Impact of Artificial Intelligent-Tutor Individualized Learning on Students' Cognitive Load Management in Integrated Science Education in Northeast Nigeria

Samuel Akinola OGUNDARE (Ph. D), Ahmed IBRAHIM (Ph. D), Sagiru ISA (Ph. D)

Science Education Department, Federal University of Kashere, Gombe State

DOI: https://doi.org/10.51244/IJRSI.2025.12120137

Received: 28 December 2025; Accepted: 06 January 2026; Published: 17 January 2026

ABSTRACT

Emerging technologies such as Artificial Intelligence (AI) tools have been proved to influence learning experience and engagement significantly. However, its complete potential in enhancing science education in the Northeast, Nigeria, remains largely unexplored. This study addresses this gap by investigating AI-tutor-based individualised learning and its impact on students' cognitive management. **The study adopted mix method research approach design.** A quasi experimental-control group design with intact class involving pretest, post-test with one experimental group and one control group and qualitative-interpretive research approach design. 55 undergraduate 300 level students that registered for the biology course titled 'General Biology for Integrated Science II in the integrated science education programme were purposely selected for the study from the two federal universities that run integrated science education programmes in the Northeast, Nigeria. Ten integrated education course lecturers also participated in the study, 5 from each of the two universities, and they serve as research assistants. The Students' Cognitive Load Management Questionnaire (SCLMQ) was developed by the researchers and was validated by peer experts to collect information on students' cognitive load. The instrument was subjected to a reliability test using the Cronbach alpha statistical tool, yielding a reliability coefficient of 0.894. Descriptive statistics such as mean rank, range, sum of ranks and median were used to test research questions. While the Kruskal-Wallis statistical test was employed to evaluate significant differences in gender-based cognitive load among students in selected concepts and the Mann-Whitney test to measure significant differences between AI-tutor individualised learning and the control groups. The findings indicated a significant difference in students' cognitive load between the control and experimental groups. Additionally, students' cognitive load management was significantly impacted by gender. Consequently, the study recommended integrating AI-tutor-based individualised learning into integrated science education courses, among other suggestions.

Keywords: Students' cognitive load management, AI-tutor individualized learning, Integrated Science education, Northeast University

INTRODUCTION

Education helps people learn, focusing on knowledge, skills, values, beliefs, and habits. This process aims to develop their intellectual, physical, spiritual, social, and other abilities. Science education covers the teaching and study of different scientific fields, including biology, chemistry, physics, and earth sciences. The main purpose is to improve students' understanding of scientific concepts, the processes of research, and the nature of scientific inquiry. This educational field has garnered significant global attention and importance, drawing interest from educators and different stakeholders (Kayan Fadlelmula et al., 2022). Science education aims to develop new abilities in students, including computational, critical, and creative thinking, which are essential for the 21st century (Wahono et al., 2020). Integrated science education, a significant part of science education, is crucial for tackling real-world problems relating to energy, the environment, and health (Struyf et al., 2019).

Consequently, many countries regard integrated science education as a national strategy for reforming and improving basic education (Dou, 2019).

Integrated science education today faces various problems. These include abstract and complex concepts, as well as students' misunderstandings, which together increase their cognitive burden. In addition, the accessible technology, the teaching and learning environment, the teaching methods, the curriculum design, the assessment strategies, student differences, and relevant social issues are all key factors. Education research consistently highlights the value of active learning and immediate feedback. On the other hand, researchers have been motivated to study the aspects that affect how people learn. In the last fifty years, many different conceptual models of human cognitive architecture have been created. Although these models might have various theoretical viewpoints or suggest philosophical implications, cognitive load has made practical and concrete developments.

Recent advancements in technology like Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT) are suggested to modify how we think, potentially influencing how well we learn (Tedre et al., 2021; Halkiopoulos et al., 2024). Cognitive Load Theory (CLT) defines learning as the act of selecting, organising, and integrating information into memory. This process is limited by the constraints of working memory (Sweller, 2019; Kennedy & Romig, 2021). Sweller's (2019) approach emphasises how good teaching design should employ cognitive resources wisely to avoid cognitive overload and promote more effective learning (Wirth et al., 2020). This is especially crucial when the learning material is complicated, as a high cognitive load can negatively affect how well information is remembered and used.

