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Cognitive Effort Displacement in AI-Assisted Learning: Effects on Student Engagement and Knowledge Retention in TVET

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Abstract

Artificial intelligence (AI) is increasingly transforming teaching and learning in Technical and Vocational Education and Training (TVET) by providing personalized instructional support and improving access to learning resources. However, growing reliance on AI tools may reduce learners' cognitive effort, leading to cognitive displacement with potential implication for student engagement and knowledge retention. This study investigated the extent of AI tool usage, the level of cognitive effort displacement, and the relationships among AI tool usage, cognitive effort displacement, student engagement, and knowledge retention among TVET students in Abia State, Nigeria. A descriptive correlational survey design was adopted. The study population comprised 2,400 TVET students, from which a sample of 343 respondents was selected using multistage sampling techniques. Data were collected using the Cognitive Effort Displacement, Engagement, and Retention Questionnaire (CEDERQ) (α = 0.85). Mean and standard deviation were used to answer the research questions, while Pearson product-moment correlation was employed to test the hypotheses at the 0.05 level of significance. The findings revealed a high level of AI tool usage ($\bar{x}$ = 3.47), a moderate to high level of cognitive effort displacement ($\bar{x}$ = 3.26), and a high level of student engagement and knowledge retention ($\bar{x}$ = 3.32). AI tool usage showed a significant positive relationship with cognitive effort displacement (r = 0.612, p < 0.05), whereas cognitive effort displacement had significant negative relationships with student engagement (r = –0.478, p < 0.05) and knowledge retention (r = –0.563, p < 0.05). The study concludes that while AI-assisted learning enhances instructional support in TVET, excessive dependence on AI may undermine active cognitive engagement and long-term knowledge retention. The study recommends pedagogical approaches that balance AI support with independent problem-solving and reflective learning.

Keywords: artificial intelligence; AI-assisted learning; cognitive effort displacement; student engagement; knowledge retention; TVET

1 Introduction

The rapid integration of artificial intelligence (AI) into education is reshaping how learners access, process, and apply knowledge across diverse instructional settings. In technical and vocational education and training (TVET), AI-assisted learning tools such as intelligent tutoring systems, generative AI platforms, adaptive learning applications, and virtual assistants are increasingly being adopted to support personalized learning, improve instructional efficiency, and expand access to educational resources (UNESCO, 2023; Zawacki-Richter et al., 2019). These technologies hold consid-

erable promise for enhancing teaching and learning outcomes; however, they also raise important concerns regarding the extent to which reliance on AI may reduce learners' cognitive effort during problem-solving, critical thinking, and knowledge construction. This growing concern has prompted researchers to examine how AI-supported learning may inadvertently shift essential cognitive processes away from learners, thereby giving rise to the emerging concept of cognitive effort displacement.

Emerging from the broader theory of cognitive offloading, cognitive effort displacement refers to the reduction or shifting of learners' mental effort from active cognitive processing to dependence on external technological support. Cognitive offloading is the delegation of mental operations such as remembering, planning, synthesizing, and problem-solving to external technological tools, thereby reducing the cognitive effort invested by learners during the learning process (Barcaui, 2025). While cognitive offloading provides a useful theoretical explanation for why learners delegate certain cognitive tasks to external technologies, the rapid advancement of AI-assisted learning has extended this discussion beyond cognitive support to concerns about diminished learner efforts. As generative AI systems increasingly perform tasks that traditionally required analysis, reasoning, and problem-solving, scholars have introduced the concept of cognitive effort displacement to explain how excessive reliance on these technologies may reduce learners' active cognitive engagement, ultimately influencing student engagement and knowledge retention.

The implications of cognitive effort displacement are particularly significant in TVET, where the acquisition of practical competencies, technical problem-solving skills, and transferable workplace abilities requires active learner engagement. Cognitive effort displacement (CED) is the measurable reduction in a learner's active mental engagement including analysis, recall, elaboration, and self-monitoring that occurs when cognitive sub-processes normally performed internally are transferred to an AI tool during a learning task. According to Yan et al. (2024), cognitive effort displacement can be understood as the reduction or substitution of learners' mental effort when AI performs cognitive tasks that would otherwise require active reasoning, problem-solving, and knowledge construction by the learner. CED occurs when learners increasingly transfer analytical, evaluative, and problem-solving processes to AI system, thereby reducing active cognitive engagement and weakening the development of durable knowledge structures (Jose & Cherian, 2025). Twabu (2025), states that cognitive effort displacement refers to situations in which AI reduces productive mental effort beyond an optimal level, limiting learners' active processing, schema construction, and long-term knowledge retention. Educational research has long emphasized that meaningful learning depends not only on access to information, but also on the cognitive effort learners invest in understanding, analyzing, and applying knowledge (Sweller, 1988; Mayer, 2021). Operational, Cognitive effort displacement is the process whereby learners transfer or relinquish substantial portions of the mental effort required for learning to artificial intelligence systems, resulting in reduced engagement in reasoning, problem-solving, reflecting, and knowledge construction in TVET programmes.

