Kontagora Journal of Mathematics(KJM)
Volume 1, Issue 1, September 2025
https://fuekjournals.org/index.php/KJM

Impact of Large Language Models in Strengthening Mathematical Foundations for Engineering and Energy Education in Nigeria

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DOI: https://doi.org/10.5281/zenodo.17367180

Abstract

Proficiency in mathematics is a key factor to students' success in engineering and energy-related disciplines. Many students in Nigeria struggle with foundational concepts in algebra and calculus. With the rapid advancement of Artificial Intelligence (AI), particularly Large Language Models (LLMs) like ChatGPT, new opportunities are emerging to bridge these educational gaps through AI-assisted instruction. This study investigates the impact of LLMs in enhancing students' conceptual understanding of mathematics within the context of engineering and energy education in Nigeria. Using a mixed-methods design, the research involves administering pre-test and post-tests, conducting student and lecturers' interviews, and facilitating classroom interventions using ChatGPT. The sample size for this study includes 200 students from three different universities, spread across three geopolitical zones in Nigeria; north, east and south. An independent samples t-test carried out revealed that the LLM-supported group performed significantly better than the traditional group ((198) = 10.35, $p < 0.0001$)*, with a large effect size (Cohen's d ≈ 1.46). These results suggest that LLM integration has a substantial impact on student learning outcomes, improving both test performance and classroom engagement. Based on these findings, we recommended that STEM curricula be revised to include AI-assisted learning activities and that a formal policy framework on the use of LLMs by students and faculty be developed.*

Keywords: Large Language Models (LLMs), ChatGPT, engineering education, energy education, AI in education

Introduction

Across sub-Saharan Africa, Nigeria confronts persistent difficulties in mathematics education, with ripple effects in engineering and energy programs. In the 2024 WAEC exams, nearly 28% of candidates failed to secure credit in mathematics (García-Méndez et al., 2025). These secondary school shortcomings directly impair learners' readiness for tertiary-level calculus and higher mathematics. Compounding the problem are shortages of qualified teachers, large-sized classrooms, outdated curricula, and inadequate laboratory resources. Mathematics is widely perceived as abstract due to its theoretical orientation and rote-learning approaches. This perception by students makes mathematics unengaging, fosters fear, disinterest, and subsequently, failure. At the university level, multiple studies in Rivers State and similar regions confirm these deficiencies. Undergraduates report struggles with core mathematics courses; the relationships between lecturer competence, unavailable lab facilities, and poor student performance are well documented (Nchelem & Ibaan, 2020). The consequence is a bottleneck in STEM education: engineering and energy students arrive underprepared for the demands of modelling, design, and quantitative analysis.

Engineering and energy disciplines fundamentally rely on strong mathematical skills. Foundational tools such as calculus (for rate dynamics and change), differential equations (for modelling systems and processes), linear algebra (for structural design and simulations), and statistics (for measurement error and system reliability) are indispensable. Student competency in these domains is directly linked to success in advanced engineering coursework and professional practice (Su et al., 2023). Beyond technical proficiency, mathematical fluency reinforces essential STEM faculties: analytical reasoning; abstraction; model formulation; hypothesis testing; and systems thinking. For example, engineers designing energy-efficient systems must leverage mathematics to simulate thermal dynamics, optimize resource allocation, and estimate risk. Without solid mathematical foundations, students remain handicapped, reducing their ability to innovate, solve complex problems, or contribute to technological growth. Cross-national data consistently show that robust math preparation correlates positively with retention and achievement in STEM disciplines. Since the advent of transformer-based language models between 2022 to 2023, LLMs like GPT-3.5,

GPT-4, and their successors have begun reshaping education (Fawehinmi et al., 2025). These models enable automated answer grading, adaptive feedback, question generation, and even code synthesis, capacities that align closely with the pedagogical needs of STEM fields (García-Méndez et al., 2025). In mathematics education, advanced tutoring systems such as AutoTutor-like hybrids have demonstrated superior performance over free-form GPT-4 in structured math word problems, combining LLM reasoning with rule-based pedagogy (Chowdhury et al., 2024). Additionally, cutting-edge tool-integrated models such as TORA (Tool-Integrated Reasoning Agent) significantly improve performance on algebra, calculus, and symbolic reasoning tasks, outperforming earlier LLMs by up to 19% in benchmark accuracy (Gou1 et al., 2024). Tools like Abacus embeddings and multi-modal reasoning agents continue pushing the frontier in mathematical reasoning. Emerging field studies in Africa also shows striking outcomes. A June 2024 pilot study in Nigeria involving English language support through GPT-based systems generated learning gains equivalent to two years of schooling over six weeks (De Simone et al., 2024). In Ghana, AI-based math tutoring boosted performance by 5.13 points (almost one year's worth of learning) after an eight-month intervention (Henkell et al., 2024). These results highlight LLMs' promise as high-leverage tools capable of accelerating educational progress in low-resource settings. Key barriers include inequitable access to devices and connectivity, teacher unfamiliarity with AI tools, digital divides, and misalignment with existing pedagogical models. There is a growing call for frameworks that integrate LLMs into teaching via hybrid systems, combining scaffolding, feedback loops, and robustness. Many argue that the future of AI in education depends on human-AI collaboration, where teachers guide and LLMs support, not on automation alone (Jacob et al., 2023).

