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Facilitating Cognitive Load Management and Improved Learning Outcomes and Attitudes in Middle School Technology and Vocational Education Through AI Chatbot

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Abstract

Junior Secondary School (JSS) or middle school education is peculiar as it involves the introduction of a wide array of subjects across the sciences, arts, humanities, business and vocational fields to young learners. This situation can be ovewhelming, resulting in high cognitive load (CL), with consequent poor learning outcomes, and other negative issues including high dropout rates, requiring urgent attention. AI tools have been explored for addressing multiple learning issues. AI chatbots are particularly useful based on their ability to support individualized learning, pre-training, and other concepts that can facilitate CL management. This study evaluated the impact of an AI-based chatbot system for reducing students' CL and improving learning outcomes, attitude and retention among JSS students. A quasi-experimental study with 120 students was conducted over an 8 week period with 24 learning sessions. The experimental group (N=60) learnt using 'iLearnTech', an AI Chatbot developed specifically for the study. The control group (N=60) learnt through the traditional approach with no chatbot. Learning content was based on the JSS Basic Technology education, a precursor to TVET. Data was collected using the Cognitive Load Measure, the Basic Technology Achievement Test, Students' Attitude Survey (SAS), and Students' Retention Test. The experimental group exhibited huge reductions in CL and corresponding improvements in learning outcomes, attitude and retention. The results also confirmed known relationship between the dependent variables and highlights the potential of AI powered educational tools for addressing diverse educational issues including promoting equitable access, and sustainable education in developing nations and resource-constrained environments. This work contributes to ongoing discussions on AI applications in education. Its novelty lies in its exploration of AI technology in addressing CL issues in the context of junior secondary education. Implications for educational policy and practice, particularly curriculum design and e-learning integration are highlighted.

1. Introduction

Cognitive load (CL) has emerged as a critical element influencing the effectiveness of learning, drawing attention from educators, researchers, and instructional designers alike. Cognitive load has been increasingly recognized as a key factor with critical implications for effective learning (Chen & Chang, 2024; Kala & Ayas, 2023; Lin et al., 2024). Its impact on attention, retention, and optimal cognitive abilities required for problem-solving has been discussed by many researchers (Kirschner et al., 2018) and in many learning contexts including instructional design and multimedia instruction has been noted. Its significance for effective education has been discussed in relation to various subjects including science (C. H. Chen & Chang, 2024), computing (Zhan et al., 2022), teacher education (Timothy et al., 2023) and others. It has also been examined at all levels of education from primary through graduate school (Du et al., 2023; Karabay & Meşe, 2024; Lin et al., 2024; Zhan et al., 2022). Cognitive Load Theory (CLT) posits that instructional strategies should be designed to optimize the capacity of the working memory for effective learning to occur.

In practice, the concept of CL has been discussed across different subjects and levels of education, however, the impact of cognitive load can become particularly pronounced at the lower secondary or middle school level, where students are introduced to a wide array of subjects simultaneously. In some countries, students may be required to study up to nine (9) subjects, whereas students in some other countries (e.g. Singapore and Nigeria) often face much greater academic demands, with twelve (12) to fifteen (15) subjects. This heavy academic load places a substantial cognitive burden on students (Estes, 2015; Kala & Ayas, 2023), making it difficult for many to cope with the mental demands of processing, integrating, and retaining large volumes of information across multiple subjects.

The high CL faced by learners at this stage of education often lead to several adverse outcomes including poor academic performance, frustration, burnout, and, in extreme cases, school dropout (Subedi, 2022; Verlumun Celestine et al., 2024). This is a particularly pressing concern in educational systems where foundational knowledge acquired at the lower secondary level serves as a critical steppingstone for future studies at upper educational levels. For many students, simultaneous exposure to subjects in science, arts, humanities, and vocational disciplines can create an unusual situation of extremely high element interactivity (Kala & Ayas, 2023),resulting in an overwhelming learning environment, and leading to disengagement and academic struggles. Addressing this challenge, therefore, has become an urgent priority for educators, policymakers, and researchers alike, as solutions are sought not only to reduce cognitive overload but also foster improved learning outcomes.

Fortunately, the rapid advancement of educational technology, particularly in the field of Artificial Intelligence (AI), has provided new avenues for tackling many educational challenges (Kabudi, 2022; Kim et al., 2022). AI-powered educational tools, including chatbots, are increasingly being explored as potential solutions for optimizing learning, improving learning environments and reducing mental stress on students (Okonkwo & Ade-Ibijola, 2021; Rudolph et al., 2023). These tools have the potential to personalize learning experiences, adapt instructional content based on individual student needs, and provide real-time feedback, all of which can contribute to reducing CL (Chandrasekaran, 2024; Chong et al., 2012). Chatbots have garnered attention due to their ability to provide immediate assistance, answer questions, and offer explanations in an interactive manner, mimicking one-on-one tutoring experiences (Guo et al., 2023; Okonkwo & Ade-Ibijola, 2021). This is critical in environments where teachers may not always be available to provide individualized support, especially in overcrowded classrooms or remote learning settings.

The promise of AI-powered chatbots lies in their ability to scaffold learning (Kay, 2023; Lim et al., 2023) by breaking down complex concepts into more manageable chunks. This approach aligns with cognitive load theory, which emphasizes the importance of reducing extraneous load and managing intrinsic load. By offering explanations in small, digestible units, chatbots can help students focus their cognitive resources on the task at hand, facilitating deeper understanding and better retention of information. Additionally, the interactivity of chatbots allows students to learn at their own pace, revisiting explanations as needed without the pressure of keeping up with the rest of the class.

AI-powered chatbots can assist in managing cognitive load by offering adaptive learning experiences tailored to each student's unique learning profile. For example, a chatbot can assess a student's current level of understanding and adjust the difficulty of questions or problems based on that assessment. This personalized approach ensures that students are not overwhelmed with material that is too complex, nor are they bored by content that is too simple. As a result, students can engage in learning activities that are appropriately challenging, which have been shown to enhance motivation and improve overall learning outcomes (Subedi, 2022). In this way, AI chatbots can serve as valuable tools for maintaining optimal levels of cognitive load, ensuring that students remain engaged and motivated to learn.

Cognitive load is a key factor that can influence students' ability to learn effectively, especially at the lower secondary level where students are required to manage diverse subjects simultaneously. AI-powered tools, particularly chatbots, thus offer promising solutions for mitigating the mental demands of learning by providing personalized, adaptive learning experiences and breaking down complex concepts into more manageable parts.

