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Evaluating human–AI collaborative pedagogical model for sustainable skill development in technical education workshops

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Abstract

The accelerating integration of artificial intelligence (AI) into educational environments has opened new possibilities for enhancing technical skill development, particularly in hands-on workshop-based settings. This study evaluated a Human–AI Collaborative Pedagogical Model designed to promote sustainable skill development among university-level building and woodwork technology education students in Nigeria. Employing a quasi-experimental design with a mixed-methods approach, the research recruited 120 participants drawn from four universities in South East Nigeria. Students were assigned to either a traditional instruction group or an artificial intelligence-supported instruction group over a six-week practical module. Mixed quantitative and qualitative data were collected through validated performance instruments and analyzed using inferential statistics and thematic analysis, respectively. Results demonstrated that students in the artificial intelligence-supported group achieved significantly higher task accuracy, reduced task completion time, lower error frequency, and superior skill transferability compared to their traditionally-instructed counterparts. Thematic analysis further identified the Scaffolded Human–AI Co-instruction Model, characterized by real-time artificial intelligence feedback, instructor mediation, and iterative experiential cycles, as the most effective pedagogical framework for workshop-based technical education. These findings inform sustainable digital transformation in TVET by highlighting how human-centered AI integration can improve skill outcomes while guiding instructor development, implementation governance, and equitable scaling in resource-constrained contexts.

Keywords: AI-supported learning; Building technology; Human–AI collaboration; Pedagogical model; Sustainable skill development; Technical education; Workshop-based pedagogy

1. Introduction

The global educational landscape is witnessing unprecedented transformation driven by artificial intelligence [AI], with implications stretching across all sectors and educational levels (Rosyadi et al., 2023). Within Technical and Vocational Education and Training [TVET], this transformation is particularly salient given the discipline's inherent orientation toward practical competence, real-world skill application, and workforce preparation (Asogwa et al., 2023). The integration of AI-supported instructional systems into workshop-based technical education represents both a compelling opportunity and a substantive challenge for educational researchers, curriculum designers, and institutional administrators, especially in developing-country contexts where infrastructure and training resources remain constrained (Rabiu et al., 2025).

In Nigeria, building and woodwork technology education programmes offered at the university level are among the most practically demanding, requiring students to acquire precision-based skills in drafting, construction, timber processing, joinery, and structural analysis (Nwobodo-Anyadiegwu & Okanya, 2026). Institutions in the South East geopolitical zone have historically faced systemic challenges including inadequate workshop facilities, outdated instructional approaches, and a widening gap between academic training and industry requirements (Ukala & Iheukwumere, 2025), prompting growing calls for pedagogical innovation that can enhance learning outcomes without requiring prohibitive capital expenditure.

Human–AI collaborative models preserve the irreplaceable role of the human instructor while leveraging AI tools to augment feedback quality, reduce error incidence, improve task monitoring, and personalise learning pathways (Bowen & Watson, 2024). This approach is particularly relevant in workshop settings, where errors can be costly, time is constrained, and the gap between competence demonstration and learning support is difficult for a single instructor to bridge across a large cohort of students. AI-driven design feedback systems, real-time error detection, computer numerically controlled [CNC] performance analytics, and AI safety monitoring interfaces represent tools that can be embedded within existing workshop pedagogies to address these limitations.

Despite the theoretical promise of AI integration in TVET, empirical evidence from sub-Saharan Africa, and from Nigerian universities specifically, remains sparse, fragmented, and largely descriptive. There is insufficient quasi-experimental evidence on whether AI-supported instruction actually improves measurable performance indicators such as task accuracy, task completion time, error frequency, and skill transferability among technical education students. Furthermore, the pedagogical models most effective for structuring human–AI interaction in practical workshop settings have not been systematically identified or evaluated in the Nigerian university context.

This study addresses these gaps through a structured quasi-experimental investigation conducted across four universities in South East Nigeria. Drawing on Sociotechnical Systems Theory (Trist & Bamforth, 1951), Kolb's Experiential Learning Theory (Kolb, 1984), and Human–AI Complementarity Theory (Dellermann et al., 2019; Holstein & Aleven, 2022), the study evaluates the impact of a Human–AI Collaborative Pedagogical Model [HAICPM] on building and woodwork technology students' practical skill development and identifies the pedagogical models that best support human–AI collaboration in workshop-based technical education. The significance of this research is threefold: it contributes empirical evidence to scholarship on AI integration in African TVET contexts; it provides actionable pedagogical recommendations grounded in mixed-methods evidence; and it supports the broader agenda of sustainable educational innovation through AI augmentation rather than wholesale technological replacement of existing instructional infrastructures.

The study was guided by the following research questions:

RQ 1) What pedagogical models best support effective human–AI collaboration in workshop-based technical education?

RQ 2) How does AI-supported workshop instruction affect: (a) task accuracy, (b) task completion time, (c) error reduction, and (d) skill transferability?

Four null hypotheses were formulated to guide the quantitative strand of the study:

H_{01}: There is no significant difference in task accuracy between students exposed to AI-supported workshop instruction and those exposed to traditional workshop instruction.

H_{02}: There is no significant difference in task completion time between students exposed to AI-supported workshop instruction and those exposed to traditional workshop instruction.

H_{03}: There is no significant difference in task error frequency between students exposed to AI-supported workshop instruction and those exposed to traditional workshop instruction.

H_{04}: There is no significant difference in skill transferability between students exposed to AI-supported workshop instruction and those exposed to traditional workshop instruction.

2. Theoretical Framework

This study is anchored in three complementary theoretical frameworks that collectively account for the technical, pedagogical, and collaborative dimensions of human–AI interaction in workshop-based education.