Despite Nigeria's large and growing Tertiary education sector, mathematics education within universities and polytechnics faces systemic challenges that hinder student outcomes and the training of future engineers and energy experts. (Jacob & Honmane, 2021) highlight the chronic under-funding of university mathematics programs, insufficient qualified educators, and inadequate infrastructure, factors that stem from unstable funding and frequent strikes. Although the Tertiary Education Trust Fund (TETFund) exists to alleviate infrastructure gaps, its impact has been inconsistent, with disparities in funding allocation and project follow-through (Education Team, 2025).

University curricula often replicate outdated British models, lacking localization and practical relevance to Nigeria's industrial needs. Teaching remains heavily lecture-based, emphasizing theoretical exposition with minimal hands-on exploration, reinforcing abstraction and missing opportunities for contextual relevance. (Aselebe et al., 2024) find that curriculum reform is essential to rekindle student interest, recommending mentoring programmes, collaborative learning, and digital transformation to reposition mathematics as a discipline of choice. Many universities in Nigeria struggle with insufficient classrooms, poor laboratory facilities, and low access to computers and mathematics-specific software. The absence of hands-on labs, software tools (Matlab, Mathematica, and Maple), and practical workshops undermines depth of understanding, especially in mathematical modelling, simulations, and energy-related computations. High levels of mathematics anxiety are widespread at Nigerian tertiary institutions. A detailed study at the University of Agriculture Makurdi (UAM), now Joseph Sarwuan Tarka University, Makurdi, shows that students hate or dislike mathematics leading to poor achievement thereby enhancing students' hatred for the subject (Adeniyi et al., 2021). Contributing factors include rote-learning beginnings, high failure rates, and lack of supportive assessments. This fosters avoidance behavior in mathematics-reliant fields such as energy engineering. Assessment of instructional quality highlights inadequate lecturer skills, lack of continuous evaluation systems, and persistent underdevelopment in formative assessment and feedback mechanisms. AI-based tools have shown promise in automating feedback, cutting marking time by 40% and enhancing student satisfaction, their integration however, remains limited by resource and capacity constraints (Fawehinmi et al., 2025).

Although global studies have explored AI-assisted learning, there is a lack of rigorous, peer-reviewed investigations focusing on LLM integration in Nigeria's STEM tertiary education system. Existing literature focus on K-12 language skills or basic math in developed nations, with limited coverage of university-level engineering and energy education. Exceptionally, some work (Guo et al., 2024) examines AI feedback in biology/economics contexts, but not engineering-math or modelling. While emerging studies such as "Mathematics Education 5.0" propose personalized, tech-enhanced learning in Nigeria, they are largely theoretical, lacking empirical evaluation or LLM integration (Fawehinmi et al., 2025). There remains a disconnect between high-level initiatives and measurable impact on student outcomes, especially in foundational mathematics skills for engineering. Furthermore, no rigorous research has been conducted to examine models for training engineering lecturers to incorporate LLMs into teaching mathematics. There are questions around curriculum redesign, scaffolding strategies, and alignment with accreditation standards in Nigeria. Equally unaddressed are cost-benefit implications, infrastructure adaptations, and policy frameworks needed for sustainable deployment of LLMs in low-infrastructure settings. This persistent gap undermines efforts to strengthen foundational mathematical competence among engineering and energy students, thereby perpetuating underperformance and limiting their capacity to meet the quantitative demands of modern technological and industrial development.

Research Objectives

The objectives to this study are to:

1. Evaluate the impact of LLM-assisted instruction (via ChatGPT) on engineering and energy students' performance in foundational mathematics, by comparing the LLM-supported group to a traditional instruction group.
2. Assess how integrating LLM tools influences students' understanding, confidence and engagement in mathematics learning.
3. Explore lecturers' perspectives on using LLMs in mathematics teaching and identify practical factors that affect effective implementation.