J. of Technical Education and Training Vol. 16 No. 3 (2024) p. 114-131

As educational technologies continue to evolve, it is essential to explore and implement these innovative tools to address the cognitive challenges faced by students in today's demanding academic environments.

2. Literature Review

2.1 Cognitive Load

Cognitive Load Theory (CLT) was developed by John Sweller (Sweller, 2011) as a comprehensive framework for understanding the use of cognitive resources in learning and problem-solving (Karabay & Meşe, 2024; Ninomiya et al., 2024; Sweller, 1988). The theory has its root in the limited capacity theory (Mayer, 2024; Ninomiya et al., 2024) which posits that the working memory is a capacity limited information channel. As such, when it is placed in a position whereby its maximum capacity is exceeded, its processing power fails. Within this capacity is where optimal learning occurs and when this maximum level is exceeded, cognitive overload results (Bruen & Kelly, 2017). Effective learning minimizes extraneous load and maximizes germane load. Understanding of these processes enables educationists and instructional designers to employ refined tools for analyzing and optimizing learning experiences.

Studies on CLT have yielded evidence-based strategies which helps reduce cognitive load in learning. These strategies include the use of worked examples (Adeniji & Baker, 2023; Costley et al., 2024; Garces et al., 2023) which provide step-by-step demonstrations of problem-solving processes. Another one is the split-attention effect (Arevalo-Mercado et al., 2023; de Koning, 2024; S. Zhang et al., 2022), which emphasizes the importance of integrating related information sources; and the modality effect (Cao et al., 2009; Castro-Alonso & Sweller, 2020; Leahy & Sweller, 2011) which leverages the benefits of presenting information through multiple sensory channels. These approaches have demonstrated efficacy across diverse educational contexts, including complex professional training environments.

2.2 Working Memory and Learning

The implication of Cognitive Load Theory (CLT) in education is highlighted by the nature and limitations of the multi-store memory system (Lerch et al., 2016; Wan et al., 2021) shown in Figure 1. According to Atkinson and Shiffrin (1968), information goes through the sensory memory into the working memory where it goes through encoding before being stored in the long-term memory. From here, it can be retrieved for future use. This is the goal of effective learning. Information can also be lost through decay (forgetting) between the sensory store and the WM, and between WM and the LTM. The WM has a limited capacity for storing information (Ninomiya et al., 2024), and when this maximum capacity is exceeded, encoding and transfer to LTM (retention) can fail (Li et al., 2022). The challenges of an overloaded working memory have wider implications for retention of learnt information. Several concerns including poor achievement (Zhan et al., 2022), confusion and frustration (Novak et al., 2023) and drop-out (Naidoo, 2024) have been linked to cognitive overload.

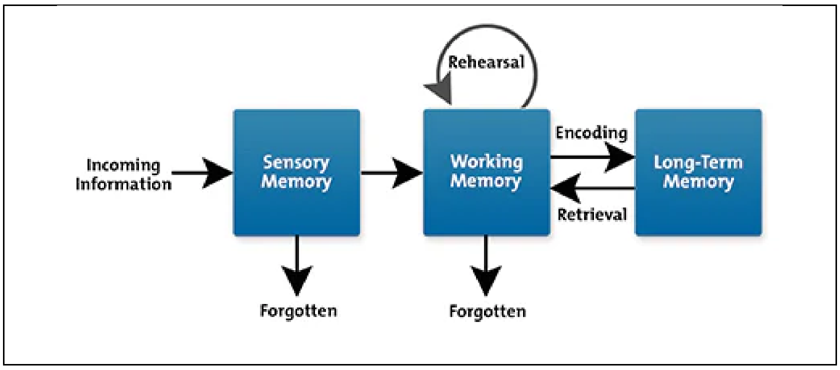

Fig. 1 *Multistore Model of Human Memory (Atkinson & Shiffrin, 1968)*

2.3 Cognitive Load, Attention, Retention

Attention refers to the selective focus of awareness on specific stimuli (Al-Furaih & Al-Awidi, 2021; Mendoza et al., 2018). In learning, it is responsible for how much decay (forgetting) happens between the reception of stimuli and its processing in the sensory memory. Retention is the ability to store and retrieve stored information over time (Goldenhaus-Manning et al., 2024). It has been shown to be influenced by several factors including how the information is stored by the learner, which is also directly linked to how the instruction is presented. Designing effective learning strategies is thus directly connected to the interplay between the concepts of attention, retention and cognitive load.

Previous studies have consistently demonstrated that excessive cognitive load can hinder learning by diverting attention from essential information and reducing the capacity for encoding and retrieval. Mayer (2011) suggested that instructional design should minimize extraneous cognitive load and maximize germane cognitive load. Kirschner and Sweller (2018) highlighted the importance of managing CL to optimize learning outcomes. Paas and van Merriënboer (Paas et al., 1994) emphasized the significance of creating learning environments that minimize extraneous load and maximize germane load.

Attention is essential for encoding and retaining knowledge (Goldenhaus-Manning et al., 2024). Learners with better attentional control have been shown to be more likely to achieve higher levels of learning outcomes (Ázmi et al., 2023; S. W. Chen et al., 2019). Attention is however a limited resource, and high CL can impair a learner's attentional capacity, leading to difficulties in focusing on relevant information. This may eventually result in reduced retention. The 'levels of processing' theory (Ewoldsen, 2020; Shen, 2024) highlights the relationship between attention and retention; they suggest that deeper levels of processing lead to better retention.

Cognitive load, attention, and retention are thus interconnected concepts that significantly influence learning outcomes. Understanding the interplay between them can help educators in designing instructional strategies that not only minimize cognitive load, but also enhance attentional focus, and promote effective retention. The complexities of the relationships between these concepts and the development of innovative approaches to optimize learning experiences are significant areas of focus for future research.

2.4 Novel Ways of Addressing Cognitive Load Issues

In recent years, researchers have explored innovative strategies to address cognitive load issues and enhance learning effectiveness. One promising approach is the use of adaptive learning technologies. These technologies can tailor instructional materials and pace to individual learners' needs, reducing cognitive load by presenting information at an appropriate level of difficulty. For example, studies by Zhang et al. (2019) have demonstrated the effectiveness of adaptive learning platforms in reducing cognitive load and improving learning outcomes in various domains.

