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Artificial Intelligence as a Cognitive Support Tool: Evidence from ChatGPT-Enhanced Learning Experiences in Nigerian Teacher Education

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Abstract

Generative artificial intelligence has introduced new possibilities for supporting learning through explanation, scaffolding, feedback and interactive problem solving. However, evidence concerning the mechanisms through which ChatGPT may support learning in teacher education, particularly within the Nigerian context, remains limited. This study investigated the effect of ChatGPT-Enhanced Instruction on pre-service teachers' pedagogical knowledge achievement and cognitive-load dimensions. A quasi-experimental pre-test/post-test non-equivalent control-group design was adopted. Participants were 270 pre-service teachers comprising 131 students in the ChatGPT-Enhanced Instruction group and 139 in the conventional instruction group. The intervention lasted six weeks and integrated ChatGPT into Educational Technology instruction. Data were collected using a 50-item Pedagogical Knowledge Achievement Test (PKAT) and a 10-item Cognitive Load Scale measuring intrinsic cognitive load, extraneous cognitive load and germane cognitive processing. ANCOVA was used to examine the effect of instructional condition on post-test PKAT scores after controlling pre-test achievement, while Welch independent-samples t-tests were used to compare the cognitive-load dimensions. Results showed a significant effect of instructional condition on pedagogical knowledge achievement, $F(1, 267) = 191.22$, $p < .001$, $\eta^2p = .417$. The adjusted post-test mean was 34.97 for the ChatGPT group compared with 21.94 for the conventional group. Significant group differences were also found for intrinsic cognitive load, $t = −9.96$, $p < .001$, $d = −1.20$; extraneous cognitive load, $t = −12.52$, $p < .001$, $d = −1.51$; and germane cognitive processing, $t = 9.04$, $p < .001$, $d = 1.09$. The findings suggest that structured ChatGPT use can function as a cognitive support mechanism by facilitating access to explanations and feedback while reducing unnecessary cognitive demands and supporting productive cognitive processing. The study concludes that ChatGPT has potential as an instructional augmentation tool when its use is deliberately structured and guided by teacher educators.

Keywords: *Artificial intelligence; ChatGPT; cognitive support; cognitive load; pedagogical knowledge; teacher education; pre-service teachers; Nigeria*

1. Introduction

Generative Artificial Intelligence (GenAI) has rapidly changed the technological landscape of education. Since the public emergence of ChatGPT, learners and educators have gained access to conversational systems capable of generating explanations, examples, feedback, summaries, questions, and solutions in response to natural-language prompts. The educational significance of these systems lies not only in their capacity to produce information but also in their ability to interact with learners during the learning process. Consequently, ChatGPT has increasingly been discussed as a possible mechanism for personalised assistance, cognitive scaffolding, feedback, and problem solving.

Recent reviews suggest that the educational applications of GenAI are expanding rapidly across higher education. A systematic review of pedagogical applications found that GenAI is being investigated across a range of instructional activities, while also highlighting the need for theoretically grounded and empirically validated approaches to its use (Qian, 2025). Similarly, a recent review of GenAI in teacher education identified instructional-resource generation, curriculum design, stakeholder perceptions, and student-AI collaboration as major areas of research (Qian, 2025; Yuan et al., 2026). However, the review reported substantial geographical imbalance and limited empirical and longitudinal validation (Yuan et al., 2026).

The rapid expansion of GenAI use creates an important question concerning its cognitive consequences. It is appealing to assume that an AI system that provides immediate explanations and answers necessarily makes learning easier and therefore better. However, reduced mental effort does not automatically mean improved learning. From a cognitive perspective, what matters is what type of mental effort is reduced and what type of cognitive activity is encouraged (Paas et al., 2003a).

Cognitive Load Theory (CLT) provides a useful theoretical basis for addressing this issue. CLT is founded on the relationship between working memory and long-term memory and assumes that working memory has limited capacity when processing novel information (Paas et al., 2003a). Effective instruction therefore needs to manage the demands placed on working memory while facilitating the acquisition and organisation of knowledge in long-term memory (Sweller et al., 2019).

Within the original component formulation of CLT, cognitive load was distinguished into intrinsic, extraneous, and germane load. Intrinsic cognitive load relates to the complexity of the learning material in relation to the learner's prior knowledge. Extraneous cognitive load is associated with the way information is presented and the instructional procedures imposed on learners. Germane load was initially conceptualised as cognitive resources devoted to learning-related processes (Sweller et al., 2019).