Research Questions

This study was guided by the following questions:

1. What is the effect of incorporating LLM-based tools on engineering and energy students' performance in foundational mathematics courses?
2. How do students describe changes in their understanding, confidence and engagement when LLMs are used as part of mathematics instruction?
3. What benefits and challenges do mathematics lecturers identify in adopting LLMs for teaching engineering and energy concepts?

Hypothesis Development

For the purpose of this study, we postulated the hypothesis below:

- **Null Hypothesis (H_0):** The integration of large language models (LLMs) into mathematics instruction does not significantly improve the foundational mathematics competence of engineering and energy students in Nigerian tertiary institutions.

Methodology

This study adopts a mixed-methods design to evaluate the impact of large language models (LLMs) on students' foundational mathematics competence. The design combines quantitative (pre/post tests and performance scores) and qualitative (interviews and observation) methods. The experimental approach allows for structured comparison between a treatment group (LLM supported learning) and a control group (traditional instruction). The mixed-methods model ensures comprehensive insight by capturing not only measurable improvements in performance but also the subjective experiences of students and instructors. The study population comprises a sample of 200 undergraduate students enrolled in mathematics, engineering and energy-related programs across three Nigerian public universities, selected to reflect diversity in geography, infrastructure, and academic ranking. The three universities were purposely selected, one each from the northern, eastern, and southern regions of Nigeria. The universities include Federal University of Technology, Minna, Niger state, Federal University of Technology, Ikot Abasi, Akwa Ibom State and Imo State university. Within each university, two 100-level mathematics courses were selected. Students were assigned into two groups:

Experimental Group (n = 100): Receives LLM-assisted instruction, and

Control Group (n = 100): Receives traditional instruction.

Simple random sampling within each university ensures balanced group composition in terms of gender, academic performance, and technological access.

Students in the experimental group received blended instruction using an LLM-powered interface like GPT-4 via ChatGPT and the LLM support includes:

1. Step-by-step problem-solving with feedback.
2. Explanation of mathematical concepts in simplified language.
3. Integration with symbolic computing (e.g., solving equations).
4. Adaptive scaffolding and real-time questions and answers.

Students used these tools during tutorials, assignments, and guided lab sessions for a period of six weeks. Data was collected through pre-test and post-tests in mathematics, official course grades, focus group discussions and lecturer interviews. Qualitative data were collected using semi-structured interviews with lecturers and focus group discussions with students in the experimental group. These instruments explored perceptions of LLM use, changes in confidence and engagement, and practical classroom challenges. Observation notes were also used to triangulate findings and strengthen validity.

Results and Discussion

Table 1 below shows the demographic profile of respondents:

Demographic variables	**Experimental Group (n=100)**	**Traditional Group (n=100)**
Gender (Male/Female)	62/38	60/40
Mean Age (Years)	18.9	19.1
Device Ownership (%)	84	86

Prior Maths Grade (WAEC)	B3 or above (28%)	B3 or above (30%)

Table 1: Demographic profile of Respondents

Pre-Test and Post-Test Score Comparison

The test scores for the pre-test and post-test for both study groups are tabulated in table 1.1 below. The table addresses Objective 1 and Research Question 1 by comparing performance between students exposed to LLM-assisted instruction and those taught traditionally. The higher post-test mean score of the experimental group (71.2) compared to the control group (58.4) indicates that LLMs significantly improved students' mathematics performance.

Group	Pre-test Mean (SD)	Post-test Mean (SD)
Experimental Group	42.5 (8.44)	71.2 (7.69)
Traditional Group	43.1 (9.02)	58.4 (9.69)

Table 2: Pre-test and post-test Comparison of the Experimental and Traditional Groups.

The pre-test and post-test score comparison for both the experimental and traditional groups are represented by figure 1.0 below. Figure 1.0 visually demonstrates the performance gains addressed in Objective 1, with the LLM-supported group showing greater post-test improvements compared to the traditional group.