2.1. Sociotechnical Systems Theory

Sociotechnical Systems Theory [STST] originated in mid-twentieth-century organizational research, most notably in Trist and Bamforth’s (1951) studies, and it provides a robust framework for explaining how performance outcomes emerge from the interdependence of (a) human actors and their social relations, (b) technical tools and workflows, and (c) the organizational arrangements that coordinate work. Central to STST is the principle of joint optimization: neither the social subsystem (e.g., people, roles, norms, skills) nor the technical subsystem (e.g., tools, automation, information systems) can, on its own, determine outcomes; rather, sustainable performance depends on designing both subsystems together so that they mutually reinforce each other (Clegg, 2000). Contemporary sociotechnical scholarship emphasizes that technology-led change is rarely plug-and-play and requires attention to work design and contextual fit (Baxter & Sommerville, 2011; Clegg, 2000).

In the context of this study, STST maps onto the workshop learning environment in four aligned components. Human actors include students and instructors, whose expertise, motivation, and interaction patterns shape learning quality. The technical subsystem comprises AI-enabled supports (e.g., AI-driven design feedback, real-time error detection, and performance analytics), which mediate how learners receive feedback and how instructors monitor progress. The organizational subsystem includes workshop layout and safety routines, curriculum sequencing, assessment practices, and institutional policies governing tool use and data practices. Task processes refer to the practical activities and iterative cycles through which learners develop competencies during the six-week module. Using an STST lens, effective AI integration should be designed to augment and coordinate with instructional roles and workshop routines (e.g. supporting feedback, scaffolding, and safe practice) rather than displacing instructors or disrupting established learning processes. This perspective underpins the study's emphasis on human–AI complementarity: skill gains are expected when AI functions are aligned with social and pedagogical structures and when the learning system is designed to sustain performance, equity, and safe participation over time (Baxter & Sommerville, 2011 Clegg, 2000).

2.2. Experiential Learning Theory

Kolb's Experiential Learning Theory [ELT] conceptualizes learning as a process in which knowledge is created through the transformation of experience, progressing through a four-stage cycle: Concrete Experience [CE], Reflective Observation [RO], Abstract Conceptualization [AC], and Active Experimentation [AE] (Kolb, 1984). ELT is particularly applicable to workshop-based technical education, where learners engage directly with tools and materials, reflect on task outcomes, develop generalized understanding, and iteratively test revised strategies in subsequent tasks—an approach widely discussed as suitable for practice-oriented and vocational learning contexts (Healey & Jenkins, 2000; Wijnen-Meijer et al., 2022).

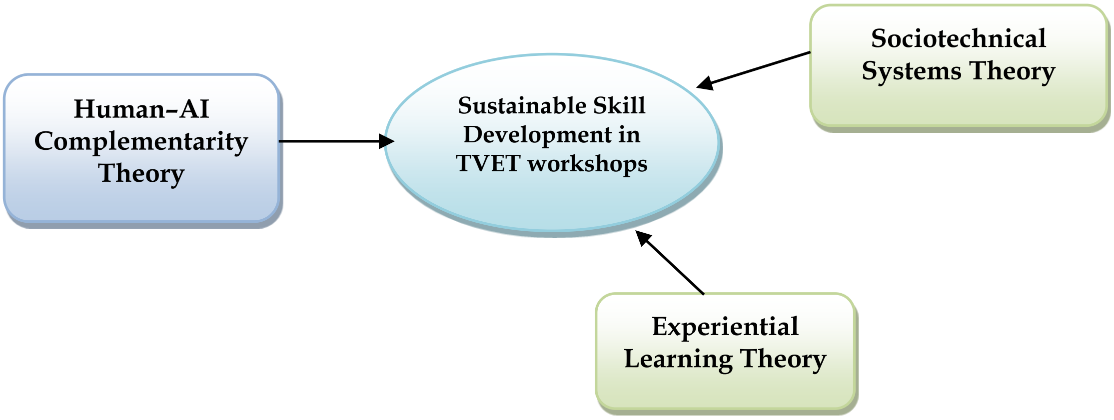
Within the Human–AI Collaborative Pedagogical Model evaluated in this study, AI support can be conceptualized as scaffolding the experiential cycle by strengthening feedback, reflection, and iterative refinement. During Concrete Experience, AI-enabled feedback (e.g., automated checks or alerts) can provide timely, task-level guidance that helps learners notice execution errors or safety-relevant behaviours as they occur, which is consistent with evidence that AI-assisted feedback can enhance learning processes when integrated with pedagogical oversight (Ba et al., 2025). During Reflective Observation, learning analytics dashboards can support data-informed reflection by summarizing performance patterns and progress indicators (Cabral et al., 2025). During Abstract Conceptualization, comparative performance information can help learners articulate principles about process quality (e.g., accuracy, sequencing, tolerances) and connect outcomes to underlying concepts, provided that interpretation is mediated through instruction rather than treated as self-explanatory (Morris, 2020). During Active Experimentation, subsequent practice cycles allow learners to apply revised strategies and test improvements under instructor guidance; where digital manufacturing or simulation tools are used, these environments can support structured experimentation and iteration, but their pedagogical value depends on alignment with workshop routines, assessment practices, and safety protocols (Kolb, 1984; Morris, 2020).

2.3. Human–AI Complementarity Theory

Human–AI complementarity is commonly framed as a hybrid intelligence perspective: the most effective AI-enabled systems in professional and educational contexts are designed to augment rather than replace human capabilities, by allocating tasks so that human and AI strengths reinforce each other (Dellermann et al., 2019; Holstein & Aleven, 2022). This perspective emphasizes that humans and AI contribute distinct competencies. In educational settings, instructors are typically advantaged in contextual judgment, pedagogical decision-making, motivational support, and ethical responsibility, whereas AI systems can provide speed, consistency, pattern detection, and data-driven feedback at scale (Holstein & Aleven, 2022). When these complementary competencies are intentionally coordinated, the resulting human–AI system can achieve better learning support than either component operating alone—particularly when AI outputs are interpreted and acted on through pedagogical expertise (Dellermann et al., 2019; Holstein & Aleven, 2022).