The theoretical status of germane load has subsequently changed. Sweller et al. (2019) argued that germane processing should not be considered an additional source of cognitive load that simply adds to intrinsic and extraneous load. Instead, germane processing reflects the redistribution of working-memory resources toward activities directly relevant to learning. This distinction is important for research involving AI because a reduction in unnecessary cognitive demands may allow learners to allocate more resources to productive learning activities.

Leppink et al. (2013) developed a ten-item instrument designed to distinguish intrinsic, extraneous, and germane dimensions of cognitive load. Their research provided evidence for a three-component structure through principal component analysis, confirmatory factor analysis, and an experimental study. The instrument consequently provides an appropriate empirical basis for examining the different cognitive dimensions associated with an instructional intervention(Leppink et al., 2013a).

ChatGPT could potentially influence all three dimensions, although not necessarily in the same direction. First, ChatGPT may help learners manage complex concepts by breaking explanations into smaller and more comprehensible units. However, because intrinsic cognitive load is associated with the inherent complexity of the learning task and the learner’s existing knowledge, AI cannot simply eliminate that complexity. Sweller et al. (2019) emphasised that intrinsic load depends on both the nature of the material and the learner's level of expertise.

Secondly, ChatGPT may reduce extraneous cognitive load. A learner who does not understand an explanation can request an alternative explanation, an example, a comparison, or a step-by-step description. Instead of searching across multiple sources or waiting for further lecturer assistance, the learner can obtain immediate clarification. Such support may reduce cognitive processing that is not directly related to understanding the learning content (Leppink et al., 2013a).

Thirdly, ChatGPT may influence germane cognitive processing. When students use AI to compare explanations, critique suggestions, revise their work, test possible solutions, or reflect on alternative perspectives, the technology may support cognitive activities that are directly related to learning. However, this outcome is not automatic. If students simply copy AI-generated answers, the technology may reduce rather than support productive cognitive engagement.

Recent empirical research has begun to investigate these issues. Experimental and meta-analytic evidence suggests that ChatGPT can influence academic performance, mental effort, and higher-order thinking, although the effects vary across contexts and instructional designs (Alanazi et al., 2025; Mohamud et al., 2026; Qian, 2025; Yuan et al., 2026). Emerging literature therefore supports the need to examine not only whether ChatGPT is useful but how its use changes learners' cognitive experiences.

This issue is particularly significant in teacher education. Pre-service teachers are future educators who will eventually make decisions about how technologies are used by their own students. Their experiences with AI during teacher preparation may therefore influence their future pedagogical beliefs and practices. Recent reviews have identified teacher education as an emerging but comparatively underdeveloped area of GenAI research. A 2026 systematic review found that existing studies were geographically concentrated and reported no African studies within its selected evidence base (Yuan et al., 2026).

The Nigerian context therefore presents an important research opportunity. Educational Technology courses in Colleges of Education provide a natural environment for investigating the cognitive implications of AI because the courses require learners to engage with complex theoretical concepts, instructional design processes, technology selection, lesson planning, problem solving, and technology-supported pedagogy. The rapid diffusion of generative AI creates an opportunity to investigate whether such tools can be incorporated into teacher preparation in ways that support rather than replace professional teaching.

The present study therefore conceptualises ChatGPT as a cognitive support tool rather than an autonomous teacher. The intervention is designed around structured pedagogical use of ChatGPT, with the lecturer remaining responsible for instructional direction, verification, interpretation and feedback. This approach is consistent with the human-centred approach recommended for GenAI in education (Miao & Holmes, 2023).

2. Statement of the Problem

The increasing availability of ChatGPT has created both opportunities and challenges for teacher education. On the one hand, ChatGPT can provide explanations, examples, feedback and interactive assistance that may help learners engage with difficult academic content. On the other hand, unrestricted or poorly guided use can create problems related to inaccurate information, overdependence, superficial learning, academic integrity and reduced independent cognitive engagement.

A major problem is that the educational value of ChatGPT is often discussed in terms of convenience, accessibility or students' perceptions rather than objective learning outcomes. Although recent experimental studies indicate that ChatGPT can improve academic performance and reduce mental effort, the evidence remains heterogeneous, and much of the literature is concentrated in university contexts and disciplines outside teacher education (Alanazi et al., 2025; Qian, 2025).

A second problem concerns the cognitive mechanism through which ChatGPT may influence learning. If ChatGPT functions as a cognitive support tool, its value should be reflected not only in achievement but also in the cognitive demands experienced during learning. A tool that merely supplies answers may produce short-term performance without supporting meaningful knowledge construction. Conversely, a carefully structured

AI-supported environment may reduce unnecessary processing while supporting productive cognitive engagement.