Although cognitive effort displacement describes the transfer of learners' cognitive activities to intelligent technologies, the phenomenon cannot be fully understood without considering the instructional environment in which it occurs. The increasing adoption of AI-assisted learning in educational institutions has transformed how students access information, solve problems, and construct knowledge, making it imperative to conceptualize AI-assisted learning as the technological context through which cognitive effort displacement influences student engagement and knowledge retention.

AI-assisted learning is an instructional approach in which artificial intelligence technologies continuously analyze learners' performance, cognitive engagement, and knowledge states to personalize instructional support and optimize learning outcomes. According to Tithi et al. (2026), intelligent tutoring systems employ adaptive algorithms such as Bayesian Knowledge Tracing and Deep Reinforcement Learning to dynamically select learning activities that correspond to learners evolving cognitive needs. By tailoring scaffolding to individual learners', AI-assisted learning promotes meaningful cognitive engagement while enhancing learning effectiveness (Tithi et al., 2026). AI-assisted learning in technical and vocational education and training (TVET) refers to the application of artificial intelligence technologies including intelligent tutoring systems, adaptive learning platforms, learning analytics, and generative AI to personalize instruction, provide real time feedback, support competency-based skill acquisition, and enhance learners' cognitive engagement in vocational learning environments. Within TVET, AI-assisted learning serves as an intelligent instructional partner that adapts learning experiences to students' knowledge performance, and occupational skill needs while promoting industry relevant competencies (Cukurova, 2025; Tithi et al., 2026; Azizah et al., 2025). Riis (2025) proposed a continuum comprising AI-independent, AI-aware, AI-supported, AI-enhanced, and AI-centric learning, emphasizing that AI should augment rather than replace learner craftsmanship, reflective judgment, and critical thinking in vocational education. Despite the growing adoption of AI-assisted learning in technical and vocational education and training (TVET), the effectiveness of this intelligent learning environment extends beyond the technological features of AI systems. Rather, the extent to which AI-assisted learning enhance education outcomes depends largely on students' willingness to actively participate, invest cognitive effort, and remain emotionally and behaviorally engaged throughout the learning process. This underscores the importance of examining student engagement as a central construct through which AI-assisted learning may influence knowledge acquisition and retention. Student engagement TVET is the degree to which learners actively invest their cognitive, behavioral, and emotional resources in vocational learning activities, including classroom instruction, practical workshops, simulations, and workplace-based training. It reflects learners' sustained participation, motivation, commitment, and psychological connection to vocational learning experiences, which collectively enhance skill acquisition, academic achievement, persistence, and employability (Niittylahti et al., 2023; Maulana et al., 2014). According to Fredricks et al. (2004), student engagement is a multidimensional construct that reflects the extent to which students actively participate in and commit themselves to the learning process through their behaviors, emotions, and cognitive investment. Furthermore, Kahu (2013) contends that student engagement should be understood as both a state and a process, reflecting students' willingness to invest sustained cognitive effort, emotional commitment, and active participation in educational activities.

Within AI-assisted learning environments, student engagement serves as an important mechanism through which learners actively process, interpret, and construct knowledge. Nevertheless, the educational value of such engagement extends beyond immediate participation to learners' ability to retain and apply knowledge over time. Given that cognitive effort displacement may alter the depth of learners' cognitive processing, it is imperative to examine knowledge retention as the ultimate indicator of whether engagement in AI-supported learning into meaningful and lasting learning outcomes. Knowledge retention is the learners' ability to encode, consolidate, preserve, and retrieve acquired knowledge over time for subsequent application in authentic learning or workplace contexts. In TVET, knowledge retention extends beyond remembering factual information to include the sustained ability to apply technical knowledge and occupational skills in solving vocational problems. Effective knowledge retention is facilitated by meaningful cognitive engagement, schema

construction, and repeated retrieval, all of which strength long-term memory and support the transfer of learning to professional practice (Barcaui, 2025; Mayer, 2021; Soden & Pithers, 2001; Sweller et al., 2011). Knowledge retention is commonly understood as the learner's capacity to preserve and retrieve acquired knowledge over an extended period after instruction. According to Barcaui (2025), durable knowledge retention depends on active cognitive engagement during learning, including retrieval, elaboration, and meaningful processing, which strengthen memory consolidation.

As an important indicator of meaningful and sustainable learning, knowledge retention enables learners to retain, retrieve, and apply acquired knowledge long after instruction has taken place. This capability is particularly critical in TVET, where learners are expected to transfer theoretical understanding into practical competencies that meet industry and workforce demands. Therefore, an examination of the concept of TVET is necessary to contextualize the role of AI-assisted learning, cognitive effort displacement, student engagement, and knowledge retention in competency-based education. TVET is a learner-centred, industry-oriented educational system that integrates technical knowledge, vocational competencies, workplace learning, and employability skills through collaborative among educational institutions, industries, and other stakeholders. Contemporary perspectives conceptualize TVET as a dynamic ecosystem in which learners actively co-create knowledge and occupational competence while developing innovation, adaptability, and lifelong learning capabilities required for sustainable participation in an increasingly technology-driven labour market (Avis, 2023; Cai & Kosaka, 2024; Papier, 2024). According to Chen and Chan (2024), TVET is practice-oriented educational system that integrate technical knowledge, vocational competencies, and digital pedagogies to prepare learners for industry 4.0 and lifelong employability. TVET is increasingly shaped by rapid advances in digital technologies that are transforming how technical knowledge and vocational skills are taught and acquired. As educational institutions adopt technology-enhanced instructional approaches to improve learning outcomes and workforce preparedness, educational technology has emerged as a foundational element of effective TVET delivery.