In workshop-based technical education, this complementarity rationale supports the HAICPM design: instructors provide contextual mentoring, adaptive scaffolding, and safety oversight, while AI tools supply real-time performance analytics, structured error detection, and personalized formative feedback. This division of cognitive and instructional labour aligns with higher education scholarship arguing that the benefits of AI are maximized when instructors explicitly scaffold learners' metacognitive monitoring and regulation rather than delegating judgment to AI systems (Atchley et al., 2024). Figure 1 presents the graphical illustration of the theoretical framework.

Figure 1
Integrated Theoretical Framework: STST, ELT, and Human–AI Complementarity



3. Literature Review

3.1. TVET in Nigerian Universities: Policy Context and Challenges

Technical and Vocational Education and Training has long been recognized as a cornerstone of national development in Nigeria, with the National Board for Technical Education [NBTE] charged with regulating and promoting TVET programmes across the country's polytechnics, colleges, and universities (NBTE, 2021). At the university level, TVET programmes; including building and woodwork technology education, are offered under the framework of Industrial Technical Education, which encompasses automobile technology, electrical technology, electronic technology, metalwork technology, and woodwork technology specializations. Despite their strategic importance, Nigerian TVET programmes have consistently faced critical challenges. Nwakile et al. (2025) identified limited digital literacy and inadequate institutional infrastructure as primary barriers to technology adoption in Nigerian TVET institutions. Izuakor et al. (2026) noted that lecturer anxiety over job displacement and insufficient incentives for professional development further constrain innovation in instructional practice. From a policy standpoint, the Nigerian government's National Digital Economy Policy and Strategy (2020–2030) explicitly mandates digital skills integration across all levels of education, creating policy headroom for AI integration into TVET instruction. However, implementation has been fragmented and largely driven by individual institutional initiative rather than coordinated national programming (Bowen & Watson, 2024). The recent Trainer-in-the-Loop AI Workshop conducted by NBTE in collaboration with the Commonwealth of Learning represents an emerging shift toward institutionalizing AI capacity in Nigerian TVET, but empirical research has lagged behind policy aspiration.

3.2. Building and Woodwork Technology Education in Nigerian Universities

Building and woodwork technology education programmes at Nigerian universities represent one of the most demanding TVET specializations in terms of practical skill requirements, workshop facility needs, and safety considerations. Curricula typically encompass wood science, structural timber engineering, furniture design, joinery, building construction, workshop safety management, and applied drawing (Ogbonna & Okanya, 2023). The practical competencies developed in these programmes are directly linked to graduate employability in Nigeria's construction and furniture manufacturing industries. Research by Vincent et al. (2022) assessed the availability and adequacy of workshop facilities for skill acquisition in technology vocational education programmes in universities in South East Nigeria, encompassing Ebonyi State University, Enugu State University, University of Nigeria Nsukka, and Nnamdi Azikiwe University, Awka. Their findings revealed that out of 150 workshop facility items identified across the three specialization areas of technology education; mechanical/automechanics, applied electrical/electronics, and building/woodwork technology, only 67 items (42.1%) were available in all four universities, and a mere nine items (5.66%) met the NUC adequacy standard.

This gross inadequacy in workshop provision has direct implications for the quality of practical instruction students receive and underscores the urgency of pedagogical innovations that can mitigate facility constraints through technological augmentation. Asogwa et al. (2024) examined woodwork technology entrepreneurial skills possessed by graduating students in Enugu State, finding that while students demonstrated adequate drafting and setting-out skills, they lacked competencies in modern digital woodworking technologies. The authors recommended that curriculum developers incorporate digital tools into practical workshops, a recommendation that aligns directly with the HAICPM evaluated in this study. Lawal et al. (2023) similarly documented significant gaps between the current state of building and woodwork technology education in Nigeria and international industry standards, citing outdated curricula, limited resources, inadequate funding, and low industry collaboration as persistent structural challenges.

3.3. AI Integration in Technical and Vocational Education

Strategic AI integration in higher education should be approached as a socio-technical transformation—not mere tool adoption—by pairing human-centred design with localized competency building and ethical governance to address infrastructure constraints, digital literacy gaps, and cultural relevance concerns. Accordingly, Simiyu et al. (2026) propose a context-sensitive framework that helps institutions diagnose acceptance/resistance drivers and implement generative AI through phased pilots, capacity development, and governance mechanisms to support equitable, sustainable scaling. Moreover, empirical evidence shows that students' intent to adopt AI for learning is driven mainly by perceived usefulness, performance expectancy, and attitude, while perceived ease of use may be less influential (Sarkar, 2025).

The integration of AI into technical and vocational education has attracted growing scholarly attention globally, with particular emphasis on adaptive learning systems, intelligent tutoring, real-time performance analytics, and AI-enabled simulation environments (Fan et al., 2025; Okereke et al., 2025). A systematic review by Rosyadi et al. (2023) identified empirical evidence from Malaysia, China, Indonesia, and Germany demonstrating measurable improvements in vocational skill acquisition through AI-supported instruction, particularly where AI tools were embedded within structured experiential learning frameworks rather than deployed as standalone interventions.