Gamification has also emerged as a promising approach to addressing cognitive load. By incorporating game-like elements into learning experiences, student motivation and engagement can be improved (Kuo & Chuang, 2016), thus reducing perceived CL. Gamified learning environments can improve learning outcomes and reduce cognitive load (C. H. Chen & Chang, 2024) especially in subjects that may be perceived as boring or challenging.

Another strategy that has gained attention in reducing cognitive load in recent years is microlearning (Lopez, 2024; Susilana et al., 2022), which involves breaking down learning content into small, digestible chunks, which can help to reduce cognitive load and improve learning efficiency. Microlearning is a concept that is related to the pretraining principle (Meyer et al., 2019), and can be an effective strategy for teaching complex topics and reducing cognitive load.

While these novel approaches offer promising solutions to addressing cognitive load issues, it is important to note that their effectiveness may vary depending on the specific learning context and learner characteristics. Further research is needed to fully understand the conditions under which these strategies are most beneficial. In addition, dealing with learners' CL in regulated learning environments of middle school may require more creativity on the part of instructors.

2.5 Middle School Education

2.5.1 Curriculum Issues

The design of school curricula that features a balance between learners' capacity and the need to cover a wide array of subjects to provide a comprehensive foundation for young learners can be challenging. This can become a source of pressure and cognitive overload for students. For example, the Junior Secondary School (JSS) Curriculum of the West African Examination Council (WAEC), which is equivalent to middle school or grade 7 – 9 curricula in other nations, have one of the highest number of compulsory subjects (Olugbade et al., 2024). It requires students to study and pass fifteen (15) subjects compared with 8 – 9 for their counterparts in other national education systems (See Table 1).

This demand has the potential to overload young learners cognitively, affecting their performance negatively, and leading to dropping out (Bolaji & Onikoyi, 2022). Recent studies (Olabisi et al., 2022; Olugbade et al., 2024) have also shown that JSS students have been increasingly scoring low grades, and highlighted a link between high dropout rates in secondary education and the enormous workload at JSS level (Bolaji & Onikoyi, 2022). The highest global out-of-school youths noted as a feature in some West African countries (Verlumun Celestine et al., 2024) may also be connected to this problem. The pressure to perform across such a diverse array of subjects may also result in reduced engagement and motivation in individual subject areas. This dilution of focus could also potentially hinder students' ability to develop genuine interest and passion for specific disciplines (Ryan & Deci, 2000) or explore opportunities for specialization, potentially impacting their long-term academic trajectories and career aspirations (Eccles & Wigfield, 2002). This issue has been identified as a key concern to the Federal Ministry of Education (Taiwo & Ajibike Aluko, 2023) and points to the need for immediate attention to the problem. Therefore, for the JSS's usually overloaded curriculum, particularly in developing nations with limited access to high-quality learning tools and resources, there is an urgent need for investigating novel ways of managing cognitive load and enhancing learning.

Table 1 *JSS/Lower secondary/middle school compulsory subjects in different countries*

USA (8th Grade)	UK (Grade 8)	Kenya (Lower Secondary)	Nigeria (Junior Secondary School)
English Language	English Language	English Language	English Language
Pre-Algebra/Algebra	Mathematics	Mathematics	Mathematics
Science	Science	Integrated Science	Basic Science
Foreign Language (optional)	Modern Foreign Languages	Kiswahili/Kenyan Sign Language	Nigerian Languages
Social Studies	Art and Design	Social Studies	Social Studies
Health Education (optional)	History	Health Education	History
Technology/ Comp. Science (optional)	Design and Technology	Religious Studies	Computer Science
Physical Education	Physical Education	Physical Education	Physical Education
Arts or Music (optional)	Music	Pre-Technical & Pre-Career Education	Religious Studies
	Citizenship	Life Skills Education	Civic Education
	Geography	Business Studies	Geography
		Agriculture	Vocational subjects (e.g., Agriculture, Home Economics, Technical Drawing)
			Fine or Creative Arts
			Business Studies
9	11	12	15

2.5.2 Nigerian JSS Basic Technology Education

The Nigerian Junior Secondary School (JSS) Basic Technology education curriculum is designed to provide students with foundational technical knowledge and skills essential for technological literacy and future vocational pursuits. Key concepts taught include materials and processing, hand tools, energy systems, basic electronics, and technical drawing, with an emphasis on hands-on activities and problem-solving (Alade & Lemo, 2024). The curriculum aims to provide students with foundational knowledge that prepares them for advanced studies in technical fields or immediate vocational skills application. By integrating practical tasks and theoretical instruction, it helps develop critical thinking and innovation, aligning with the broader goals of STEM education (Danjuma Dami, 2019; Federal of Nigeria, 2004).

This curriculum closely aligns with Technical and Vocational Education and Training (TVET) by preparing students for technical and industrial careers. Basic Technology equips learners with the foundational skills necessary for various trades, thereby creating a pathway to TVET programs and addressing workforce development needs (Sani, 2020). Furthermore, the curriculum contributes significantly to Nigeria's national development by fostering self-reliance, reducing unemployment, and addressing skill gaps in the economy. Its emphasis on practical skills and creativity positions students as future contributors to industrial growth and sustainable development (Adedigba & Abdullahi, 2023; Alade & Lemo, 2024).

2.6 Artificial Intelligence in Education

Artificial Intelligence (AI) has become a powerful tool in various fields including education where it promises to revolutionize learning experiences and results (Chiu et al., 2023; Okonkwo & Ade-Ibijola, 2021; Ouyang et al., 2018). There has been a remarkable growth of the integration of Artificial Intelligence (AI) in education, especially the roles of several AI-powered applications like chatbots (Okonkwo & Ade-Ibijola, 2021), personalized learning systems and advanced intelligent tutoring platforms (Edwards & Cheok, 2018). In particular, AI Chatbots, as key AI applications have shown commendable potential in human-like interactions and personalized learning experiences (Gherhes & Obrad, 2018; Sanusi et al., 2023). These AI-driven educational tools can adapt to individual student needs, offer immediate feedback, and provide round-the-clock support, thereby enhancing the learning process in ways that traditional methods often cannot. These AI technologies present various solutions for educational challenges, including cognitive load management.