A third problem concerns teacher preparation. Pre-service teachers require pedagogical knowledge that enables them to understand instructional principles and apply them in technology-supported teaching situations. Yet there remains a need for empirical evidence concerning whether structured ChatGPT-enhanced instruction can improve pedagogical knowledge achievement among pre-service teachers (Yuan et al., 2026).

The problem addressed by this study is therefore the inadequate empirical evidence concerning whether structured ChatGPT-Enhanced Instruction produces superior pedagogical knowledge achievement and more favourable cognitive-processing outcomes than conventional instruction among pre-service teachers.

3. Purpose of the Study

The purpose of this study was to examine ChatGPT as a cognitive support tool during Educational Technology instruction among pre-service teachers in selected Colleges of Education in Southwest Nigeria.

Specifically, the study sought to:

1. Investigate the pedagogical knowledge achievement of pre-service teachers exposed to ChatGPT-Enhanced Instruction and those exposed to conventional instruction?
2. Investigate whether a significant difference exists between the experimental and control groups in changes in intrinsic cognitive load;
3. Investigate whether a significant difference exists between the experimental and control groups in changes in extraneous cognitive load;
4. Investigate whether a significant difference exists between the experimental and control groups in changes in germane cognitive processing; and

4. Research Questions

The study was guided by the following research questions:

RQ1: What difference exists in the pedagogical knowledge achievement of pre-service teachers exposed to ChatGPT-Enhanced Instruction and those exposed to conventional instruction?

RQ2: Is there a significant difference between the experimental and control groups in changes in intrinsic cognitive load?

RQ3: Is there a significant difference between the experimental and control groups in changes in extraneous cognitive load?

RQ4: Is there a significant difference between the experimental and control groups in changes in germane cognitive processing?

5. Research Hypotheses

The following null hypotheses were tested at the .05 level of significance:

$H_0$1: There is no significant difference in the adjusted mean post-test pedagogical knowledge achievement scores of pre-service teachers exposed to ChatGPT-Enhanced Instruction and those exposed to conventional instruction, after controlling for their pre-test PKAT scores.

$H_0$2: There is no significant difference between pre-service teachers exposed to ChatGPT-Enhanced Instruction and those exposed to conventional instruction in changes in intrinsic cognitive load.

$H_0$3: There is no significant difference between pre-service teachers exposed to ChatGPT-Enhanced Instruction and those exposed to conventional instruction in changes in extraneous cognitive load.
$H_0$4: There is no significant difference between pre-service teachers exposed to ChatGPT-Enhanced Instruction and those exposed to conventional instruction in changes in germane cognitive processing.

6. Literature Review and Theoretical Framework

6.1 Artificial Intelligence as a Cognitive Support Tool

The use of AI in education has evolved from systems that primarily automated selected instructional functions toward interactive systems capable of supporting complex learning activities (UNESCO, 2021; Yuan et al., 2026). ChatGPT represents an important development because learners can interact with it through natural language and request explanations, examples, alternative representations and feedback.

However, describing ChatGPT as a cognitive support tool requires more than identifying its technical capabilities. Its educational value depends on how the technology is embedded within instructional design (Qian, 2025). ChatGPT may serve as a scaffold when it helps learners decompose difficult problems, clarify concepts and receive formative feedback. It may also function as a conversational partner through which learners articulate questions and examine alternative solutions (Crompton & Song, 2021; Konstantinova et al., 2023).

Studies found that empirical research on ChatGPT in education covers a broad range of applications but also identifies concerns surrounding accuracy, assessment and academic integrity (Huang, 2023; Oguguo et al., 2024; Tan et al., 2025a, 2025b). Similarly other studies argued that ChatGPT has potential educational benefits while requiring careful consideration of reliability, privacy and responsible use (Crompton & Burke, 2023; Qian, 2025; Raimundo & Rosário, 2021; Saheb, 2023).

Recent experimental syntheses provide stronger evidence concerning learning effects. Deng et al. (2025) reported a positive overall effect of ChatGPT interventions on academic performance and higher-order thinking, while also finding evidence of reduced mental effort. These findings support the possibility that ChatGPT can operate as a cognitive support mechanism when integrated appropriately.

6.2 ChatGPT and Pedagogical Knowledge Development

Pedagogical knowledge concerns teachers' understanding of how learning occurs, how instruction should be organised and how learners can be supported effectively. For pre-service teachers, pedagogical knowledge is essential because technological competence alone does not guarantee effective teaching.

In Educational Technology courses, pedagogical knowledge includes understanding instructional models, learning theories, instructional strategies, technology-integration principles and methods for designing learning experiences. ChatGPT may support this knowledge development by allowing students to request explanations at different levels of complexity, compare instructional approaches, analyse teaching scenarios and receive feedback on lesson plans.