Within the Nigerian context, Rabiu et al. (2025) conducted a systematic review examining AI adoption for skills development in Nigeria, finding significant positive associations between AI-enabled instructional tools and improvements in student learning ability, problem-solving skills, and critical thinking. The review further found that AI tools such as intelligent tutoring systems, adaptive learning management systems, and AI-powered feedback mechanisms held substantial promise for vocational education in Nigerian universities, though uptake remained constrained by digital literacy gaps and infrastructure limitations. These findings establish a compelling evidence base for the potential of AI-supported instruction in TVET settings while simultaneously identifying the implementation challenges that must be addressed through carefully designed pedagogical frameworks, particularly in resource-constrained contexts such as South East Nigeria.

3.4. Human–AI Collaboration in Educational Settings

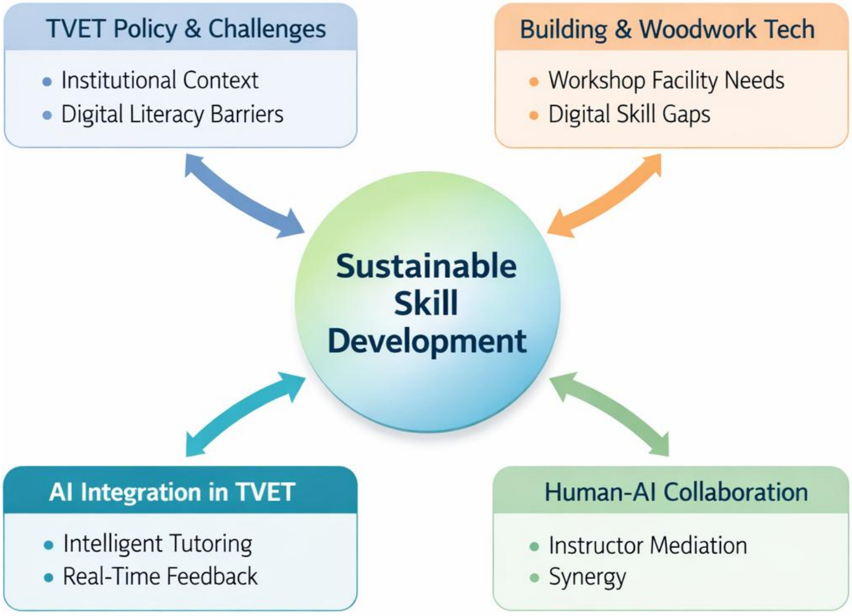
The emerging literature on human–AI collaboration in education has moved beyond examining AI as an isolated technological tool to explore the quality and dynamics of interaction between human learners, instructors, and AI systems (Chung, 2019). Atchley et al. (2024), in a comprehensive review published in Cognitive Research: Principles and Implications, argued that AI should be conceptualized as a critical collaborator in higher education, with metacognition and collaborative AI literacy serving as foundational competencies for maximizing educational benefits. Their model emphasizes the complementary rather than competitive relationship between human instructors and AI tools, directly informing the HAICPM evaluated in this study.

Li et al. (2025), examining human–AI collaboration in hybrid intelligence learning environments, proposed a Human–AI Synergy Degree Model that operationalizes the quality of collaboration between human teachers and AI systems. Their case study found that the order degree between human and AI participants remained at a moderate level with dynamic fluctuation, suggesting that the design of collaborative protocols and clear role delineation between human and AI actors is critical for optimizing educational outcomes. This finding supports the structured, instructor-mediated AI integration approach adopted in the HAICPM. In collaborative learning contexts, Chen et al. (2025) proposed an AI-Agent-supported Collaborative Learning approach for programming education and found significantly higher learning achievement and self-efficacy in the AI-supported group compared to conventional computer-supported collaborative learning, with the AI agent's real-time scaffolding identified as the critical differentiating factor. Fan et al. (2025) found that while AI feedback enhanced short-term task performance, it risked encouraging metacognitive laziness when students over-relied on AI judgments without engaging their own critical faculties. This risk underscores the importance of maintaining instructor mediation and structured reflection phases within human–AI pedagogical models; a principle embedded in the HAICPM's design.

3.5. Sustainable Skill Development and Pedagogical Models

Sustainable skill development in technical education refers to the capacity to foster competencies that are not only immediately applicable to assessed tasks but transferable to novel, industry-relevant contexts and maintainable over time without requiring constant external support (UNESCO-UNEVOC, 2023). This construct is distinct from short-term performance improvement, and its evaluation requires skill transfer assessments that go beyond the immediate instructional context. Proença et al. (2024) argued that sustainable learning outcomes in the AI era require deliberate design of human–AI interaction protocols that preserve student agency, foster metacognitive development, and encourage active rather than passive engagement with AI outputs. This prescription aligns with the experiential learning cycle embedded within the HAICPM and with the Scaffolded Human–AI Co-instruction Model identified through thematic analysis in the present study. Nwobodo-Anyadiegwu and Okanya (2026) identified the most effective technology-enhanced pedagogical approaches in vocational education as those that: (a) maintained clear instructor leadership, (b) used technology to augment rather than replace experiential learning activities, (c) embedded formative assessment within practical tasks, and (d) included explicit skill transfer activities. The HAICPM evaluated in this study was designed to embody all four of these characteristics, providing a theoretically coherent and practically grounded approach to sustainable skill development in the South East Nigerian technical education context. Figure 2 shows a graphical illustration of the theoretical framework.

Figure 2
Theoretical framework



4. Method

4.1. Research Design

The study employed a quasi-experimental mixed-methods research design, specifically a pretest–posttest control group design with two intact workshop classes. This design was selected for its appropriateness in educational intervention research where true random assignment to groups is not feasible; as is characteristic of intact classroom settings in Nigerian universities. The quasi-experimental design allowed the research team to exercise control over the independent variable (instructional method) while preserving the ecological validity of the natural classroom environment. The quantitative strand addressed RQ2 and the four null hypotheses, evaluating differences in task accuracy, task completion time, error frequency, and skill transferability between the two instructional groups. The qualitative strand addressed RQ1, identifying effective pedagogical models for human–AI collaboration through instructor interviews, student focus groups, and structured observations. Integration of the two strands followed an explanatory sequential mixed-methods approach, with quantitative findings informing the focus of qualitative inquiry.