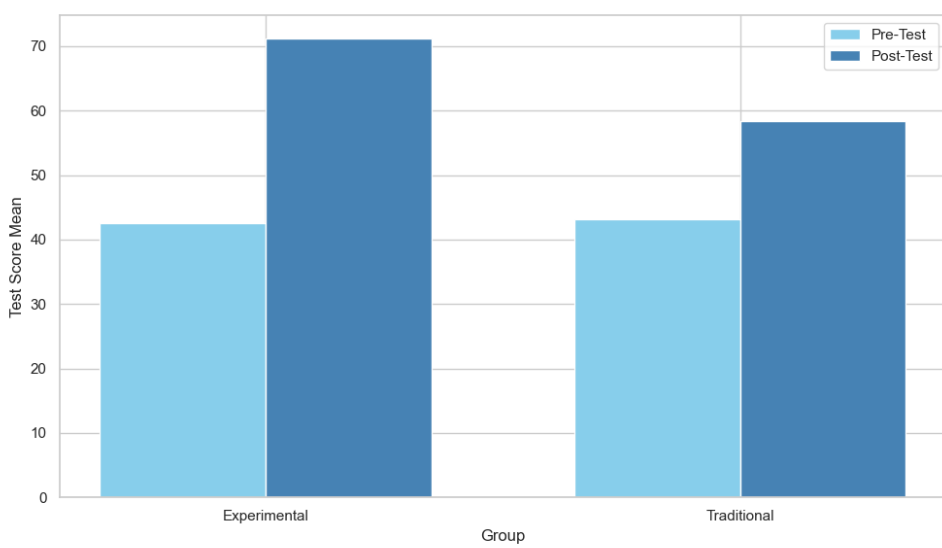

Figure 1.0: Comparison of Pre-test and Post-test Scores by Groups

Statistics Test

Table 3 below further supports Objective 1 and Research Question 1. It shows that the experimental group achieved a 67.5% improvement, nearly double the 35.5% improvement of the control group, confirming the effectiveness of LLM integration. These results suggest that the use of LLMs by students leads to fast learning improvement.

Test	Experimental Group	Traditional Group
Pre-test Mean	42.5	43.1
Post-test Mean	71.2	58.4
Improvement	28.7	15.3
Percentage Improvement (%)	67.5	35.5

Table 3: Summary of Test Statistics by Groups

Figure 1.2 below also addresses Objective 1, showing that the LLM-supported group maintained a consistent upward trend in performance across the 6-week period, unlike the slower improvement of the control group.

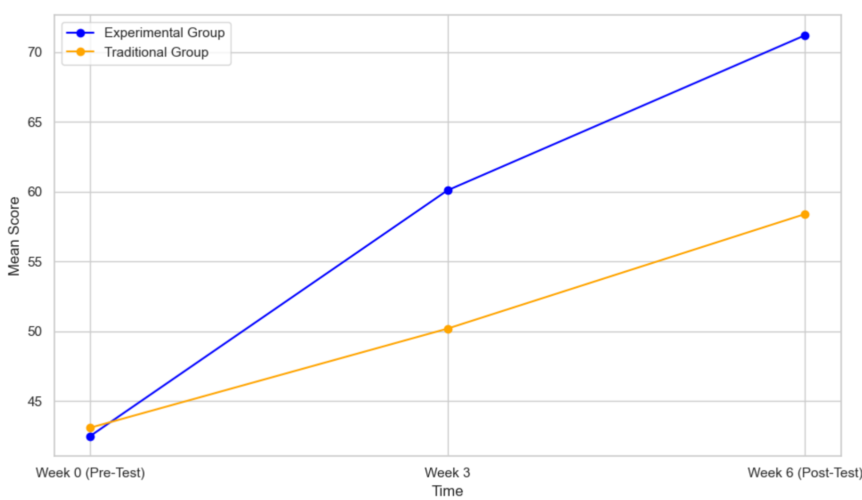

Figure 1.2: Performance Trend Over Time by Groups

Given the above results, we reject the null hypothesis, and therefore, conclude that the integration of LLMs into mathematics instruction does significantly improve the foundational mathematics competence of engineering and energy students in Nigerian tertiary institutions.

Inferential Statistical Analysis: Impact of LLMs on Mathematics Performance

To evaluate the statistical significance of the observed differences in student performance, an independent samples t-test was conducted on post-test scores between the experimental group and the traditional group. The analysis revealed that the experimental group ($M = 71.2, SD = 7.69$) significantly outperformed the traditional group (M = 58.4, SD = 9.69). The difference in mean was 12.8 points. The t-test produced the following result:

$$t(198) = 10.35, p < 0.0001$$

This result is considered extremely statistically significant by conventional standards. The 95% confidence interval for the mean difference ranged from 10.36 to 15.24, confirming that the observed improvement is robust and unlikely due to chance.

To determine the practical significance of this result, Cohen's d was calculated as follows:

$$d = \frac{M_1 - M_2}{SD_{pooled}}$$

Where: M_1 is the mean of the experimental group

M_2 is the mean of the traditional group

SD_{pooled} is the pooled standard deviation of both groups

The pooled standard deviation is given by $SD_{pooled} = \sqrt{\frac{{SD_1}^2 + {SD_2}^2}{2}}$, where SD_1 and SD_2 are the standard deviation for the experimental and traditional groups respectively.