2.6.1 The Promise of AI Chatbots in Education

AI-powered chatbots are particularly applicable in school education due to both their novelty and interactive interfaces which enable them to mimic human-like interactions and provide personalized support to learners. Recent studies (Hume et al., 2022) have shown that chatbots have the capacity to significantly improve student participation levels and enhance their learning performance. These technologies help learners to learn more effectively by supporting diverse learning styles (Kaiss et al., 2023; Rajkumar & Ganapathy, 2020) and providing access to extensive information to support learning for both instructors and learners. In addition, AI systems can simplify the subject matter by breaking it into smaller units that students find easier to understand (Rossi et al., 2011) or deliver content at a pace that matches the ability of individual learners and provide just-in-time learning support and assistance. Chatbots thus hold the potential for cognitive load management for learners facing the challenges of huge subject demands as well as contribute to fostering a positive attitude to learning. The potential of AI chatbots, particularly in the context of overloaded curriculum in middle school education remains largely untapped. This study therefore addresses a significant gap in the literature by combining insights from CLT with cutting-edge AI technology. Findings will contribute valuable insights in the applications of emerging technologies, especially AI in education while simultaneously addressing pressing challenges related to CL, performance, attitude, and other working memory-related issues.

2.6.2 Limitations of AI-Powered Chatbots in Education

While AI-powered chatbots offer significant potential to enhance education, they also present several technical, educational, and practical limitations that must not be overlooked. The high dependency of chatbots on the quality and quantity of the data they are trained on means biased training data will result in inaccurate, or incomplete systems which may also mean the chatbot's responses may be flawed. As technological tools, chatbots have limited understanding of context and lack emotional intelligence; they may therefore struggle to understand complex queries or context-specific details and unable to empathize with students or provide the emotional support necessary for effective learning and well-being. Since AI models can inadvertently perpetuate biases present in the data they are trained on, unfair or discriminatory responses may result.

In terms of educational implications, over-reliance on chatbots can diminish opportunities for meaningful human interaction, which is essential for social and emotional development. AI may also struggle with limited creativity and critical thinking skills, having been designed in many cases to provide pre-programmed or factual responses. Several studies have also focused on concerns about data privacy and security when AI tools are used in education, especially when dealing with sensitive student information.

Some of the practical Considerations borders around cost and accessibility, and the technical expertise required for development and implementation which may not be readily available in all educational settings. The ethical implications of using AI in education, including potential biases and misuse of data are also practical issues to be carefully considered.

To mitigate these limitations, AI chatbots are therefore best employed as tools to augment, rather than replace, human interaction. Careful selection and monitoring are essential to ensure appropriate and ethical use. This also highlight an important area of focus for ongoing research and development in the use of AI chatbots in education.

2.7 Adaptability of AI Chatbots to Diverse Learning Styles

AI-powered chatbots can be a valuable tool in education, offering personalized learning experiences that cater to diverse learning styles. AI chatbots can provide visual aids like diagrams, charts, and infographics to enhance understanding or offer audio explanations, read-aloud features, and audio summaries to cater to auditory learners. While direct physical interaction is limited, chatbots can guide learners through simulations, virtual experiments, and interactive problem-solving exercises, thereby catering to kinesthetic learners. By providing text-based information, quizzes, and writing prompts, they can both engage and cater to read/write learners these learners.

Within dynamic classroom settings however, chatbots may struggle with real-time, spontaneous interactions, especially in fast-paced classroom discussions. Their comprehension of complex queries and unstructured or open-ended questions may also affect the accuracy of their responses. While internet technology has made giant strides in recent years, connectivity and software glitches remain major challenges in resource-constrained areas and can hinder the effectiveness of chatbot interactions.

3. Theoretical Framework and Hypotheses Development

This study is primarily grounded in Cognitive Load Theory (CLT), which provides an essential framework for understanding how the human brain processes, stores, and retrieves information. CLT explains that the human working memory has limited capacity, and when learning tasks become too demanding, cognitive overload can occur, which hinders learning and retention (Sweller et al., 2011).

For learners at the lower secondary level, where academic demands are often heavy, cognitive overload is a significant concern. Educational technology, specifically AI-powered chatbots, can tailor content to the learner's pace, providing individualized support, or intervene by reducing extraneous load through personalized, adaptive learning interventions. They can offer real-time feedback and explanations, or act as cognitive scaffolds, thereby reducing both extraneous and intrinsic load (Chaudhri et al., 2013). The ability of chatbots to interact with students in a dynamic, conversational manner also allows for the immediate addressing of questions, reducing the mental strain that comes with delayed feedback in traditional classroom settings.

According to CLT, reducing CL can facilitate better retention by allowing learners to focus more mental resources on constructing and automating schemas, that is, the mental structures necessary for understanding and storing new knowledge (Clause, 2016; Gilboa & Marlatte, 2017). AI-powered chatbots can enhance retention by optimizing opportunities for active learning through quizzes, practice tasks, and interactive problem-solving activities to support long-term memory formation (Subedi, 2022). The lowering of CL also has potential for improved learning outcomes which in turn has implications for improved learner attitudes (Olutosin et al., 2017).

Given this theoretical foundation, the following hypotheses are proposed:

H1: The use of AI-powered chatbots will significantly reduce junior secondary school students' CL.
H2: Learners who use AI-powered chatbots will show improved learning outcomes.
H3: Learners who use AI-powered chatbots will exhibit greater retention of information.
H4: Cl will have a strong inverse relationship with learning outcomes, retention and attitude
H5: Learning outcomes, retention and attitude will have strong direct relationships.

These hypotheses build on the premise that when extraneous and intrinsic cognitive loads are managed, students can devote more cognitive resources to meaningful learning processes, resulting in improved educational outcomes.

By exploring how AI-driven personalized learning support can be leveraged to reduce cognitive load and enhance learning outcomes in Nigerian junior secondary schools, this study stands at the forefront of efforts to revolutionize education in developing contexts. The findings from this research could have far-reaching implications, not only for the national education system grappling with the challenges of balancing the demands of curriculum design, cognitive load management, and the integration of educational technologies at middle school levels. Specific research objectives of the study include to verify:

1. If AI chatbots significantly reduces junior secondary school students' CL.
2. If AI chatbots significantly improves junior secondary school students' learning outcomes.
3. If AI chatbots significantly improves junior secondary school students' attitude.
4. If AI chatbots significantly improves junior secondary school students' retention.
5. The nature of the relationship between the dependent variables.