4.2. Participants and Study Context

A total of 120 university-level building and woodwork technology students participated in the study, drawn from four universities in South East Nigeria; a geopolitical zone comprising Abia, Anambra, Ebonyi, Enugu, and Imo States. This zone was selected because it hosts a concentration of federal, state, and private universities offering building and woodwork technology education within departments of Industrial Technical Education, and its universities face the intersection of high practical skills training demand and constrained workshop resources; precisely the context in which AI augmentation offers the most significant educational leverage. Additionally, the region's strong artisan and manufacturing traditions in furniture production and building construction provide ecological validity for the skill transfer assessments employed. Thirty students were recruited from each institution, with intact class groups assigned to either the traditional or AI-supported instructional condition. Participants were enrolled in the penultimate year of their Bachelor of Technology degree in Industrial Technical Education, ensuring comparable prior practical experience. The four participating universities are anonymised as University 1, University 2, University 3, and University 4.

Two intact workshop classes were assigned to treatment conditions: Group A (n = 60) received Traditional Instruction (TI), characterized by direct instructor-led demonstration, verbal feedback, and manual task correction; Group B (n = 60) received AI-Supported Instruction (ASI), in which AI tools were embedded within the instructional process to provide real-time error detection, design feedback, and performance analytics. Both groups completed the same six-week practical module in building and woodwork technology, using identical task requirements and assessment criteria.

4.3. Intervention

The AI-Supported Instruction intervention was implemented through a suite of AI-enabled tools integrated into the workshop instructional protocol across the six-week module. Four AI tools were deployed.

AI-driven design feedback: A computer-aided design [CAD] platform equipped with AI-powered geometric analysis provided students with immediate visual and textual feedback on design accuracy, dimensional compliance, and structural integrity of planned woodwork joints and building components.

Real-time error detection system: Sensor-equipped workstations monitored students' tool use patterns, alerting both students and instructors when deviations from standard technique were detected; for example, inappropriate cutting angles, irregular feed rates, or unsafe posture during machine operation.

AI-powered CNC performance analytics: For students engaging in CNC machining tasks, an AI analytics interface tracked cutting paths, cycle times, material waste rates, and tool condition indicators, generating individualized performance profiles that students reviewed during reflection periods.

AI safety monitoring interface: An integrated safety monitoring system using camera-based computer vision flagged personal protective equipment [PPE] non-compliance and proximity hazards in real time, providing an additional layer of instructional safety support in the workshop environment. Group A (Traditional Instruction) received equivalent instructional time, identical task content, and the same practical assessment requirements, but without access to any AI monitoring or feedback tools. Instructors in Group A relied on direct observation, manual inspection, and verbal feedback to support student task completion.

4.4. Instruments

The following instruments were used to collect data across both the quantitative and qualitative strands of the study.

Practical Skill Assessment Rubric [PSAR]: A validated rubric assessing the quality of completed woodwork and building technology tasks across five dimensions: dimensional accuracy, joint quality, surface finish, structural integrity, and safety compliance. The PSAR was validated by a panel of five expert judges drawn from TVET departments in Nigerian universities and was found to have a content validity index [CVI] of .89 and inter-rater reliability coefficient of .86.

Task Accuracy Checklist [TAC]: A binary checklist recording compliance with 20 specific technical accuracy criteria for each practical task, developed in alignment with NUC minimum academic standard specifications for building and woodwork technology programmes.

Error Log Sheet [ELS]: A structured observational instrument completed by trained research assistants and AI monitoring systems, recording the frequency, type, and severity of technical errors committed during each practical session.

Stopwatch and Automated Time Tracker: Task completion times were recorded for each student using a combination of manual stopwatch timing (for Group A) and automated time-stamping via the AI monitoring system (for Group B), ensuring comparability across conditions.

Skill Transfer Task [STT]: A novel but related practical project, distinct from the six-week module tasks, was administered during Week 6 to assess students' ability to apply acquired skills in a new context. The STT was scored using an adapted version of the PSAR, and its novelty was confirmed through expert panel review.

Cognitive Engagement Scale [CES]: A five-item Likert-type scale assessing students' behavioural, emotional, and cognitive engagement with the instructional process, adapted from the Student Engagement Instrument (Appleton et al., 2006) and re-validated for technical education workshops (Cronbach's α = .82).

AI Trust Scale [ATS]: A 12-item scale measuring students' trust in AI-generated feedback and monitoring systems, adapted from Lee and Moray's (1994) trust in automation framework, with psychometric validation yielding a Cronbach's α = .79.

Qualitative instrument: Semi-structured interview protocols for instructors (n = 8), focus group discussion guides for students (n = 4 groups of 6), and a structured observation protocol for workshop sessions.

4.5. Data Analysis

4.5.1. Quantitative analysis (RQ2 and H_{01}–H_{04})

Analysis of Covariance [ANCOVA] was the primary statistical technique for testing H_{01}–H_{04}, with pretest scores entered as covariates to control for pre-existing group differences in practical skill level. This approach yielded adjusted posttest means, enabling clean attribution of post-intervention differences to the instructional condition. Independent samples *t*-tests were used to examine group differences on individual outcome variables. Multivariate Analysis of Variance [MANOVA] was applied to test for simultaneous group differences across all four outcome variables, controlling for family-wise error rate. Multiple regression analysis was used to examine the contribution of AI trust and cognitive engagement to skill outcomes in Group B.