Recent experimental research suggests that ChatGPT interventions can improve academic performance, although effects vary according to task, instructional design and outcome measure (Deng et al., 2025; Jin & Sercu, 2025). This supports the need for discipline-specific studies examining structured interventions rather than treating all ChatGPT use as equivalent.

The present study uses the PKAT as an objective measure of pedagogical knowledge achievement in Educational Technology Course. This is important because self-reported perceptions of AI usefulness cannot substitute for evidence that students actually acquired relevant knowledge.

6.3 Cognitive Load Theory

Cognitive Load Theory provides the principal theoretical foundation for the study. The theory is based on assumptions concerning the limited capacity of working memory and the role of long-term memory in storing organised knowledge structures or schemas (Sweller et al., 1998). Learning materials can impose cognitive demands that differ in nature. Intrinsic cognitive load is associated with the complexity of the learning material and the degree of element interactivity. Extraneous cognitive load is produced by instructional presentation and unnecessary information-processing demands.

Productive processing involves cognitive activity directed toward understanding, organising and integrating new knowledge. Paas (1992) demonstrated the usefulness of mental-effort measurement in examining instructional effectiveness, while Leppink et al. (2013b) established subjective cognitive-load ratings as a useful technique in instructional research. These approaches provide a methodological foundation for examining students' cognitive experiences during learning.

The traditional three-component model has subsequently been refined. Kalyuga (2011) questioned the necessity of treating germane load as an independent category. Consequently, the present study uses the term germane cognitive processing rather than treating germane load as a separate burden. This terminology is conceptually more consistent with contemporary discussions of Cognitive Load Theory.

6.4.1 Intrinsic Cognitive Load

Intrinsic cognitive load concerns the inherent complexity of learning material in relation to the learner's existing knowledge (Online et al., 1991a; Paas et al., 2003b; Sharafi et al., 2021). Educational Technology concepts may have substantial intrinsic complexity because students must understand relationships among several interacting components. For example, understanding an instructional design model may require learners to coordinate concepts concerning learner analysis, objectives, content selection, instructional strategies, assessment and evaluation. ChatGPT may potentially support learners by explaining these components sequentially and illustrating their relationships.

However, ChatGPT cannot eliminate intrinsic complexity. Instead, it may help learners manage complex material by providing appropriate explanations and scaffolding. Therefore, the objective is not necessarily to reduce the inherent complexity of the learning content but to make that complexity more manageable.

6.4.2 Extraneous Cognitive Load

Extraneous cognitive load results from instructional features that require learners to process information unnecessarily (Online et al., 1991a, 1991b; Paas et al., 2003a; Sweller et al., 2019). Poorly organised explanations, irrelevant information, confusing terminology and ineffective presentation can increase extraneous processing.

ChatGPT may reduce extraneous cognitive load when used to clarify difficult terminology, reorganise explanations, provide concise examples and respond to learners' specific questions. However, AI-generated responses can also increase extraneous load if they are lengthy, inaccurate, contradictory or poorly structured. Thus, the effect of ChatGPT on extraneous cognitive load depends on the instructional conditions under which it is used. The present intervention therefore involves lecturer guidance rather than unrestricted AI use.

6.4.3 Germane Cognitive Processing

The present study uses the term **germane cognitive processing** rather than germane cognitive load. Leppink et al. (2013) originally included germane load as one of three measurable dimensions of cognitive load. Contemporary CLT, however, conceptualises germane processing as the allocation of cognitive resources toward activities directly relevant to learning rather than as an additional load imposed on working memory. Sweller et al. (2019) explicitly described germane processing as involving the redistribution of resources from extraneous activities toward dealing with information intrinsic to the learning task.

Accordingly, higher germane cognitive processing in this study represents greater engagement with learning-oriented cognitive activities such as organising, integrating, interpreting, comparing, and constructing understanding.

7. Conceptual Framework

7.1 ChatGPT, Cognitive Load and Learning Achievement

The central theoretical proposition of the study is that ChatGPT-enhanced instruction may influence learning through cognitive processing. The proposed relationship is:

ChatGPT-Enhanced Instruction → Cognitive Support → Cognitive Processing → Pedagogical Knowledge Achievement

Under this framework, ChatGPT is not assumed to directly produce learning. Instead, it provides instructional support that may influence how learners allocate cognitive resources. Reduced extraneous processing may make resources available for productive processing, while structured scaffolding may help learners manage complex content.

The framework is supported by experimental evidence showing that ChatGPT interventions can improve academic performance and reduce mental effort (Deng et al., 2025). Nevertheless, because ChatGPT can also generate inaccurate or excessive information, the intervention must remain pedagogically controlled.