4. Methodology

This section describes the research design, procedure, participants and instrumentation for this study. It provides detailed information on the conduct of the experimental study to address the research objectives.

4.1 Study Design

The primary aim of this research is to investigate the capability of AI-powered chatbots to effectively reduce learners' CL, improve performance, attitude, and retention. The study employed a quasi-experimental design with pre-test, post-test, control group design (Jangland et al., 2012; Morris et al., 2019). An experimental design is appropriate based on the focus of the study to evaluate the effectiveness of a learning tool. The study was conducted within the context of the junior secondary school system in south-western Nigeria. The learning content was developed using the Basic Technology subject syllabus. Among other things, the subject covers "foundations, building components, woodworking joints, electrical circuits, and workshop tools. Students are also expected to demonstrate understanding of key technical concepts and skills including the ability to "define terms, draw diagrams, differentiate between concepts, and give examples". The Basic Technology JSS subject was also reported to have a high rate of failure (Afuwape & Olugbuyi, 2019).

4.2 Participants

One hundred and twenty (120) JSS2 students, aged 12-14 years, were recruited from four public secondary schools in the Ibadan, Nigeria to participate in the study. The schools were purposefully selected based on criteria, including the availability of ICT facilities, and similar socio-economic backgrounds and academic performance levels, ensuring that the effect of potential confounding variables were minimized and both groups were comparable. Participants were then randomly assigned to the experimental group (n = 60) or the control group (n = 60), with an equal distribution of male and female participants. Ethical approval was obtained from the First Technical University Ethics Committee and the Oyo State Ministry of Education, Science and Technology. Informed consent was obtained from the parents/guardians of participating students who also gave verbal assent for the study. Data was anonymized to ensure confidentiality, adhering to stringent ethical standards.

4.3 Development of the AI Chatbot

The AI Chatbot tool employed in this study is named iLearnTech. It was built using the intuitive no-code, conversational chatbot builder, Landbot, was employed in building the chatbot. Landbot "allows users to build conversational assistants for the web, WhatsApp, Facebook Messenger, or use API to create a bot for any other third-party app." (Landbot, 2024). The no-code platform is ideal for non-developers, allowing users to employ the visual builder. The inbuilt conditional logic allows the creation of personalized and dynamic conversations and the integration options supports APIs, webhooks, and third-party apps like Zapier. Landbot also supports analytics, providing insights for optimizing chatbot performance. These characteristics enables users to effectively design and deploy chatbots tailored to specific needs.

Building a chatbot on the Landbot is thus a user-friendly process that involves creating conversational workflows without the need for advanced programming skills. The user can choose from a range of pre-built templates designed for various use cases or build from scratch to create a fully customized chatbot experience. Landbot further allows integration of third-party tools that might be useful for various tasks. Third-party apps (e.g., Google Sheets, Mailchimp, etc.) can also be connected, thus allowing for automation of tasks such as sending collected data to a database or sending important notifications to team members.

Landbot provides a real-time preview of the conversation, allowing the user to test the bot to see how it responds to user inputs, and ensuring that all flows and logic are functioning correctly. The bot's appearance can be customized to according to user requirements. This is followed by monitoring and analysis and performance tracking using the bot's built-in analytics. Metrics like conversation completion rate, drop-off points, and user engagement provide insights into how the bot is performing and where improvements can be made. The feedback can be used to make adjustments to the bot's flow, improve responses, or add more features.

4.4 iLearnTech: AI Chatbot for Basic Technology Education

The AI chatbot in this study, iLearnTech, was developed as an instructional tool for learning Basic Technology concepts and ideas rather than as a general Generative AI tool like ChatGPT. Basic technology education provides foundational knowledge and skills in areas such as mechanics, electronics, and computer applications, which are essential for success in TVET programs. It introduces students to the principles of design, problem-solving, and technical systems, preparing them for more specialized training in TVET. The landbot platform is subscription-based and accessible online. During the study period, students interacted with the Chatbot based on the learning content. The experimental group engaged with iLearnTech as their primary tutoring tool for the Basic Technology subject. By contrast, the control group attended their regular Basic Technology classes without access to the iLearnTech chatbot. iLearnTech provided the experimental group with consistent and focused support, while the control group received traditional instruction. Figures 2 - 5 are screenshots of iLearnTech in action (introducing itself, answering questions intelligently, etc.).