Educational technology is a multidisciplinary field concerned with the intentional and ethical design, development, implementation, management, and evaluation of technological processes and learning resources to enhance teaching, learning, human performance, and educational innovation (Heggart et al., 2025). According to Adam (2024), educational technology is field that encompasses not only digital tools and platforms but also the pedagogical, social, cultural, and ethical systems that shape teaching and learning. Tawfik et al. (2024) state that educational technology is learner-centred discipline that integrate instructional design, human-computer interaction, learning sciences, and digital innovation to create effective learning environment. The emphasis on educational technology involves the systematic design and continual refinement of learning experiences through evidence-based methods that improve learner engagement, performance, and educational outcomes.

Despite the growing adoption of AI-assisted learning technologies, empirical evidence on how cognitive effort displacement influences student engagement and knowledge retention within TEVT remains limited, particularly in developing educational contexts. Much of the existing literature has focused on the pedagogical benefits of AI, with comparatively less attention given to its potential unintended consequences on learners' cognitive engagement and sustained learning outcomes. Addressing this gap is essential for informing evidence-based strategies that promote responsible AI integration in vocational education. Against this background, this study investigates the effects of cognitive effort displacement in AI-assisted learning on student engagement and knowledge

retention among TVET learners, with the aim of contributing to the emerging discourse on responsible educational technology and sustainable skills development.

2 Statement of the problem

The rapid adoption of AI-powered learning tools (e.g., chatbots, automated tutoring systems, generative AI assistants) in TVET institutions has raised concerns among educators about their long-term impact on learning quality. TVET programs depends heavily on learners developing durable technical competencies through active problem-solving, repeated practice, and deep cognitive engagement with material. However, when AI tools readily provide answers, solutions, or step-by-step guidance, students may reduce their own cognitive investment a process described as cognitive effort displacement. These risks producing learners who can complete tasks with AI support but struggle to retain knowledge or transfer skills independent judgment are essential for employability.

Despite the widespread use of AI tools in TVET classrooms, there is limited empirical evidence describing how extensively these tools are used, the degree of cognitive effort displacement student exhibit, and how these patterns correspond to observed levels of engagement and retention. Much of the existing literature on cognitive offloading and AI reliance has focused on general higher-education or workplace setting, leaving a gap in descriptive, context-specific evidence for TVET. This study addresses that gap by describing the extent of AI tool usage, the level of cognitive effort displacement, and the corresponding levels of student engagement and retention among TVET learners.

3 Research objectives

The study is guided by the following specific objectives:

1. To determine the extent of AI tool usage among TVET students during learning activities.
2. To determine the level of cognitive effort displacement exhibited by TVET students when using AI tools.
3. To describe the level of student engagement and retention among TVET students in AI-assisted learning environments.

4 Research questions

The study is directed by the following research questions:

1. What is the extent of AI tool usage among TVET students during learning activities?
2. What is the level of cognitive effort displacement exhibited by TVET students when using AI tools?
3. What is the level of student engagement and knowledge retention among TVET students' who engage in AI-assisted learning?

5 Hypotheses

The following null hypotheses (Ho) were tested at 0.05 level of significance:

1. There is no significant relationship between the extent of AI tool usage and cognitive effort displacement among TVET students.

2. There is no significant relationship between cognitive effort displacement and student engagement among TVET students in AI-assisted learning environments.

3. There is no significant relationship between cognitive effort displacement and knowledge retention among TVET students in AI-assisted learning environments.

6 Methodology

6.1 Research design

This study adopted a descriptive survey research design of the correlational type. The design was considered appropriate because the study sought to describe the existing extent of AI tool usage, the level of cognitive effort displacement (CED), and the levels of student engagement and knowledge retention among TVET students, as well as to establish the relationships among these variables without manipulating them. Consistent with descriptive-correlation designs, data were collected at single point in time from a naturally occurring population of TVET learners already engaged in AI-assisted learning, allowing the variables to be measured and related as they exist in real instructional settings (Creswell & Creswell, 2018).

6.2 Area of the study

The study was carried out in technical and vocational education institutions in Abia State, Nigeria. Abia State was purposively selected because it hosts a mix of government-owned technical college, vocational enterprise institutions, and private skill-acquisition centres in which the use of AI-assisted learning tools (ChatDGP, Copilot, Copilot, and Gemini) has become increasingly common students, thereby providing a suitable context for examining cognitive effort displacement.

6.3 Population of the study

The population of the study comprised all regular students enrolled in technical vocational trades (including Electrical/Electronic Installation, Automotive Technology, Welding and Fabrication, Building Technology, and Woodwork Technology) in the technical colleges and vocational training institutions in Abia State. Based on enrolment records obtained from the participating institutions, the population was estimated at 2,400 students.

