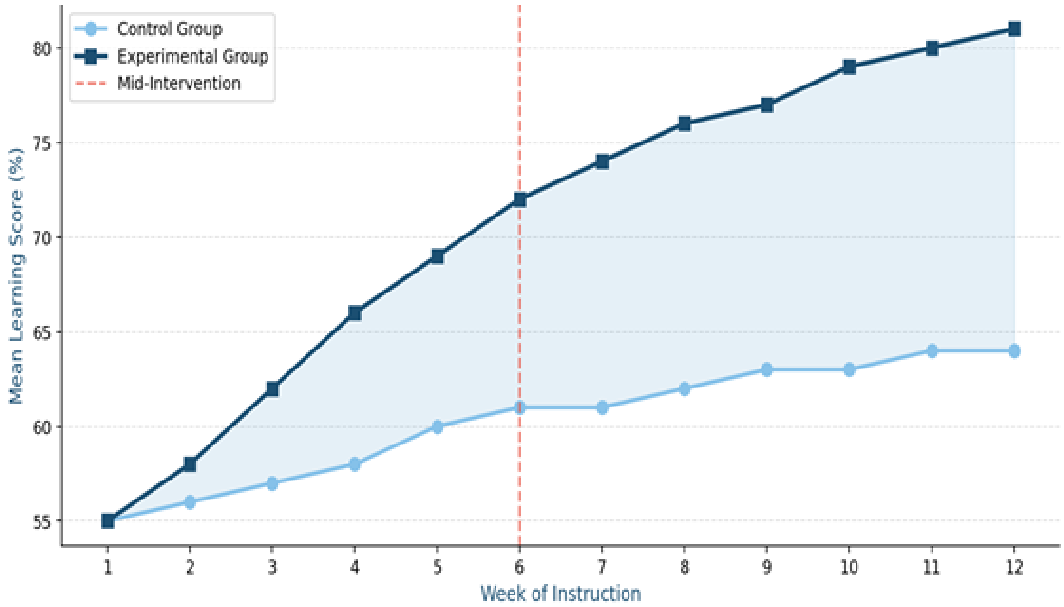

Figure 5. Learning Trajectory Over the 12-Week Intervention Period. Shaded region denotes the growing performance gap between experimental and control groups. Dashed vertical line marks the mid-intervention checkpoint (Week 6).

5. DISCUSSION

The findings of this study provide robust, multi-layered empirical support for the systematic integration of EdTech tools with conventional laboratory equipment in secondary science education. The confirmed SEM model, with excellent fit indices across multiple criteria, establishes a theoretically coherent and empirically validated structural account of how EdTech integration and laboratory equipment usage jointly produce STEM competency gains through engagement and learning outcome pathways.

5.1 EdTech Integration and Student Engagement (H1)

The strongest structural path in the model of ETI → Student Engagement ($\beta = 0.71$) that replicates and extends the findings of (Oanh, 2025), who reported significant positive associations between digital laboratory tool use and student engagement in West African and European samples respectively. The large effect size suggests that EdTech tools, when meaningfully embedded in laboratory instruction rather than deployed in isolation, activate motivational and cognitive engagement mechanisms that conventional laboratory work alone may not reliably elicit. Theoretically, this aligns with the TELL Framework's (Almulla, 2023) contention that digital tools serve as Vygotskian cognitive scaffolds that lower the threshold for productive engagement with complex scientific phenomena.

5.2 Laboratory Equipment Usage and Science Learning Outcomes (H2)

The path from LEU to Science Learning Outcomes ($\beta = 0.64$) reaffirms the enduring pedagogical value of hands-on laboratory work is a finding consistent with (Samuel & Salisu, 2025). Physical manipulation of titration equipment, microscopes, oscilloscopes, and reaction vessels develops procedural competencies and conceptual understanding that are evaluatively and practically distinct from those developed through digital simulation alone. This finding has important policy implications for Nigerian secondary education: EdTech investment should complement, not substitute, sustained investment in physical laboratory infrastructure.