4.5.2. Qualitative Analysis (RQ1)

Thematic analysis, following Braun and Clarke's (2006) six-phase framework, was applied to interview transcripts, focus group recordings, and observation field notes. Data were coded inductively to generate initial codes, which were then organized into categories and, ultimately, overarching themes. Member-checking with three instructor participants and peer debriefing with independent researchers enhanced the trustworthiness of the analysis. NVivo 14 software was used to support systematic coding and theme development.

5. Results

5.1. Descriptive Statistics and Pretest Equivalence

Table 1 presents the descriptive statistics for both groups at pretest and posttest across the four primary outcome variables. Independent t-tests conducted on pretest scores confirmed no significant differences between Group A and Group B prior to the intervention (all p > .05), establishing baseline equivalence.

Table 1
Descriptive Statistics for Outcome Variables at Pretest and Posttest

Variable	*Group A Pre M(SD)*	*Group A Post M(SD)*	*Group B Pre M(SD)*	*Group B Post M(SD)*	*Pre-t*	*Pre-p*	*Post-t*
Task Accuracy (%)	58.4 (7.2)	65.1 (6.8)	57.9 (7.6)	78.6 (5.9)	0.42	.678	12.87***
Completion Time (min)	48.3 (8.1)	43.6 (7.4)	49.1 (8.5)	37.2 (6.2)	0.59	.557	6.14**
Error Frequency	6.8 (2.1)	5.4 (1.9)	7.1 (2.3)	3.1 (1.4)	0.81	.419	9.23***
Skill Transfer Score	55.2 (8.4)	62.8 (7.1)	54.8 (9.0)	74.3 (6.4)	0.28	.778	10.61***

Note. M = Mean; *SD* = Standard Deviation; Group A = Traditional Instruction (n = 60); Group B = AI-Supported Instruction (n = 60). $^{**}p < .01$; $^{***}p < .001$.

The pretest scores in Table1 confirmed statistically equivalent baselines across both groups for all four outcome variables, providing a rigorous foundation for the attribution of posttest differences to the instructional intervention. By posttest, Group B demonstrated markedly higher task accuracy, shorter completion times, lower error frequencies, and higher skill transfer scores compared to Group A, with all differences reaching statistical significance.

5.2. Effects of AI-Supported Instruction: ANCOVA Tests of H_{01}–H_{04}

Table 2 presents the ANCOVA results for each of the four hypotheses, with pretest scores as covariates to control for pre-existing individual differences.

Table 2

ANCOVA Results for Primary Outcome Variables (Pretest Covariate Controlled)

Dependent Variable	*Adj. Mean Group A*	*Adj. Mean Group B*	*F*	*df*	*p*	*η²*	*Decision*
Task Accuracy (%)	65.2	78.4	87.43	1, 117	< .001	.428	Reject H01
Completion Time (min)	43.7	37.3	34.12	1, 117	.003	.226	Reject H02
Error Frequency	5.3	3.2	64.18	1, 117	< .001	.354	Reject H03
Skill Transfer Score	62.9	74.2	72.35	1, 117	< .001	.382	Reject H04

Note. Adj. Mean = Adjusted posttest mean (controlling for pretest); η^2 = partial eta squared (effect size). α = .05 significance level.

The ANCOVA results in Table 2 revealed statistically significant differences between Group A and Group B on all four outcome variables after controlling for pretest performance. All four null hypotheses were rejected at the α = .05 level. Effect sizes (η^2) were large for task accuracy, error frequency, and skill transfer and moderate for task completion time, indicating that the AI-supported instructional condition explained a substantive proportion of the variance in practical skill outcomes. These findings provide robust evidence that AI-supported workshop instruction produces meaningfully superior learning outcomes compared to traditional instruction across all four performance dimensions evaluated.

5.3. MANOVA Results for Combined Outcome Variables

A one-way MANOVA was conducted to test the combined effect of instructional condition on all four outcome variables simultaneously. Table 3 shows the result.

Table 3

MANOVA Summary — Effect of Instructional Condition on Combined Outcome Variables

Multivariate Test	*Value*	*F*	*Hypothesis df*	*Error df*	*p*	*η²*
Wilks' Lambda (Λ)	0.531	25.37	4	115	< .001	.469
Pillai's Trace	0.469	25.37	4	115	< .001	.469
Hotelling's Trace	0.883	25.37	4	115	< .001	.469

Results in Table 3 indicated a statistically significant multivariate effect, confirming that the combined set of outcome variables differed significantly between the two instructional groups and that the AI-supported instructional condition explained approximately 46.9% of the multivariate variance. Table 3 presents the MANOVA summary. The significant multivariate effect confirms that AI-supported instruction produced a holistic, multi-dimensional improvement in practical skill development, rather than an improvement limited to a single performance indicator. This finding strengthens the case for HAICPM as an integrative pedagogical approach that simultaneously enhances multiple dimensions of technical competence.

5.4. Predictors of Performance: Multiple Regression on AI Trust and Cognitive Engagement

A multiple regression analysis was conducted within Group B to examine the extent to which AI Trust Scale scores and Cognitive Engagement Scale scores predicted overall practical skill performance (composite of all four outcome variables). Results are presented in Table 4.

Table 4

Multiple Regression – Predictors of Skill Performance in AI-Supported Group (Group B)

Predictor	*B*	*SE B*	*β*	*t*	*p*	*95% CI*
Constant	24.31	5.62	–	4.33	< .001	[13.18, 35.44]
AI Trust Scale	0.48	0.11	.41	4.36	< .001	[0.26, 0.70]
Cognitive Engagement Scale	0.37	0.09	.34	4.11	< .001	[0.19, 0.55]

Note. $R^2 = .42$, $F(2, 57) = 20.69$, $p < .001$. B = unstandardized coefficient; SE B = standard error; β = standardized coefficient.