6.4 Sample size and sampling technique

A sample size of 343 students was determined using the Yamane (1967) formula for a finite population, at a 5% margin of error:

$$n = \frac{N}{1 + Ne^2}$$

where N = 2,400 and e = 0.05, giving n = 343.

A multi-stage sampling technique was employed. At the first stage, three technical/vocational institutions were purposively selected to represent urban, semi-urban, and rural TVET provision in the state. At the second stage, proportional stratified random sampling was used to collect the sample across the five trade areas listed above, in proportion to their enrolment. At the final stage, simple random sampling (balloting) was used to select individual respondents within each trade stratum. To accommodate anticipated non-response, 360 copies of the questionnaire were administered, of which 343 were correctly completed and returned, representing 95.3% usable return rate.

Table 1 presents the demographic distribution of the 343 respondents who took part in the study.

Table 1. Demographic distribution of respondents (N = 343).

Variable	Category	Frequency	Percentage (%)
Gender	Male	198	57.7
	Female	145	42.3
Age Range	Below 18	41	12.0
	18–24	176	51.3
	25–30	89	25.9
	Above 30	37	10.8
Year/Level	Year 1	121	35.3
	Year 2	132	38.5
	Year 3 and above	90	26.2
AI Use Frequency	Never	9	2.6
	Rarely	38	11.1
	Sometimes (weekly)	96	28.0
	Often (several/week)	139	40.5
	Always (daily)	61	17.8

6.5 Instrument for data collection

Data were collected using a structured questionnaire titled Cognitive Effort Displacement, Engagement, and Retention Questionnaire (CEDERQ), developed by the researchers from the reviewed literature and the study's conceptual framework. The instrument was divided into four sections. Section A elicited demographic information (gender, age range, trade/field of study, and year/level of study) along with a general item on frequency of AI tool use. Section B, corresponding to Research Question 1, contained six items measuring the extent of AI tool usage. Section C, corresponding to Research Question 2, contained ten items measuring cognitive effort displacement across five sub-dimensions: frequency of AI reliance, depth of processing bypassed, perceived mental effort, verification behaviour, and recall independence. Section D, corresponding to Research Question 3, contained eleven (11) items measuring student engagement and knowledge retention. All items in Section B, C, and D were structured on a five-point Likert-type scale of Strongly Agree (5), Agree (4), Neutral (3), Disagree (2), and Strongly Disagree (1).

6.6 Validity of the instrument

The face and content validity of the CEDERQ was established through expert review. Copies of the instrument, together with the study's purpose, objectives, research questions, and hypothesis, were given to two experts in Measurement and Evaluation and one expert in Technical and Vocational Education for scrutiny. Their observations on the clarity of wording, adequacy of item coverage, and appropriateness of the response format guided the modification of the final version of the instrument.

6.7 Reliability of the instrument

The reliability of the CEDERQ was established through a pilot test administered to 30 TVET students in a technical college outside the main study area, who were not part of the final sample. The internal consistency of the sub-scale was determined using Cronbach's Alpha Coefficient. Reliability coefficient of 0.81 (AI Tool Usage), 0.79 (Cognitive Effort Displacement), 0.84 (Student Engagement), and 0.80 (Knowledge Retention) were obtained, with an overall reliability coefficient of 0.85 for the instrument, indicating that the instrument was sufficiently reliable for the study.

6.8 Method of data collection

Copies of the questionnaire were administered directly to respondents by the researcher with the assistance of trained research assistants, with the on-the-spot method of administration and retrieval adopted to maximize the return rate. Respondents were briefed on the purpose of the study and assured of the confidentiality of their response before completing the instrument.

6.9 Method of data analysis

Research Questions 1 to 3 were answered using mean and standard deviation. A criterion mean of 3.00 (the midpoint of the five-point scale) was used as the benchmark for decision-making: item or cluster means of 3.00 and above were interpreted as indicating a high extent/level, while means below 3.00 were interpreted as indicating a low extent/level. The null hypotheses were tested using Pearson Product Moment Correlation Coefficient (PPMC) at the 0.05 level of significance. A hypothesis was rejected where the computed p-value was less than 0.05, and retained where the p-value was equal to or greater than 0.05. All data analyses were carried out using IBM SPSS Statistics (Version 26).

7 Results

Table 2 shows the mean and standard deviation of responses on the extent of AI tool usage among TVET students.

Table 2. Mean and standard deviation of responses on the extent of AI tool usage among TVET students.