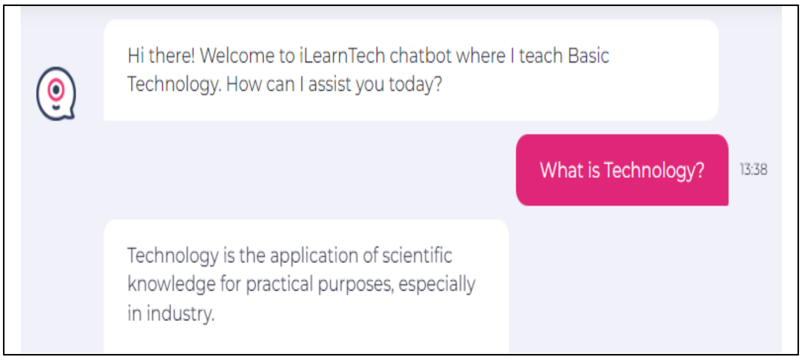

Fig. 2 *AI Chatbot iLearnTech Introducing itself*

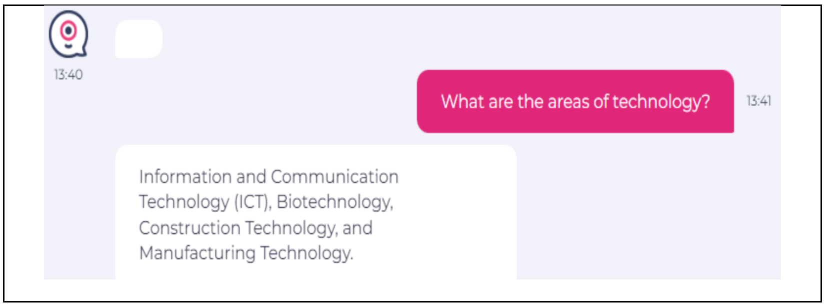

Fig. 3 *iLearnTech answering questions*

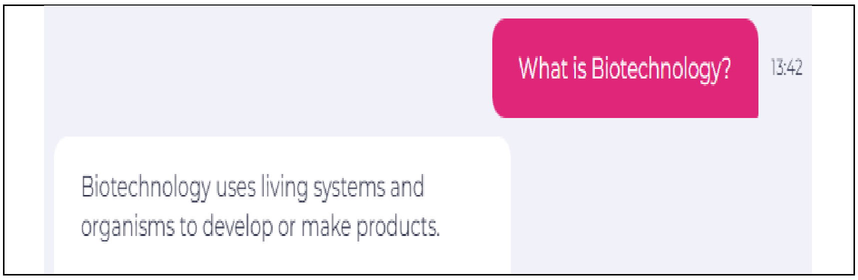

Fig. 4 *iLearnTech chatbot answering more questions*

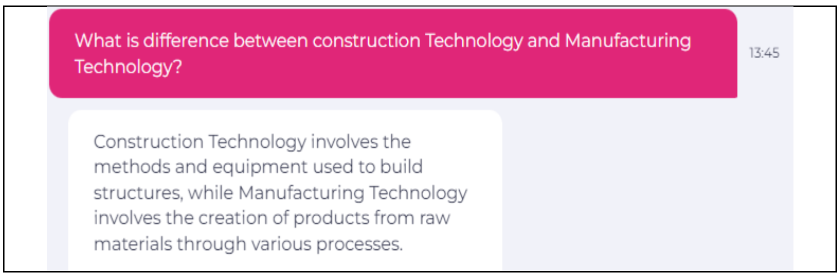

Fig. 5 *iLearnTech accurately differentiating*

4.5 Research Instruments

Based on the four (4) dependent variables (DVs), the study utilized four research instruments: the Cognitive Load Measure (CLM), the Basic Technology Achievement Test (BTAT), Students' Attitude Survey (SAS), and Students' Retention Test (SRT). The CLM was adapted for educational purposes from the NASA Task Load Index (NASA-TLX) by Hart & Staveland (1988) to measure perceived cognitive load.

The NASA-TLX includes six subscales measuring mental demand, physical demand, temporal demand, performance, effort, and frustration on a scale from 0 to 100, with higher scores indicating higher CL. The tool's reliability and validity in educational contexts have been well-documented (Rubio et al., 2004). Participants completed the CLM after their learning sessions to provide a measure of the cognitive demands imposed by the learning tasks.

Learning outcome was measured with the BTAT; a 10-item multiple-choice test adapted from an existing instrument by Olugbade et al. (2024). BTAT measures students' knowledge and understanding of Basic Technology concepts. The 10 multiple-choice items were derived from standardized past questions from the Basic Education Certificate Examination (BECE), a National Examination Council (NECO)-administered test for students completing the JSS programme. The BECE assesses proficiency in core subjects including Math, English, Science, and Social Studies. BTAT items are rigorously validated by experts in science curriculum development and Special Education from the Ministry of Education, as well as senior researchers in the field of tests and measurement at Obafemi Awolowo University. The BTAT has undergone several refinements and standardization and has been reported with a high internal consistency score of $\alpha=0.871$ and a Kaiser-Meyer-Olkin (KMO) coefficient of 0.881, indicating high factorability for identifying underlying patterns or constructs within the research variables.

Attitude to learning was measured using a 20-item SAS instrument based on Olugbade et al. (2024). The SAS questionnaire has also been reported with high internal consistency ($\alpha=0.867$) and KMO coefficient (0.936). Retention was measured using the Students' Retention Test (SRT) which is a modified version of the BTAT. It was administered four weeks after intervention to measure retention of the same Basic Technology concepts that were measured by the BTAT.

4.6 Procedure

Pre-intervention, all participants completed the BTAT and SAS. The intervention lasted for eight-weeks of regular 40-minute Basic Technology class periods with the experimental group using the iLearnTech chatbot as the basic tutor. Lessons were conducted for 3 days each week. The Control group attended their classes without access to the iLearnTech chatbot during the same days and weeks. Post-intervention, participants completed the NASA-TLX, BTAT, and SAS followed by the SRT four weeks after the intervention.

The experimental and control groups were set up in week 1. All participants also took the pretest in week 1. This is to ensure that pre-intervention performances are recorded for all participants. There were eight weeks of learning from weeks 2 – 9 involving 3 class sessions per week for both groups during which the experimental group learnt using iLearnTech while the control group learnt through the normal class sessions and standard learning periods. There were twenty-four (24) learning sessions for each of the experimental and control groups.

At the end of the learning sessions in week 9, the cognitive load and attitude instruments and the performance test were administered to all participants. The feedback from these instruments will allow comparison with pre-intervention feedback to assess the effectiveness of the intervention. Four (4) weeks later, in week 13, the retention test was administered to compare with scores on the performance test for assessing how well the learnt materials have been retained by learners in the 2 groups.

5. Results

The result section answers the question; can AI Chatbot help reduce the enormous cognitive load of JSS students to enhance students' working memory to improve performance, retention and attitude?

Pre-intervention, all participants completed the BTAT and SAS. The intervention lasted for 8 weeks of regular 40-minute Basic Technology class periods with the experimental group using the iLearnTech chatbot as the basic tutor. Lessons were conducted for 3 days each week. The Control group attended their classes without access to the iLearnTech chatbot during the same days and weeks. After the intervention, participants completed the NASA-TLX, BTAT, and SAS followed by the SRT four weeks after the intervention.

5.1 The Use of AI-powered Chatbots Will Significantly Reduce CL Among Learners

5.1.1 Comparison of Pre-test CL Scores for Experimental and Control Groups

Table 2 shows the mean cognitive load score for the experimental group was 57.8 (SD = 11.5), while the control group had a mean score of 58.2 (SD = 11.8). This minimal difference is reflected in the t-value of -0.19, which is not statistically significant ($p> 0.5$. The effect size, measured by Cohen's d, is 0.03, is negligible, suggesting that both groups started with comparable levels of cognitive load before the intervention, ensuring a fair baseline for comparison. The results indicate no significant difference in cognitive load between the experimental group and the control group at the pre-test stage and confirms that participants in both groups have comparable CL.