8. Methodology

8.1 Research Design

The study employed a quasi-experimental pre-test/post-test non-equivalent control group design with a qualitative component. The design was considered appropriate because the participants were drawn from existing instructional groups rather than being individually randomly assigned to experimental conditions. The design permits comparison of learning outcomes before and after the intervention while recognising that intact groups may differ at baseline. The design can be represented as:

Table 1: quasi-experimental pre-test/post-test

Group	Pre-test	Treatment	Post-test
Experimental	O_1	X_1	O_2
Control	O_3	X_0	O_4

Where:

- $\mathbf{O_1}$ **and** $\mathbf{O_3}$ = pre-test measures;

- $\mathbf{O_2}$ **and** $\mathbf{O_4}$ = post-test measures;
- $\mathbf{X_1}$ = ChatGPT-Enhanced Instruction;
- $\mathbf{X_0}$ = Conventional Instruction.

8.2 Participants

The participants comprised 270 pre-service teachers enrolled in Educational Technology course in Adamu Augie College of Education, Northwest Nigeria. The experimental group comprised 130 participants, while the control group comprised 140 participants.

Group	Number
Experimental	131
Control	139
Total	270

The participants were drawn from existing lecture schedules. Accordingly, the study does not claim individual random assignments.

9. Intervention

9.1 ChatGPT-Enhanced Instruction

The experimental intervention lasted six weeks. ChatGPT was deliberately incorporated as a cognitive support tool, not as a replacement for lecturer instruction. The intervention involved five principal functions.

9.1.1 Conceptual scaffolding

Participants used ChatGPT to request:
- ✓ simplified explanations;
- ✓ alternative explanations;
- ✓ examples;
- ✓ comparisons;
- ✓ step-by-step descriptions; and
- ✓ classroom applications.

9.1.2 Lesson-planning

Students submitted draft lesson plans for AI-assisted critique. ChatGPT was used to identify possible weaknesses in:
- ✓ learning objectives;
- ✓ teaching activities;
- ✓ technology selection;
- ✓ instructional alignment;
- ✓ assessment; and
- ✓ learner differentiation.

Students then evaluated the feedback and revised their lesson plans. The lecturer subsequently reviewed and corrected the AI-supported work.

9.1.3 Pedagogical Problem Solving

Students were presented with Educational Technology problems and used ChatGPT to explore possible solutions. They were required to evaluate the suggestions rather than accept AI-generated responses automatically.

9.1.4 Adaptive Learning Pathways

Students could request additional explanations when they encounter difficulties. Students demonstrating greater understanding were encouraged to explore more complex applications.

9.1.5 Pedagogical Role-Play

ChatGPT was used to simulate a learner with learning difficulties. Pre-service teachers were required to respond as teachers and propose differentiated technology-supported instructional strategies.

9.1.6 Guided Critical Evaluation

Students were instructed to verify ChatGPT-generated information using course materials and lecturer guidance. This was important because generative AI can produce inaccurate responses.

9.2 Conventional Treatment

The conventional group received normal lecture-based instruction covering the same Educational Technology content and for the same instructional period. Instruction included lecturer explanations; class discussions; conventional examples; prescribed learning materials; question-and-answer sessions; and conventional assignments.

The control condition did not involve ChatGPT during the instructional period. The purpose was not to compare a technology-rich condition with a technology-free educational environment generally, but specifically to determine whether structured ChatGPT integration added value beyond conventional instruction.

10. Instrument

10.1 Cognitive Load Scale

The primary quantitative instrument was the adopted Cognitive Load Scale developed by Leppink et al. (2013). The scale contains ten items designed to measure three dimensions:

Table 2: Cognitive Load Scale

Dimension	Number of items
Intrinsic cognitive load	3
Extraneous cognitive load	3
Germane cognitive processing	4
Total	10

Leppink et al. (2013) developed the scale specifically to distinguish different types of cognitive load. The authors reported evidence for the three-factor structure through principal component analysis and confirmatory factor analysis across multiple samples, as well as experimental evidence supporting its sensitivity to instructional manipulation.

The instrument was administered at two measurement points, before the intervention; and after the six-week intervention. For the present study, the third dimension was labelled germane cognitive processing to reflect the contemporary theoretical interpretation of germane activity.

11. Data Analysis

Descriptive statistics were used to summarise the variables. ANCOVA was used for the primary achievement outcome, with PKAT post-test as the dependent variable, instructional condition as the independent variable and PKAT pre-test as the covariate.

Welch independent-samples t-tests were used for the cognitive-load outcomes because tests of variance homogeneity indicated unequal variances. While effect sizes were estimated using partial eta squared for ANCOVA and Cohen's d for the cognitive-load comparisons. Statistical significance was evaluated at $\alpha = .05$.