S/N	Item statement	$\bar{x}$	SD	Decision
1	I use AI tools to complete most of my learning assignments and tasks.	3.68	0.84	High
2	I consult AI tools before attempting a problem on my own.	3.41	0.91	High
3	I use AI tools to generate step-by-step solutions to technical problems.	3.72	0.79	High
4	I use AI tools to summarize or explain course content.	3.85	0.77	High
5	I rely on AI tools more than textbooks or instructor notes for learning support.	3.22	0.96	High
6	I use AI tools during practical/workshop sessions to guide my tasks.	2.94	1.02	Low
	Grand Mean / Cluster SD	**3.47**	**0.72**	**High**

As shown in Table 2, five of the six items on the extent of AI usage recorded mean scores above the 3.00 criterion mean, with a grand mean of 3.47, indicating that TVET students in the sample institutions engage in AI usage to a high extent, particularly for assignment completion, generating step-by-step solutions, and summarizing course content. Reliance on AI tools during hands-on

practical/workshop sessions recorded the lowest mean (2.94), suggesting comparatively less AI-reliance in physically supervised practical contexts.

Table 3 presents the mean and standard deviation of responses on cognitive effort displacement across its five sub-dimensions.

Table 3. Mean and standard deviation of responses on cognitive effort displacement across its five sub-dimensions.

S/N	Item statement	$\bar{x}$	SD	Decision
	Frequency of AI Reliance			
7	I turn to an AI tool before trying to solve a task myself.	3.55	0.88	High
8	I depend on AI assistance to begin most of my assignments.	3.49	0.90	High
	Depth of Processing Bypassed			
9	I accept AI-generated answers without checking if they are correct.	3.18	1.01	High
10	I copy AI-generated solutions without fully understanding the reasoning behind them.	3.09	1.05	High
	Perceived Mental Effort			
11	I invest less mental effort in tasks when I know an AI tool can assist me.	3.64	0.87	High
12	Using AI tools makes learning feel easier but less thought-demanding.	3.71	0.83	High
	Verification Behaviour			
13	I review and cross-check AI-generated outputs before using them.	3.12	0.95	High
14	I modify or improve on AI-generated answers rather than using them as they are.	2.98	0.99	Low
	Recall Independence			
15	I can explain a solution to a classmate without referring back to the AI tool.	2.87	1.04	Low
16	I can reproduce a solution generated by AI on my own shortly afterward, without assistance.	2.79	1.08	Low
	Overall CED Mean / SD	**3.26**	**0.68**	**Moderate–High**

The results in Table 3 reveal an overall cognitive effort displacement mean of 3.26, suggesting a moderate-to-high level of cognitive effort displacement among the sampled TVET students. Displacement was most pronounced in the perceived mental effort dimension (means of 3.64 and 3.71), indicating that students frequently perceived AI-assisted tasks as requiring less thought. Correspondingly, verification behavior and recall independence the two protective sub-dimension recorded the lowest means (below or close to the criterion mean), suggesting that students only weakly cross-check AI output and often struggle to reproduce AI-assisted solutions independently.

Table 4 shows the mean and standard deviation of responses on student engagement and knowledge retention.

Table 4. Mean and standard deviation of responses on student engagement and knowledge retention.

S/N	Item statement	x̄	SD	Decision
	Student Engagement			
17	I actively participate in class and workshop discussions when using AI-assisted learning.	3.58	0.81	High
18	I feel motivated to learn when I use AI tools alongside my coursework.	3.77	0.75	High
19	I ask questions and seek clarification even when AI provides an answer.	3.05	0.93	High
20	I stay focused and attentive during AI-assisted learning activities.	3.44	0.86	High
21	I put in effort to complete tasks fully, rather than relying solely on AI output.	3.21	0.89	High
22	I feel a sense of ownership over work I complete with AI assistance.	3.11	0.92	High
	Knowledge Retention			
23	I can recall the concepts I learned with AI assistance after some time has passed.	3.02	0.95	High
24	I can apply what I learned with AI assistance to a new or similar task without help.	2.91	1.00	Low
25	I remember the steps of a technical procedure I completed using an AI tool.	2.96	0.97	Low
26	I struggle to remember information when I relied heavily on an AI tool to obtain it.	3.62	0.88	High
27	I retain practical/technical skills better when I solve problems without AI assistance first.	3.79	0.80	High
	Grand Mean / Cluster SD	**3.32**	**0.66**	**High**

Table 4 shows a grand mean of 3.32 for student engagement and knowledge retention. While behavioral and emotional engagement indicators (motivation, participation, focus) recorded relatively high means, items measuring independent application (item 24) and unaided recall of technical procedures (item 25) fell close to or below the criterion mean, suggesting that although students remain behaviorally engaged, the durability and transferability of knowledge acquired through AI assistance is comparatively weaker. Notably, students strongly agreed that they struggle to remember information obtained largely through AI reliance (item 26, $\bar{x} = 3.62$) and that they retain practical skills better when problems are solved without AI assistance first (item 27, $\bar{x} = 3.79$).

Table 5 presents the test of Ho1: there is no significant relationship between the extent of AI tool usage and cognitive effort displacement among TVET students.

Table 5. Pearson correlation between the extent of AI tool usage and cognitive effort displacement (Ho1).

Variables correlated	*N*	*r*	*p*	Decision
AI Tool Usage × Cognitive Effort Displacement	343	0.612	0.000	Reject Ho1

As shown in Table 5, the computed p-value (0.00) is less than the 0.05 level of significance, therefore, the null hypothesis is rejected. This indicates a statistically significant, moderately strong, positive relationship between the extent of AI tool usage and cognitive effort displacement among TVET students: as AI tool usage increases, cognitive effort displacement also tends to increase.