The regression model was statistically significant, with AI Trust and Cognitive Engagement together explaining 42% of the variance in composite skill performance among students in the AI-supported group. Both predictors were independently significant. These findings underscore the importance of cultivating both trust in AI feedback systems and active cognitive engagement as mediating mechanisms through which AI-supported instruction translates into improved skill outcomes.

5.5. Qualitative Findings on Effective Pedagogical Models for Human–AI Collaboration (RQ1)

Thematic analysis of instructor interviews, student focus groups, and observation field notes generated five overarching themes related to effective pedagogical models for human–AI collaboration in workshop-based technical education. Table 5 presents a summary of themes and representative quotations.

Table 5

Summary of Qualitative Themes from Instructor Interviews, Focus Groups, and Observations

Theme	*Description*	*Representative Excerpt*
1. Scaffolded Human–AI Co-instruction	Instructors positioned AI as a diagnostic partner, interpreting AI feedback for students and guiding corrective action	"The AI tells them what is wrong. I tell them why it is wrong and how to fix it." (Instructor, University 2)
2. Real-Time Formative Feedback Loops	AI-generated real-time alerts enabled immediate error correction, reducing the feedback delay typical of instructor-only environments	"We knew our mistake straight away. We didn't wait till the end." (Student Focus Group, University 1)
3. Instructor Mediation as Critical Bridge	The instructor's interpretive role was seen as essential; students distrusted AI feedback without instructor validation	"When the instructor confirmed what the machine said, then I believed it." (Student Focus Group, University 3)
4. Iterative Experiential Cycles	AI analytics enabled more frequent and structured cycling through Kolb's experiential stages within a single session	"Students were doing, reflecting, and doing again; all in one hour." (Observation notes, University 4)
5. AI Trust Building as a Pedagogical Goal	Effective AI-supported instruction required deliberate orientation activities to build student trust in AI feedback systems	"The first week, they were sceptical. By week three, they were checking the AI before checking me." (Instructor, University 1)

The five themes converged into an overarching pedagogical model identified as the Scaffolded Human–AI Co-instruction Model [SHAICM], characterized by four structural principles: (a) explicit instructor framing of AI tools as diagnostic supports rather than authoritative judges; (b) structured real-time feedback loops enabling within-session iterative learning; (c) instructor mediation of AI outputs to bridge the gap between algorithmic feedback and pedagogically meaningful explanation; and (d) deliberate AI trust-building activities in the early weeks of implementation.

6. Discussion

6.1. Task Accuracy: Artificial Intelligence as a Precision Amplifier

The finding that students in the AI-supported instruction group demonstrated significantly higher task accuracy confirms the rejection of H_{01} and is consistent with the growing body of literature on AI-enhanced practical skill development (Ba et al., 2025). Okanya et al. (2023) reported similarly significant improvements in precision-based task accuracy when students received real-time AI feedback compared to conventional instructor-only monitoring. The large effect size observed in the present study suggests that AI augmentation of instructor feedback does more than incrementally improve performance; it substantially strengthens the precision with which students execute technical tasks in workshop settings. This finding can be theoretically explained through both Sociotechnical Systems Theory and the Human–AI Complementarity framework. From an STST perspective, the AI real-time error detection system extended the instructor's observational capacity through continuous, criterion-referenced alerts/feedback, enabling more timely monitoring and response across multiple workstations than would be feasible through sequential instructor-only checks (Alfredo et al., 2024). From a complementarity perspective, the AI tool's capacity for consistent, criterion-referenced accuracy assessment allowed instructors to allocate more time to contextual mentoring, motivational support, and adaptive scaffolding—human competencies that are difficult to automate reliably.

6.2. Task Completion Time: Efficiency without Sacrifice

Students in the AI-supported group completed practical tasks in significantly less time than their traditionally instructed counterparts, confirming the rejection of H_{02}. This aligns with Ukala and Iheukwumere's (2025) comparative study, which documented not only superior skill acquisition but also greater procedural efficiency in the AI-supported condition. The moderate magnitude of time improvements, relative to the larger gains in accuracy, error reduction, and skill transfer, suggests that task completion time in workshop settings is also influenced by factors such as material handling, equipment setup, and physical fatigue that are less amenable to AI augmentation. Importantly, the reduction in completion time was accompanied by improvements in quality indicators, reducing the likelihood that students in Group B were simply rushing through tasks. Because baseline performance differences were statistically controlled, these efficiency gains are also less likely to be attributable to pre-existing group differences. This finding challenges a common concern in educational technology research that technology-mediated speed gains are achieved at the expense of quality (Nwakile et al., 2025). The present results suggest that when AI feedback is structured within a pedagogically coherent framework—as in the HAICPM—it enables students to identify and correct errors more rapidly without compromising task quality, thereby achieving efficiency and accuracy gains simultaneously (Ba et al., 2025).

6.3. Error Reduction: The Diagnostic Power of Artificial Intelligence Monitoring

The marked reduction in error frequency among AI-supported students represents a practically significant finding for workshop-based skill development and safety-relevant practice. Error reduction is not only a performance indicator but also has potential safety implications, particularly in technical workshops where errors involving power tools, CNC equipment, and structural materials can pose risks. The large effect size underscores the capacity of AI-enabled monitoring and real-time error detection to support more consistent error identification and correction, which may contribute to safer practice when integrated with instructor oversight. This consideration is particularly relevant to South East Nigerian institutions, which have historically operated with limited safety enforcement infrastructure due to resource constraints (Orji, 2025). These findings are congruent with the human–AI collaborative learning literature reviewed by Rabiu et al. (2025), who found that AI-mediated real-time feedback substantially reduced knowledge construction errors by enabling more frequent and targeted reflective observation. In the STST framework, the AI interface helped compensate for the structural limitation that a single instructor cannot simultaneously observe all students, thereby addressing a critical constraint within the workshop learning system through technological augmentation (Alfredo et al., 2024).