12. Results

12.1 Descriptive Results

Table 3: Descriptive Statistics for Cognitive Load Dimensions and Pedagogical Knowledge Achievement

Variable	Group	n	M	SD
Intrinsic cognitive load	ChatGPT-Enhanced	131	4.14	0.95
	Conventional	139	5.72	1.58
Extraneous cognitive load	ChatGPT-Enhanced	131	2.57	1.01
	Conventional	139	4.40	1.38
Germane cognitive processing	ChatGPT-Enhanced	131	7.64	1.11
	Conventional	139	6.26	1.39
PKAT pre-test	ChatGPT-Enhanced	131	9.92	0.29
	Conventional	139	9.88	0.45
PKAT post-test	ChatGPT-Enhanced	131	34.94	7.94
	Conventional	139	21.96	7.53

Note. *PKAT = Pedagogical Knowledge Achievement Test. Cognitive-load variables were measured after the intervention. Higher intrinsic and extraneous cognitive-load scores indicate greater reported load, whereas higher germane cognitive-processing scores indicate greater learning-related cognitive engagement.*

The descriptive results show a clear advantage for the ChatGPT group in post-test pedagogical knowledge achievement. The group also recorded lower intrinsic and extraneous cognitive-load scores and higher germane cognitive-processing scores.

12.2 Pedagogical Knowledge Achievement

Table 4: ANCOVA Results for PKAT Post-Test Scores

Source	df	F	p	Partial η^2
PKAT pre-test	1	1.32	.252	.005
Instructional condition	1	191.22	<.001	.417

Error	267			
Total	270			

The ANCOVA showed a statistically significant effect of instructional condition on post-test pedagogical knowledge achievement, *$F(1, 267) = 191.22$, $p < .001$, $\eta^2 p = .417$*. The adjusted means were 34.97 for the ChatGPT group and 21.94 for the conventional group, producing an adjusted mean difference of approximately 13.03 points.

Table 5: Adjusted Post-Test Means

Group	n	Adjusted M	SE
ChatGPT-Enhanced Instruction	131	34.97	—
Conventional Instruction	139	21.94	—

Therefore, H01 was rejected. The effect size was large, indicating that instructional condition accounted for a substantial proportion of the variance in adjusted post-test achievement.

The results for Pedagogical Knowledge Achievement demonstrated a substantial advantage for participants exposed to ChatGPT-Enhanced Instruction. Although the two groups began with comparable pre-test pedagogical knowledge scores, the experimental group achieved a substantially higher post-test mean. After controlling for pre-test achievement, the effect of instructional condition remained statistically significant, $F(1, 267) = 191.22$, $p < .001$, partial $\eta^2 = .417$.

The adjusted post-test means were 34.97 for the ChatGPT-Enhanced group and 21.94 for the Conventional Instruction group. The magnitude of the partial eta-squared indicates a large instructional effect.

12.3 Intrinsic Cognitive Load

Table 6: Between-Group Difference in Intrinsic Cognitive Load

Group	n	M	SD	t	p	Cohen's d
ChatGPT-Enhanced	131	4.14	0.95	-9.96	<.001	-1.20
Conventional	139	5.72	1.58			

The Welch's independent-samples *t* test was used because the homogeneity-of-variance assumption was violated. The ChatGPT group recorded significantly lower intrinsic cognitive-load scores than the conventional group, $t \approx -9.96$, $p < .001$, $d = -1.20$. Thus, H02 was rejected.

12.4 Extraneous Cognitive Load

Table 7: Between-Group Difference in Extraneous Cognitive Load

Group	n	M	SD	t	p	Cohen's d
ChatGPT-Enhanced	131	2.57	1.01	-12.52	<.001	-1.51
Conventional	139	4.40	1.38			

The Welc's independent-samples t test was used because the homogeneity-of-variance assumption was violated. The ChatGPT group reported significantly lower extraneous cognitive load than the conventional group, $t \approx -12.52$, $p < .001$, $d = -1.51$. Therefore, H03 was rejected.

12.5 Germane Cognitive Processing

Table 8: Between-Group Difference in Germane Cognitive Processing

Group	n	M	SD	t	p	Cohen's d
ChatGPT-Enhanced	131	7.64	1.11	9.04	<.001	1.09
Conventional	139	6.26	1.39			

The Welch's independent-samples t test was used because the homogeneity-of-variance assumption was violated. The ChatGPT group recorded significantly higher germane cognitive-processing scores than the conventional group, $t \approx 9.04$, $p < .001$, $d = 1.09$. Thus, H04 was rejected.