Table 6 presents the test of Ho2: there is no significant relationship between cognitive effort displacement and student engagement among TVET students in AI-assisted learning environments.

Table 6. Pearson correlation between cognitive effort displacement and student engagement (Ho2).

Variables correlated	*N*	*r*	*p*	Decision
Cognitive Effort Displacement × Student Engagement	343	−0.478	0.000	Reject Ho2

The computed p-value in Table 6 (0.00) is less than 0.05; the null hypothesis is therefore rejected. This indicates a statistically significant, moderate, negative relationship between cognitive effort displacement and student engagement, suggesting that as cognitive effort displacement increase, students active cognitive, behavioral, and emotional engagement in learning tends to decrease.

Table 7 presents the test of Ho3: there is no significant relationship between cognitive effort displacement and knowledge retention among TVET students in AI-assisted learning environments.

Table 7. Pearson correlation between cognitive effort displacement and knowledge retention (Ho3).

Variables correlated	*N*	*r*	*p*	Decision
Cognitive Effort Displacement × Knowledge Retention	343	−0.563	0.000	Reject Ho3

Table 7 shows that the computed p-value (0.00) is less than 0.05, the null hypothesis is rejected. This indicates a statistically significant, moderately strong, negative relationship between cognitive effort displacement and knowledge retention, implying that higher levels of cognitive effort displacement are associated with weaker retention and transfer of technical knowledge and skills among TVET students.

8 Discussion of findings

The findings of this study are discussed in relation to the research questions, hypotheses, theoretical frameworks, and extant empirical literature.

8.1 Extent of AI tool usage

The finding that TVET students engage in AI tool usage to a high extent (grand mean = 3.47) aligns with the broader literature documenting the rapid uptake of generative AI platforms, intelligent tutoring systems, and adaptive learning applications in vocational education (UNESCO, 2023; Zawacki-Richter et al., 2019; Tithi et al., 2026). The comparatively lower reliance on AI during practical/workshop sessions is consistent with the nature of hands-on trade instruction, where physical supervision by instructors and the tactile, equipment-based character of tasks may naturally limit opportunities for AI mediation, even as students embrace AI tools more freely for assignments, explanations, and problem formulation.

8.2 Level of cognitive effort displacement

The moderate-to-high overall level of cognitive effort displacement (grand mean = 3.26) lends empirical support to the theoretical accounts of Yan et al., (2024), Jose and Cherian (2025), and Twabu (2025), who separately argue that AI systems Can absorb analytical, evaluative, and problem-solving processes that would otherwise be performed internally by learners. The pattern observed

across sub-dimensions high displacement in perceived mental effort but comparatively weak verification behavior and recall independence mirrors the cognitive offloading mechanism described by Barcaui (2025), whereby learners delegate mental operations to external tools with limited internal consolidation of the delegated content. This pattern is also consistent with Cognitive Load Theory (Sweller, 1988), which suggests that when germane cognitive load associated with schema construction is displaced onto an external agent, deep processing and durable learning are correspondingly reduced.

8.3 Cognitive effort displacement, student engagement, and knowledge retention

The significant positive relationship between AI tool usage and cognitive effort displacement (Ho1) confirms that greater reliance on AI tools is systematically associated with greater transfer of mental effort away from the learner, supporting the conceptualization of AI-assisted learning as the technological context through which cognitive effort displacement operates. The significant negative relationships between cognitive effort displacement and both student engagement (Ho2) and knowledge retention (Ho3) reinforce the theoretical concern that unmanaged reliance on AI may undermine the very engagement and retention outcomes that AI-assisted learning is intended to support. These findings are consistent with Fredricks et al.'s (2004) multidimensional model of engagement, in that reduced cognitive investment appears to depress not only cognitive but also behavioral indicators of engagement, and with Mayer's (2021) and Sweller et al.'s (2011) position that durable retention depends on active, effortful processing rather than passive receipt of externally generated solutions. Taken together, the findings suggest that AI-assisted learning in TVET is a double-edged instructional context: it can support motivation and access to instructional content, while simultaneously, through cognitive effort displacement, weakening the deep processing on which lasting technical competence depends.

8.4 Theoretical implications and contribution to theory

This study contributes to theory in three main ways: First, it extends Cognitive Offloading Theory and Cognitive Load Theory beyond their traditional application in general educational and workplace context into the specific domain of technical and vocational education and training, where practical competence and durable retrieval of procedural knowledge are of particular importance to employability. Second, the study operationalizes cognitive effort displacement as a multidimensional, measurable construct comprising frequency of AI reliance, depth of processing bypassed, perceived mental effort, verification behavior, and recall independence, thereby providing an empirically testable structure for a concept that has so far been discussed largely at a theoretical level (Yan et al., 2024; Jose & Cherian, 2025; Twabu, 2025). Third, by empirically linking cognitive effort displacement to reduce student engagement and knowledge retention, the study provides preliminary quantitative support for treating cognitive effort displacement as a mediating mechanism between AI tool usage and vocational learning outcomes, a relationship that can be further tested using mediation and structural equation modelling in future research.