6.4. Skill Transferability: Beyond Task Performance

The finding that AI-supported instruction produced significantly superior skill transferability is theoretically important because it speaks directly to the “sustainability” dimension of the HAICPM—namely, whether learning extends beyond immediate task performance. Skill transfer, defined as the capacity to apply acquired competencies in novel, real-world contexts, is a central criterion for evaluating the sustainability of technical education outcomes (UNESCO-UNEVOC, 2023). The large effect size for skill transfer suggests that, within the study timeframe, AI-supported instruction did not merely improve performance on familiar, practiced tasks but supported deeper and more transferable competence. This finding is consistent with Kolb’s Experiential Learning Theory, which positions abstract conceptualization and active experimentation as key stages underpinning transfer. The AI analytics dashboards available to Group B students appear to have supported abstract conceptualization by providing structured, data-rich performance summaries that helped students derive generalizable principles from their concrete experiences. Rosyadi et al. (2023) raised concerns that AI feedback might reduce knowledge transfer capacity by encouraging metacognitive laziness. The present findings do not support this concern within the HAICPM context, which was deliberately designed with instructor-mediated reflection phases that ensured students actively processed AI feedback rather than passively receiving it. This suggests that any risk of over-reliance on AI feedback is likely contingent on the pedagogical architecture in which the tools are embedded, and can be mitigated through structured reflection and instructor mediation.

6.5. Pedagogical Models: The Scaffolded Human–AI Co-instruction Framework

The qualitative finding that the Scaffolded Human–AI Co-instruction Model [SHAICM] represents the most effective pedagogical approach for human–AI collaboration in workshop-based technical education contributes a practically actionable framework to the existing literature. These themes emerged consistently across participant accounts, indicating that effectiveness was attributed not to AI tools alone but to the structured organization of human–AI interaction. The model’s four structural principles—(1) instructor framing of AI as a diagnostic partner, (2) structured real-time feedback loops, (3) instructor mediation of AI outputs, and (4) deliberate AI trust-building—reflect a complementary division of instructional and cognitive labour. The centrality of instructor mediation resonates with Atchley et al.’s (2024) metacognitive model for human–AI collaboration in higher education, which positions the instructor’s role as helping students interpret, critique, and integrate AI feedback rather than merely receive it. The finding that students initially distrusted AI feedback without instructor validation, and that trust built progressively over the six-week module, underscores the importance of AI trust-building as an explicit pedagogical goal rather than an incidental by-product of AI exposure. This extends Li et al.’s (2025) synergy degree model by identifying specific trust-building mechanisms that enable effective human–AI educational collaboration. The SHAICM also aligns with Nwobodo-Anyadiegwu and Okanya’s (2026) framework, which identified instructor leadership, technology augmentation of experiential activities, embedded formative assessment, and explicit skill transfer tasks as defining features of effective technology-enhanced TVET pedagogy. The present study provides empirical support for these principles in the specific context of building and woodwork technology education in South East Nigeria. For sustainable and responsible scaling, these findings also imply the need for implementation governance—such as transparency about AI feedback limits, basic data-protection practices, and clear accountability for instructional decisions—alongside ongoing instructor professional development (OECD, 2023; UNESCO, 2024).

7. Conclusion

This study evaluated a Human–AI Collaborative Pedagogical Model for sustainable skill development in building and woodwork technology workshops across four universities in South

East Nigeria using a quasi-experimental mixed-methods design. The findings show that AI-supported workshop instruction led to statistically significant and practically meaningful improvements in task accuracy, task completion time, error reduction, and skill transferability compared to traditional instruction. Accordingly, all null hypotheses were rejected, with large effect sizes particularly evident for task accuracy, error reduction, and skill transfer.

Qualitative evidence further indicates that the most effective approach was a Scaffolded Human–AI Co-instruction Model, where instructors framed AI as a diagnostic support (not an authoritative evaluator), mediated AI outputs, and structured real-time feedback loops while building learner trust in early implementation. This structure operationalises Sociotechnical Systems Theory, Experiential Learning Theory, and Human–AI Complementarity Theory in a manner suited to Nigerian technical education contexts.

Overall, the study provides evidence that human–AI collaboration can enhance workshop-based technical learning in resource-constrained environments without displacing the essential pedagogical role of instructors. The results support policy and practice directions that prioritise instructor AI literacy, guided AI integration, and sustainable implementation strategies aligned with national TVET goals and broader digital transformation and sustainable education agendas, including progress toward SDG 4.

8. Limitations and Directions for Future Research

Several limitations of this study warrant acknowledgement. First, the six-week duration of the intervention, while sufficient to detect significant performance differences, may not capture the long-term sustainability of skill development over an academic year or beyond graduation. Longitudinal follow-up studies tracking graduates' workplace performance would provide stronger evidence regarding the career-long sustainability of HAICPM-induced skill gains. Second, the anonymisation of participating universities, while ethically necessary, limits the generalizability of findings to specific institutional contexts and prevents comparison with institution-level characteristics such as workshop quality ratings. Third, the AI tools deployed in this study represent a specific configuration of available technologies; future research should evaluate alternative AI tool combinations and examine which tool types contribute most substantially to particular skill outcomes.

Future research should also explore the differential effects of human–AI collaborative instruction across different technical specializations within TVET, including electrical/electronics technology and automotive technology, which present distinct practical skill profiles and safety considerations. Additionally, comparative studies examining student performance trajectories under HAICPM versus blended learning approaches incorporating virtual reality and simulation technologies would provide valuable evidence for curriculum planning.

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Data availability: The dataset analyzed during the study is available from the corresponding author upon reasonable request.

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