Artificial intelligence (AI) and machine learning (ML) have rapidly influenced several fields, including education (Alam & Mohanty, 2023). Artificial intelligence (AI) includes computer systems meant to accomplish activities that usually require human intelligence, such as recognising patterns, making decisions, and understanding natural language (AlShaikh et al., 2024). Meanwhile, machine learning, a subset of artificial intelligence, allows systems to learn and improve from experience, without needing explicit programming. This lets them adapt dynamically to new obstacles (Murtaza et al., 2022). This technology offers considerable potential in education, notably for personalised learning, adaptive teaching methods, and managing cognitive load. Artificial intelligence uses technology, particularly machine learning algorithms and computational models, to improve the learning process and make educational methods more effective for each student's individual needs (Schueller et al., 2017).

In the context of scientific education at Nigerian universities, artificial intelligence can be used in several ways, including intelligent tutoring systems, adaptive learning platforms, and virtual simulations. These technologies aim to examine students' learning habits, deliver personalised feedback, and create engaging educational experiences. Artificial intelligence in education uses several methods, including natural language processing, computer vision, and data analytics, to create a learning environment that is both dynamic and flexible. Unlike traditional teaching methods, this approach uses computing power to adjust to each student's strengths and weaknesses, creating a more personalised and effective learning experience. AI shows significant potential in education, particularly in the area of personalisation.

Research has shown that AI-driven adaptive learning systems can improve student engagement and information retention (Suryani et al., 2024). These systems use machine learning approaches, like supervised and reinforcement learning, to analyse how students learn and then adjust teaching methods accordingly (Nazareno & Schiff, 2021). Studies reveal that personalised, AI-based learning systems increase learning outcomes by adjusting content difficulty according to the principles of cognitive load manipulation (Tedre et al., 2021). In the linked experiment, the use of AI-enhanced learning settings, which change dynamically, reduces both unnecessary and germane cognitive load through these dynamic interventions (Bai et al., 2023). Most past research has established that artificial intelligence (AI) can improve learning by adjusting the difficulty of content, which is based on how cognitive load is managed. In contrast, there has been little research on using AI-based, personalised learning to help lessen students' cognitive burden. This study attempts to overcome this gap by examining how artificial intelligence-driven personalised learning can minimise the cognitive burden students experience when studying genetics concepts in Integrated Science Education.

LITERATURE REVIEW

Theoretical framework:

Cognitive load theory (CLT) addresses working memory constraints in education, emphasising that instructional design must manage limited cognitive capacity to facilitate learning (Fombona et al., 2020). The theory categorises cognitive load into three types: intrinsic, extraneous, and germane (Haryana et al., 2022).Intrinsic Cognitive Load (ICL) relates to material complexity and prior knowledge (Chen et al., 2021). Highly structured tasks, like algebra, increase ICL; however, strategies like segmenting and scaffolding can help learners manage this complexity (Yang et al., 2023; Lovell & Sherrington, 2020).Extraneous Cognitive Load (ECL) stems from poor instructional design, such as redundant information or split attention (Vu et al., 2022; Xu et al., 2021). Reducing ECL through dual-channel processing like using audio narration over onscreen text, improves retention (Skulmowski & Xu, 2021; Castro-Alonso et al., 2021). Germane Cognitive Load (GCL) supports deep learning and schema construction (Haryana et al., 2022). Techniques like self-explanation and active retrieval foster GCL (Paas & van Merriënboer, 2020), while guided inquiry helps students connect ideas for better long-term retention (Derry, 2020; Schnotz & Rasch, 2003). Modern AI-driven adaptive systems further optimise these loads by modifying materials and providing rapid feedback (Du et al., 2022; Wu et al., 2022).