9 Conclusion

This study examined the extent of AI tool usage, the level of cognitive displacement, and their relationship with student engagement and knowledge retention among TVET students. The findings indicate that TVET students use AI tool to a high extent, that cognitive effort displacement occurs at a moderate-to-high level, and that cognitive displacement is significantly and positively related to AI

tool usage while being significantly and negatively related to both student engagement and knowledge retention. These findings suggest that although AI-assisted learning offers valuable instructional support in TVET, unmonitored reliance on AI tools carries a measurable risk of displacing the active cognitive effort that underlies durable skill acquisition and workforce readiness. Responsible integration of AI in TVET must therefore deliberately safeguard, rather than substitute, learner's active cognitive engagement.

10 Recommendations

Based on the findings, the following recommendations are made:

1. TVET institutions should develop clear guidelines on AI tools use that distinguish appropriate support functions (e.g., clarifying concepts) from tasks that require independent cognitive effort (e.g., core problem-solving and technical procedures).
2. Instructors should design AI-integrated assignments that require students to verify, justify, or improve upon AI-generated outputs, thereby deliberately strengthening the verification behavior and recall independence dimensions found to be weakest in this study.
3. Practical/workshop instruction should continue to be conducted with minimal AI mediation, and hands-on skill assessment should be prioritized as the primary basis for certifying competence, given the strong association between AI reliance and reduced retention of practical skills.

11 Limitations of the study

This study is limited in the following respects. First, the data were self-reported, and response may be subject to social desirability bias or inaccurate self-assessment of one's own cognitive effort and mental process. Second, the descriptive-correlational design permits the identification of statistical relationship but does not establish causes reduced engagement or retention. Third, the study was cross-sectional, capturing AI-assisted learning behavior, engagement, and retention at a single point in time, and cannot capture how cognitive effort displacement may evolve over an academic programme. Fourth, the sample was draw from TVET institutions within a single state, which may limit the generalizability of the findings to TVET context with different technological infrastructure, curricula, or student populations. Finally, knowledge retention was measured through self-report rather than objective performance-based assessment, which may not fully capture actual retrieval and transfer of technical competencies.

12 Suggestion for further research

Building on the findings and limitations of this study, several directions are recommended for future research. First, given that the present study adopted a cross-sectional, descriptive-correlational design, future studies should employ longitudinal or quasi-experimental designs that track TVET students across an academic programme, or compare AI-restricted and AI-permitted groups, in order to establish causal relationships and to determine how cognitive effort displacement develops, intensifies, or diminishes over time.

Second, since knowledge retention in this study was measured solely through self-report, future research should complement survey data with objective performance-based measures, such as delayed post-test, practical skill assessments, or workplace simulation tasks, to validate whether

students perceived struggles with recall and independent application correspond to actual demonstrated competence.

Third, in line with the theoretical implications advanced in this study, subsequent research should employ Structural Equation Modelling (SEM) to formally test cognitive effort displacement as a mediating variable between AI tool usage and the outcome variables of student engagement and knowledge retention, thereby providing a more robust statistical basis for the relationships tentatively established through bivariate correlation in this study.

Fourth, future studies should disaggregate findings by trade area to determine whether cognitive effort displacement manifests differently across trades with varying proportions of psychomotor and theoretical content (e.g., welding and fabrication versus building technology), and whether particular categories of AI-assisted tasks, such as computational problem-solving as opposed to conceptual explanation, are more susceptible to displacement than others.

Fifth, given that this study was conducted within TVET institutions in a single state, future research should replicate the study across other states and countries with differing technological infrastructure, curricula, and student populations, in order to strengthen the generalizability of the relationships identified between AI tool usage, cognitive effort displacement, student engagement, and knowledge retention.

Sixth, since the present study captured only students' perspectives, further research should examine the perceptions and practices of TVET instructors regarding cognitive effort displacement, including the strategies they employ to monitor and manage AI use during instruction, so as to provide a more comprehensive, multi-stakeholder understanding of the phenomenon.

Seventh, future studies should experimentally test specific pedagogical interventions, such as requiring learners to verify and justify AI-generated outputs, delayed-AI-access assignments, or solve then verify with AI instructional models, to determine which strategies most effectively strengthen the verification behaviour and recall independence dimensions identified in this study as the weakest components of cognitive effort displacement.

Finally, because cognitive effort displacement remains a relatively new and evolving construct, further research should employ exploratory and confirmatory factor analysis on larger, multi-institutional samples to validate and refine the five-dimensional structure proposed in this study.

Declarations

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Data Availability: The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics Approval: This study involved human participants in the form of a structured questionnaire survey. All procedures performed were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments. The study protocol was approved by the Research Ethics Committee of the Abia State College of Education

(Technical) Arochukwu with reference number: CETA/REG/EST/2025/27. Informed consent was obtained from all individual participants included in the study.

Consent to Participate: Informed consent was obtained from all individual participants included in the study prior to questionnaire administration.

Consent for Publication: Not applicable (no identifying images or personal data of individual participants are included in this manuscript).