Table 2 *T-test of pre-tests cognitive load scores for experimental and control group*

Group	Mean	SD	t	p	D
Experimental	57.8	11.5	-0.19	0.850	0.03
Control	58.2	11.8			

5.1.2 Comparison of Post-test CL Scores of Experimental and Control Groups

The results in Table 3 indicate a substantial reduction in cognitive load for the experimental group, who used AI chatbot, compared to the control group, who did not. The mean cognitive load score for the experimental group was 42.3 (SD = 11.2), while the control group had a mean score of 58.7 (SD = 12.1). This difference is significant ($t = -7.62$, $p< 0.05$). The large effect size ($d = 1.39$) also suggests a strong impact of the chatbot intervention in reducing the cognitive load experienced by students. In practical terms, this means that students who utilized iLearnTech found it easier to manage their cognitive resources while learning Basic Technology compared to those who did not have access to this tool.

Table 3 *T-test of post-test cognitive load scores for experimental and control group*

Group	Mean	SD	t	p	d
Experimental	42.3	11.2	-7.62	0.000	1.39
Control	58.7	12.1			

5.2 Reduced Cognitive Load Will Lead to Improved Learning Outcomes

5.2.1 Comparison of Pre-test Achievement Scores for Experimental and Control Groups

Table 4 presents the results of the pre-test achievement test of experimental and control groups. It indicates no significant difference in participants' scores on the Basic Technology Achievement Test (BTAT) between the experimental and the control group at the pre-test stage. The mean BTAT score for the experimental group was 4.2 (SD = 1.1), while the control group had a mean score of 4.3 (SD = 1.2). This difference is not statistically significant ($t = -0.47$, $p > 0.05$. The effect size is also low ($d = 0.09$). This result suggests that both groups started with similar levels of knowledge in Basic Technology before the intervention, providing a fair starting point for assessing the impact of the chatbot.

Table 4 *T-test of pre-test BTAT for experimental and control group*

Group	Mean	SD	t	p	d
Experimental	4.2	1.1	-0.47	0.639	0.09
Control	4.3	1.2			

5.2.2 Comparison of Post-test CL Scores of Experimental and Control Groups

Table 5 shows the result of post-test achievement tests for experimental and control groups. The results indicate a substantial improvement in BTAT scores for the experimental group, who used the chatbot, compared to the control group, who did not. The mean BTAT score for the experimental group was 7.8 (SD = 1.2), while the control group had a mean score of 6.3 (SD = 1.4). This difference is significant ($t = 6.32$, $p < 0.05$). The effect size is very large ($d = 1.15$), suggesting a strong impact of the iLearnTech intervention in improving students' achievement. In practical terms, this means that students who utilized iLearnTech demonstrated significantly better understanding and performance in Basic Technology, as compared to those who did not have access to this tool.

Table 5 *T-test of post-test BTAT scores for experimental and control group*

Group	Mean	SD	t	p	d
Experimental	7.8	1.2	6.32	0.000	1.15
Control	6.3	1.4			

5.3 Reduced Cognitive Load Will Lead to Improved Student Attitude

5.3.1 Comparison of Pre-test Attitude Scores for Experimental and Control Groups

The results presented in Table 6 show the Students' Attitude Survey (SAS) scores between the experimental group and the control group at the pre-test stage. The mean SAS score for the experimental group was 68.3 (SD = 9.1), while the control group had a mean score of 67.9 (SD = 9.3). This difference is not significant ($t = 0.24$, $p > 0.05$), indicating that. The effect size is also low ($d = 0.04$), suggesting that participants in both groups started with similar attitudes towards Basic Technology before the intervention, providing a fair baseline for assessing the impact of iLearnTech on students' attitudes.

Table 6 *T-test of SAS pre-test scores for experimental and control group*

Group	Mean	SD	t	p	d
Experimental	68.3	9.1	0.24	0.811	0.04
And another entry	67.9	9.3			

5.3.2 Comparison of Post-test Attitude Scores for Experimental and Control Groups

The results presented in Table 6 show the Students' Attitude Survey (SAS) scores between the experimental group and the control group at the post-test stage. The mean SAS score for the experimental group was 76.5 (SD = 8.3), while the control group had a mean score of 67.2 (SD = 9.1). This difference is significant ($t = 5.84$, $p < 0.05$). The very large effect size ($d = 1.07$) suggesting that the use of the chatbot has a strong impact on participants attitude in the experimental group who used the chatbot for learning.

Table 7 *T-test of SAS post-test scores for experimental and control groups*

Group	Mean	SD	t	p	d
Experimental	76.5	8.3	5.84	0.000	1.07
Control	67.2	9.1			

5.4 Learners Who Use AI-powered Chatbots Will Exhibit Greater Retention of Information Due to Reduced Cognitive Load

Table 8 presents the results of the retention test administered four weeks after the intervention to measure students' retention. Using a modified version of the BTAT, students in both groups were tested for retention of Basic Technology concepts. The mean SRT score for the experimental group, which used iLearnTech, was 7.2 (SD = 1.3), while for the control group, a mean score of 5.6 (SD = 1.5) was recorded. This difference is statistically significant ($t = 6.18$; $p < 0.05$). The effect size is also very large ($d = 1.13$), suggesting a substantial impact of the chatbot intervention on the retention of Basic Technology concepts over the four-week period.

Table 8 *Calculated Post-test t-test scores and Cohen's d of SAS for Experimental and Control group*

Group	Mean	SD	t	p	d
Experimental	7.2	1.3	6.18	0.000	1.13
Control	5.6	1.5			

5.5 There is a Strong Relationship Between the Dependent Variables

To explore relationships between variables, Pearson correlations were computed. The correlation matrix in Table 9 provides insights into the relationships among CL, Achievement, Student Attitude, and Retention.

Cognitive load demonstrated strong negative correlations with achievement ($r = -0.62$, $p < 0.01$), attitudes ($r = -0.57$, $p < 0.01$), and retention ($r = -0.58$, $p < 0.01$), indicating that lower cognitive load is associated with better performance, more positive attitudes, and improved long-term retention of concepts. Conversely, achievement showed positive correlations with attitudes ($r = 0.53$, $p < 0.01$) and retention ($r = 0.68$, $p < 0.01$), suggesting that higher achievement is linked to more favorable attitudes and better retention of knowledge.

Additionally, a positive correlation between attitude and retention ($r = 0.49$, $p < 0.01$) was observed, implying that students with more positive attitudes towards Basic Technology tend to retain information better over time.

These interconnected relationships underscore the complex dynamics between cognitive load, academic performance, student attitudes, and knowledge retention in the context of Basic Technology education.