Substituting the values of SD_1 and SD_2 of the post-test as captured in table 1.1, $SD_{pooled} = 8.75$. Therefore,

$$d = \frac{12.8}{8.75} \approx 1.46$$

The effect size (Cohen's d ≈ 1.46) indicates a very large practical impact of LLM integration, demonstrating not just statistical significance, but also meaningful improvement in students' mathematical competence.

Qualitative Feedback

Qualitative feedback was obtained through semi-structured interviews, focus group discussions, and observation notes, which provided insights into students' and lecturers' experiences. The feedback from students directly address Objective 2 and Research Question 2. They illustrate improved understanding, increased confidence, and reduced fear of asking questions, showing that LLMs positively shaped students' learning experiences. Lecturers' feedback addresses Objective 3 and Research Question 3. They reported increased classroom participation and reduced workload when LLMs were used to grade students. However, they also cautioned about students' over-reliance on AI and challenges with digital infrastructure, highlighting practical considerations for adoption. Some of the feedback from students include:

1. **Clarity and Confidence**: "I now understand integration steps better with AI explanation, it feels like a personal tutor."
2. **Engagement and Exploration:** "It's easier to ask the LLM questions than asking the lecturer, I have no fear of looking or sounding stupid."
3. **Challenges Noted:** Internet access during tutorials was inconsistent and some students struggled to interpret mathematical notation generated by the ChatGPT.

Some feedback from lecturers include:

1. **Positive Feedback:** Increased student participation and attendance in LLM-supported classes and LLM helped offload repetitive questions during office hours.
2. **Cautions:** Some students relied too heavily on LLMs without understanding the basic concepts leading to ethical concerns about AI writing assignments.
3.

Conclusion

This study investigated the impact of large language models (LLMs) on improving foundational mathematics competence among engineering and energy students in Nigerian tertiary institutions. Motivated by persistent challenges; ranging from poor secondary mathematics preparation to outdated pedagogical approaches, the study aimed to assess whether integrating LLMs could serve as a transformative educational tool. Grounded in a mixed-methods design, the research compared academic performance and learning experiences between a traditional group and an experimental group (LLM-supported instruction). Quantitative data from pre- and post-tests, along with official course grades, were complemented by qualitative insights gathered through focus groups and instructor interviews.

The results were statistically and practically significant. An independent samples t-test revealed a notable improvement in the LLM-supported group ($t(198) = 10.35$, $p < 0.0001$), with a mean score increase of 12.8 points. The effect size (Cohen's $d \approx 1.46$) confirms that this is not only statistically meaningful but also pedagogically impactful. These findings affirm that LLMs can serve as transformative tools in mathematics education, especially in resource-constrained environments. Students experienced increased clarity, confidence, and participation, while instructors reported reduced cognitive load and improved student engagement. Nonetheless, issues such as infrastructure limitations and over-reliance on AI highlight the need for structured implementation strategies.

In conclusion, LLMs hold tremendous promise in addressing long-standing challenges in STEM education. When properly integrated, they can democratize access to high-quality learning, accelerate conceptual understanding, and equip students with the quantitative tools required for innovation in engineering and energy sectors. Future research should examine longitudinal learning outcomes, integrate LLMs into curriculum reform strategy, and develop training models for educators to ensure sustainable and ethical implementation.

Recommendation

Based on our findings, we made the following recommendations to guide policy development around AI integration into Nigerian tertiary STEM education:

1. Universities and policymakers should invest in reliable internet connectivity, power supply and sufficient computing devices. Funding bodies such as TETFund and state governments can prioritize upgrading campus networks and computer labs so that all students and faculty can access LLM tools without technical barriers.
2. Universities should organize professional development workshops for instructors on effective use of LLMs. The training should emphasize the teacher's role in an "AI-enhanced" classroom, guiding students and validating AI outputs to prevent over-reliance on technology. Developing formal training programs for educators will help ensure the sustainable and ethical use of AI tools.
3. The Federal Ministry of Education should revise STEM curricula to include AI-assisted learning activities and contextually relevant math problems. Encouraging mentoring programmes and collaborative problem-solving supported by LLMs. Instructors might use LLMs to generate step-by-step tutorial problems or adaptive hints, leveraging AI to automate feedback and cut grading time while engaging students more deeply.
4. The Federal Ministry of Education should establish guidelines on acceptable AI use in coursework and assess academic integrity. Formal policy frameworks can define how students may use LLMs on assignments and how faculty will monitor its usage. Universities on the other hand, should collect data on learning outcomes and adjust strategies as needed, effectively creating structured implementation plans.

Each of these recommendations will help Nigerian tertiary institutions harness LLMs as powerful learning tools while mitigating the challenges identified in this study.

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