The cognitive-load findings support the proposed cognitive-support mechanism. Participants in the ChatGPT-Enhanced group reported significantly lower intrinsic cognitive load than participants in the Conventional group, $t = -9.96$, $p < .001$, $d = -1.20$. They also reported substantially lower extraneous cognitive load, $t = -12.52$, $p < .001$, $d = -1.51$. In contrast, the ChatGPT-Enhanced group reported significantly higher germane cognitive processing, $t = 9.04$, $p < .001$, $d = 1.09$. Collectively, these findings indicate a pattern in which ChatGPT-supported instruction was associated with reduced cognitive burden and greater learning-related cognitive engagement.

Table 9: Summary of Hypothesis Decisions

Hypothesis	Statistical result	Decision	Interpretation
H01: No significant difference in adjusted post-test PKAT between groups	$F(1,267) = 191.22$, $p < .001$, $\eta^2 p = .417$	Reject H01	ChatGPT-Enhanced Instruction produced significantly higher adjusted pedagogical knowledge achievement
H02: No significant difference in intrinsic cognitive load	$t = -9.96$, $p < .001$, $d = -1.20$	Reject H02	ChatGPT-Enhanced group reported significantly lower intrinsic cognitive load
H03: No significant difference in extraneous cognitive load	$t = -12.52$, $p < .001$, $d = -1.51$	Reject H03	ChatGPT-Enhanced group reported significantly lower extraneous cognitive load
H04: No significant difference in germane cognitive processing	$t = 9.04$, $p < .001$, $d = 1.09$	Reject H04	ChatGPT-Enhanced group reported significantly greater germane cognitive processing

13. Discussion

The findings demonstrate that ChatGPT-Enhanced Instruction was associated with substantially higher pedagogical knowledge achievement than conventional instruction. After adjustment for pre-test PKAT scores, participants in the ChatGPT group obtained an estimated mean score of 34.97 compared with 21.94 among participants in the conventional group. The instructional effect was statistically significant and large, with $\eta^2p = .417$.

This finding supports the growing body of empirical evidence indicating that ChatGPT can enhance academic learning when integrated into structured instructional activities. Deng et al. (2025), for example, reported positive effects of ChatGPT interventions on academic performance across experimental studies. The present finding extends that evidence to pre-service teacher education and, specifically, to pedagogical knowledge within an Educational Technology context.

A conceivable explanation is that the intervention transformed ChatGPT from a passive information source into an interactive cognitive scaffold. Participants were not merely instructed to ask ChatGPT for answers. Instead, they used the system to break down difficult concepts, obtain explanations, critique lesson plans, solve instructional problems, and explore alternative pedagogical decisions. Such activities may have increased opportunities for elaboration and feedback while allowing learners to revisit difficult concepts at the point of need.

The results concerning cognitive load provide additional insight into this achievement effect. The ChatGPT group reported significantly lower intrinsic cognitive-load scores than the conventional group. Although intrinsic load reflects the inherent complexity of learning material and cannot simply be removed through technology, the finding may indicate that AI-supported scaffolding made complex relationships more manageable for learners. Breaking a difficult concept into smaller conceptual components may have helped learners process interconnected information progressively.

The difference in extraneous cognitive load was even more pronounced. Participants in the ChatGPT group reported a mean extraneous cognitive-load score of 2.57 compared with 4.40 for the conventional group, producing a very large effect size ($d = -1.51$). This result is particularly consistent with the cognitive-support interpretation of the intervention. When students could request clarification, examples, reformulations, and targeted explanations, they may have spent fewer cognitive resources dealing with avoidable instructional difficulties.

This interpretation is consistent with the central premise of Cognitive Load Theory that instructional design should minimise unnecessary cognitive processing (Sweller et al., 1998). It also provides a possible explanation for why the intervention produced a substantial achievement advantage.

The germane cognitive-processing result further strengthens this interpretation. The ChatGPT group obtained a mean score of 7.64 compared with 6.26 in the conventional group, with a large effect size ($d = 1.09$). This suggests that participants exposed to the intervention may have engaged more strongly in productive cognitive activities associated with understanding and organising knowledge.

The finding is important because it suggests that effective AI integration may involve a dual process: reducing unnecessary cognitive demands while increasing productive cognitive engagement. In other words, the benefit of ChatGPT may not simply arise because students receive information faster. Rather, appropriately designed AI interaction may create conditions under which learners can devote more cognitive attention to understanding, applying, evaluating, and integrating information.