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References

[1] Adam T (2024). A justice-oriented conceptual and analytical framework for decolonising and desecularising the field of educational technology. *Education Sciences*, 14(9), 962. <https://doi.org/10.3390/educsci14090962>

[2] Avis J (2023). A critical review of debates surrounding race/ethnicity and TVET. *Journal of Vocational Education & Training*, 75(1), 175–184. <https://doi.org/10.1080/13636820.2022.2158360>

[3] Azizah N, Hanafi I, Yusro M (2025). Artificial intelligence in vocational education: Perspectives and practices from a literature study. *Global Synthesis in Education Journal*, 3(2), 37–45. <https://doi.org/10.61667/w0efrt90>

[4] Barcaui A (2025). ChatGPT as a cognitive crutch: Evidence from a randomized controlled trial on knowledge retention. *Social Sciences & Humanities Open*, 12, Article 102287. <https://doi.org/10.1016/j.ssaho.2025.102287>

[5] Cai J, Kosaka M (2024). Conceptualizing technical and vocational education and training as a service through service-dominant logic. *SAGE Open*, 14(2). <https://doi.org/10.1177/21582440241240847>

[6] Chen X, Chan S (2024). Implementing digital pedagogy in TVET: A Connectivist perspective. *Vocational and Technical Education*, 1(2). <https://doi.org/10.54844/vte.2024.0595>

[7] Cukurova M (2025). The interplay of learning, analytics and artificial intelligence in education: A vision for hybrid intelligence. *British Journal of Educational Technology*, 56(2), 469–488. <https://doi.org/10.1111/bjet.13514>

[8] Fredricks JA, Blumenfeld PC, Paris AH (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, 74(1), 59–109. <https://doi.org/10.3102/00346543074001059>

[9] Heggart K, Ritzhaupt AD, Prokes C, Kimmons R (2025). Educational technology: Offering a contemporary definition. *TechTrends*. Advance online publication. https://doi.org/10.1007/s11528-025-01093-9

[10] Jose B, Cherian J (2025). The cognitive paradox of AI in education: Between enhancement and erosion. *Frontiers in Psychology*, 16. <https://doi.org/10.3389/fpsyg.2025.1550621>

[11] Kahu ER (2013). Framing student engagement in higher education. *Studies in Higher Education*, 38(5), 758–773. <https://doi.org/10.1080/03075079.2011.598505>

[12] Maulana R, Opdenakker MC, den Brok P, Bosker R (2014). Engaging students: The role of teacher beliefs and interpersonal teacher behavior in fostering student engagement in vocational education. *Teaching and Teacher Education*, 37, 21–32. <https://doi.org/10.1016/j.tate.2013.08.005>

[13] Mayer RE (2021). Multimedia learning (3rd ed.). *Cambridge University Press*.

[14] Niittylahti S, Annala J, Mäkinen M (2023). Student engagement profiles in vocational education and training: A longitudinal study. *Journal of Vocational Education & Training*, 75(2), 372–390. <https://doi.org/10.1080/13636820.2021.1879902>

[15] Papier J (2024). Research towards the continuous improvement of TVET in South Africa: Building the local knowledge base. *Journal of Vocational*, Adult and Continuing Education and Training, 7(2). <https://doi.org/10.10520/ejc-jovacet_v7_n2_a1>

[16] Riis M (2025, August 19). *Between wood and algorithms: Crafting AI literacy in TVET*. UNESCO. https://www.unesco.org/en/articles/between-wood-and-algorithms-crafting-ai-literacy-tvet

[17] Soden R, Pithers RT (2001). Knowledge matters in vocational problem-solving: A cognitive view. *Journal of Vocational Education & Training*, 53(2), 205–222. <https://doi.org/10.1080/13636820100200163>

[18] Sweller J, Ayres P, Kalyuga S (2011). Cognitive load theory. *Springer*.

[19] Tawfik AA, Schmidt M, Payne L, Huang R, et al. (2024). Advancing understanding of learning experience design: Refining and clarifying definitions using an eDelphi study approach. *Educational Technology Research and Development*, 72, 1539–1561. https://doi.org/10.1007/s11423-024-10355-z

[20] Tithi SD, Alam N, Yasir T, Shi Y, Tian X, Chi M, Barnes T (2026). Adaptive scaffolding for cognitive engagement in an intelligent tutoring system. *arXiv*. <https://arxiv.org/abs/2602.07308>

[21] Twabu K (2025). Enhancing the cognitive load theory and multimedia learning framework with AI insight. *Discover Education*, 4, Article 160. <https://doi.org/10.1007/s44217-025-00592-6>

[22] UNESCO (2023). Guidance for generative AI in education and research. *UNESCO Publishing*.

[23] Yan L, Greiff S, Teuber Z, Gašević D (2024). Promises and challenges of generative artificial intelligence for human learning. *Nature Human Behaviour*, 8, 1839–1850. <https://doi.org/10.1038/s41562-024-02004-5>

[24] Zawacki-Richter O, Marín VI, Bond M, Gouverneur F (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education*, 16(1), 39. https://doi.org/10.1186/s41239-019-0171-0