Table 9 *Correlation matrix for cognitive load, performance, attitude and retention*

Variable	CLM	BTAT	SAS	SRT
CLM	1			
BTAT	-.62**	1		
SAS	-.57**	.53**	1	
SRT	-.58**	.68**	.49**	1

** Correlation is significant at the 0.01 level (2-tailed)

6. Discussion

The findings of this study support the efficacy of AI-powered chatbot in reducing students' cognitive load and improving learning outcomes. The significant reduction in cognitive load observed in the experimental group aligns with the principles of Cognitive Load Theory (CLT) as outlined by Paas, Renkl and Sweller (2003). This reduction in cognitive load also likely contributed to the marked improvement in the achievement test scores from the pre-test to the post-test for the experimental group. The substantial gains in achievement, coupled with more positive attitudes and improved retention of concepts further suggests that the AI Chatbot effectively addresses the challenges posed by the overloaded Nigerian JSS curriculum as highlighted by Bolaji and Onikoyi (2024).

The significant correlations observed between cognitive load, achievement, attitudes, and retention further underscore the interconnected nature of these variables in the learning process. The strong negative correlation between cognitive load and achievement supports the fundamental premise of CLT that managing cognitive load is crucial for effective learning (Chen, Paas & Sweller, 2023). Moreover, the positive correlations between achievement and attitudes and between attitudes and retention aligns with the findings of Deci and Ryan (2000) on the importance of motivation in learning outcomes. These results imply that AI tools like Chatbots, in addition to promoting better performance by reducing cognitive load, can also aid in effective knowledge storage and potentially information retrieval, by ensuring learners' working memories are rendered free from extraneous processing for effective and efficient processing learning information.

The findings underscore how AI-powered educational tools can help with systemic challenges faced by education systems in developing countries. Managing cognitive load efficiently and delivering personalized learning experiences makes it possible to address concerns associated with curriculum intensity and limited resources that lead to high dropout rates and poor academic performance (Ndanusa et al., 2021; Oyekan et al., 2023). The integration of CLT principles with AI technology thus represents a significant advancement in educational technology, building upon the work of Okonkwo and Ade-Ibijola (2021) on chatbot applications in education. This strategy not only resolves immediate learning needs but has the potential to contribute towards wider educational objectives such as reduction of out-of-school youth population and improvement of overall educational outcomes.

The chatbot's ability to break down complex concepts, support paced content delivery and provide additional support to learners aligns with the strategies suggested by CLT for optimizing instruction and maximizing learning (Sweller, 2011). According to Marton and Saljo (1976), this personalized or tailored approach to teaching might solve some of the concerns related to curriculum structure that led to cognitive overload.

7. Limitations of the Study

The study focused on the Basic Technology subject to explore the effects of AI chatbots on learners CL, performance, retention and attitude. The Basic Technology subject has been identified as a subject that has a heavy material content and one in which very low student performance has been reported consistently; it therefore provides an ideal basis to test out the impact of AI chatbot. While this limited subject focus might impact generalizability of the result, it provides information on the impact of AI tools on content-heavy subjects and highlights an area for future exploration and replication of the study in other subjects. The study can also be replicated in other regions to highlight the potential scalability and applicability of the findings to other contexts.

The study also focused on short-term retention and highlights the potential of Ai chatbot to support improved memory and retention on short-term basis. Future studies are however needed on potential long-term impacts.

8. Implications for Policy and Practice

There are several practical and policy implications for the findings of this study. The need to put in place strong data privacy regulations to protect student information and ensure responsible data handling practices cannot be overestimated. Policies should also be implemented to ensure equitable access to AI-powered tools for all students, regardless of their socio-economic background or geographic location in line with SDG4. With the drastic changes that technological advancement is bringing about in the education space, ongoing professional development opportunities should be provided to educators to help them integrate advanced technologies, including AI effectively into their teaching practices. Clear accountability measures should also be established to ensure that AI tools are used appropriately and ethically.

In terms of classroom implementation and practice, educators need training to effectively integrate AI chatbots into their teaching strategies. Such training should include understanding the capabilities and limitations of the technology, as well as how to use it to enhance student learning. At the same time, students should be taught how to use AI chatbots effectively and ethically. This includes understanding the limitations of the technology and how to critically evaluate the information provided.

Schools and districts should develop clear guidelines for the ethical use of AI chatbots, including data privacy, bias mitigation, and responsible AI practices. The performance of AI chatbots should also be regularly evaluated to identify areas for improvement and to ensure they are meeting the needs of students.

By carefully considering these factors, educators can effectively harness the power of AI chatbots to enhance student learning and address the diverse needs of their students.

9. Conclusion and Future Studies

The application of AI powered chatbot in secondary education has shown considerable potential for addressing the problems of cognitive overload and increasing learning outcomes. Findings from the study confirm the effectiveness of AI tools in decreasing cognitive load, improving academic performance, promoting positive attitudes towards learning and improving retention of knowledge. In many developing nations, the continued struggle with education highlights the need for innovative approaches and educational technologies in fostering meaningful changes. AI tools like Chatbots can make learning more effective, efficient and enjoyable for young students.

Although the study shows short-term effectiveness with the iLearnTech Chatbot, there are needs for studies examining long-term retention rates as well as well as other educational outcomes. Additionally, the potential for scaling this approach across different subjects and educational levels should also be explored. Future research on the impact of AI Chatbots and other AI tools on students' time management skills and stress levels, addressing concerns raised by Claessens et al. (2007) and Pascoe et al. (2020) regarding students' ability to manage academic responsibilities. Furthermore, as AI technology continues to evolve, it will be crucial to ensure that both students and educators develop AI literacy (Sanusi, 2023). This will enable them to effectively leverage AI-powered tools while maintaining a critical understanding of their capabilities and limitations. AI-powered educational tools like iLearnTech integrated with targeted curriculum changes along with teacher training can be instrumental in addressing intricate educational challenges faced in many developing countries, thereby contributing to the achievement of access to equitable educational opportunities by all.

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Conflict of Interest

The authors declare that there are no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *All authors;* ***data collection:*** *Damola Olugbade;* ***analysis and interpretation of results:*** *Damola Olugbade, Bosede Iyiade Edwards, Olayinka Anthony Ojo;* ***draft manuscript preparation:*** *Damola Olugbade, Bosede Iyiade Edwards, Olayinka Anthony Ojo. All authors reviewed the results and approved the final version of the manuscript.*

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