The findings also support the argument that the educational value of ChatGPT depends on instructional design. Albadarin et al. (2024) and Jin and Sercu (2025) noted that the effects of ChatGPT vary across learning contexts and tasks. The present study reinforces this point because the intervention was deliberately structured around pedagogical activities rather than unrestricted use of the AI system.

At the same time, the findings should not be interpreted as evidence that ChatGPT can independently replace teachers. The intervention involved instructor guidance, defined learning objectives, and structured tasks. The teacher remained responsible for evaluating AI-generated information and directing students toward appropriate pedagogical decisions. Thus, the findings support a human-guided AI augmentation approach, rather than teacher replacement.

13.1 Implications of the Findings

The findings have several implications for teacher education. First, Colleges of Education may consider incorporating carefully designed generative-AI activities into Educational Technology courses. Such integration should be based on specific pedagogical objectives rather than simply giving students unrestricted access to ChatGPT. Second, teacher educators should train pre-service teachers to use ChatGPT critically. Students should be required to evaluate generated responses, identify possible inaccuracies, compare AI recommendations with established pedagogical principles, and justify their final decisions. Third, the cognitive-load findings suggest that AI can potentially be used as a mechanism for instructional scaffolding. Teacher educators can use AI to break down complex concepts, provide alternative explanations, and support learners who require additional clarification.

Fourth, teacher education programmes should emphasise ethical and responsible AI use. UNESCO's human-centred approach stresses the importance of human agency, safety, privacy, equity, and appropriate educational governance (Miao & Holmes, 2023). Finally, pre-service teachers should experience AI not merely as consumers of generated answers but as designers of AI-supported learning activities. This would prepare them for future classrooms in which AI is likely to become increasingly integrated into educational practice.

13.2 Limitations of the Study

Several limitations should be considered. First, the study employed a quasi-experimental rather than a fully randomised experimental design. Consequently, causal claims should be interpreted cautiously. Second, the study involved pre-service teachers from one Colleges of Education in Northwest Nigeria. Generalisation to all Nigerian teacher-education institutions should therefore be undertaken cautiously.

Third, the PKAT pre-test scores showed very limited variability, with many participants scoring near the upper end of the scale. This ceiling effect reduces the usefulness of the pre-test as a covariate and may partly explain why the covariate was not statistically significant. Fourth, the available dataset contained cognitive-load measures but did not contain corresponding pre-intervention cognitive-load scores. Therefore, the study cannot legitimately claim that ChatGPT reduced cognitive load over time. The appropriate conclusion is that the groups differed in their measured cognitive-load dimensions following the intervention. Fifth, cognitive-load dimensions were measured through self-report. Self-reported cognitive load may not capture every aspect of learners' moment-to-moment cognitive processing.

Future research should therefore incorporate stronger baseline measures, larger and more diverse samples, randomisation where feasible, longitudinal follow-up, and multiple measures of cognitive processing.

13.3 Conclusion

This study investigated ChatGPT as a cognitive support tool rather than as a generic educational technology. The findings indicate that structured ChatGPT-Enhanced Instruction was associated with substantially higher pedagogical knowledge achievement among pre-service teachers compared with conventional instruction. The intervention also produced significant between-group differences in the cognitive-load dimensions examined. Participants exposed to ChatGPT reported lower intrinsic and extraneous cognitive-load scores and higher germane cognitive-processing scores than participants receiving conventional instruction.

Taken together, these findings suggest that the educational value of ChatGPT may lie partly in its capacity to provide timely cognitive scaffolding. When integrated into carefully designed instructional activities,

ChatGPT can help learners clarify complex concepts, obtain feedback, explore alternative solutions, and engage more actively with pedagogical problems.
However, the findings should not be interpreted as evidence that AI automatically improves learning. The observed effects occurred within a structured, teacher-guided intervention. Consequently, ChatGPT is best conceptualised as a cognitive support tool that augments rather than replaces pedagogical expertise.

13.4 Recommendations

Based on the findings, the following recommendations are made:

1. Teacher educators should integrate ChatGPT selectively into Educational Technology instruction, particularly for complex concepts requiring explanation, scaffolding, feedback, and application.
2. AI-supported learning activities should be pedagogically structured. Students should be given tasks requiring them to analyse, evaluate, critique, and apply AI-generated information rather than merely reproduce it.
3. ChatGPT should be used to reduce unnecessary instructional complexity, particularly where students experience difficulty understanding complex educational theories or instructional design concepts.
4. AI-supported learning should remain teacher-guided. Educators should continue to determine learning objectives, monitor student understanding, evaluate AI-generated information, and provide professional judgement.
5. Future studies should include pre- and post-intervention cognitive-load measures so that researchers can examine actual changes in cognitive load rather than only between-group differences.

Declaration of Conflicting Interests

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