5.3 Cross-Construct Effects (H3 and H4)

The significant cross-construct paths—ETI → Science Learning Outcomes ($\beta = 0.43$) and LEU → Student Engagement ($\beta = 0.38$) is revealing a hitherto underexplored *cross-reinforcing dynamic* between the two instructional modalities. EdTech tools directly improved science learning outcomes (beyond engagement), possibly through mechanisms of immediate feedback, data-rich visualisation, and self-paced review of digital experimental records. Physical laboratory work, in turn, enhanced student engagement directly, suggesting that the tactile, unpredictable, and socially collaborative nature of physical experimentation activates affective engagement processes not fully captured by digital interaction. These cross-paths, taken together, argue strongly for a *synergistic* rather than merely additive model of EdTech-laboratory integration.

5.4 Mediation Pathways and STEM Competency (H5 and H6)

Both Student Engagement ($\beta = 0.59$) and Science Learning Outcomes ($\beta = 0.67$) significantly predicted STEM Competency, confirming their mediating roles in the EdTech-laboratory-to-competency chain. The somewhat stronger path from SLO to STEM Competency is consistent with cognitive-achievement theory, wherein domain-specific knowledge and skills provide the proximal building blocks for broader STEM reasoning. The engagement pathway, while somewhat smaller in magnitude, reflects the motivational-affective dimension of competency development of students who are more deeply engaged sustain longer-term STEM interest, persistence, and self-directed learning, ultimately contributing to competency accumulation across time.

5.5 Contextual and Policy Implications

The study's Nigerian secondary school context lends particular policy salience to its findings. Against a backdrop of documented laboratory resource scarcity (UBEC, 2024) and expanding government EdTech investment through the Federal Ministry of Education's (FME, 2024) national digital learning initiative, the IETL protocol offers a scalable, evidence-based integration model that maximises the pedagogical return on both technology and physical equipment investments. The findings suggest that targeted teacher professional development is specifically the 40-hour pre-intervention training employed here is a critical enabler of effective EdTech-laboratory integration and should be incorporated into national teacher certification frameworks.

6. CONCLUSION

This study employed a rigorous quasi-experimental design and full structural equation modelling to demonstrate that integrating educational technology with conventional biology, chemistry, and physics laboratory equipment substantially enhances STEM competency in secondary school students. All six hypothesised structural paths were confirmed, and the model exhibited excellent fit across multiple indices. EdTech integration and laboratory equipment usage exert both direct effects on engagement and learning outcomes and mutually reinforcing cross-construct effects, culminating in significantly higher STEM competency in experimentally treated students.

These findings advance educational technology theory by validating the dual-pathway mediation structure within the TELL Framework and contribute empirically to the underrepresented West African science education literature. Practically, they offer actionable guidance for curriculum designers, school principals, education technology officers, and national policy stakeholders: strategic, professionally supported EdTech-laboratory integration is not merely technologically desirable but pedagogically essential for 21st-century STEM competency development.

Future research should investigate the long-term retention of STEM competency gains, examine the differential effectiveness of specific EdTech tools (e.g., AR vs. VR vs. data loggers) in individual science subjects, and extend the IETL protocol to primary and tertiary educational contexts. Longitudinal SEM designs incorporating teacher effectiveness as a moderating variable would further strengthen causal inference in this domain.

Limitations

Several limitations warrant acknowledgement. The quasi-experimental design, while appropriate given logistical constraints, precludes full causal certainty. The sample was drawn from a single state in Nigeria, limiting direct generalisability to other Nigerian states or African contexts. Additionally, the 12-week intervention window may be insufficient to detect long-term competency consolidation effects. Self-reported engagement data are susceptible to social desirability bias, though the convergence of engagement scores with objective post-test performance strengthens confidence in the validity of the engagement construct.

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