Self-Determination Theory (SDT)

The Self-Determination Theory, as proposed by Ryan and Deci (2020), suggests that three psychological needs – autonomy, competence, and relatedness – are crucial for both motivation and learning. AI's participation in academia must be consistent with these values. Self-Determination Theory (SDT) suggests that when the three basic psychological needs are better met—autonomy (the sensation of having control and making choices), competence (the feeling of being skilled), and relatedness (the feeling of connection and belonging)—the consequences are better, such as increased student engagement (Ryan & Deci, 2020). Therefore, Self-Determination Theory (SDT) provides a useful theoretical framework for examining how to reduce students' cognitive load in social settings, such as during teacher-led teaching or when using AI tutors.

Conceptual Framework

This study's conceptual framework is based on theories from science education and the adoption of AI-based learning, considering elements like perceived utility, simplicity of use, institutional support, and gender differences, as described by Venkatesh et al. (2003). This study examines how these issues interact with the specific possibilities of using artificial intelligence in scientific education in Nigeria. This section presents an overview of current research on using artificial intelligence in education, with a focus on integrated science within the field of scientific education. The main topics include the use of artificial intelligence in science education, its impact on how students manage their cognitive load, and the important role of teachers in creating learning environments that use AI.

Science Education in Nigerian Universities

Nigerian universities are increasingly pressured to update curricula to keep pace with global technological advancements, particularly within science education (National Universities Commission [NUC], 2017). Given the vital role of science and technology in national growth, integrating Artificial Intelligence (AI) is viewed as a strategic necessity rather than a mere pedagogical shift (NUC, 2017).

By incorporating AI, Nigerian universities aim to strengthen their scientific research capabilities and drive domestic innovation. This proactive alignment with the shifting technological landscape is intended to equip students with the tools required for modern discovery (NUC, 2017). Beyond meeting international benchmarks, the integration of AI in higher education is central to achieving Nigeria's broader goals for economic and societal progress. Ultimately, this transition seeks to position the nation as a leader in scientific excellence and technological development.

Artificial Intelligence in Science Education

In Nigerian university science education, AI tools like intelligent tutoring systems, adaptive platforms, and virtual simulations leverage natural language processing and data analysis to create personalized learning environments (Alneyadi & Wardat, 2023). Unlike traditional methods, these technologies adapt to individual student needs, offering interactive simulations and immediate feedback to boost engagement and efficiency.

Research highlights a complex impact on performance. While some studies, including those from Stanford University, report a 15% improvement in standardized results through AI platforms (Top 6 AI Tools Revolutionizing Math Tutoring Techniques, n.d.), others raise concerns regarding conceptual depth. For instance, Alneyadi and Wardat (2023) found that AI integration significantly enhanced academic scores and provided beneficial cognitive offloading.

Conversely, a University of Pennsylvania study involving ChatGPT showed that while students' problem-solving accuracy increased by 48%, their conceptual understanding scores actually dropped by 17% (Barshay, 2024). This suggests that while AI excels at improving procedural skills, it may not inherently foster deep learning. Consequently, to maximize educational benefits, AI tools should be integrated with teaching strategies that prioritize active participation and critical thinking to ensure students move beyond surface-level mastery (Barshay, 2024).

Personalisation in Science Education

Artificial intelligence has great promise in personalising scientific teaching, which is a crucial field. However, research has shown that AI-driven adaptive learning systems can improve student engagement and help them remember what they learn (Suryani et al., 2024). These systems use machine learning approaches, like supervised and reinforcement learning, to analyse how students learn and then adjust teaching methods accordingly (Nazareno & Schiff, 2021). Studies show that personalised, AI-driven learning platforms increase learning outcomes. They do this by adjusting the complexity of the information based on principles of cognitive load management (Tedre et al., 2021). In the linked study, the use of dynamic interventions in AI-enhanced learning settings was found to reduce both superfluous and Germane Cognitive Load (Bai et al., 2023).

Cognitive load and AI-driven tools.

The integration of Artificial Intelligence (AI) and Machine Learning (ML) is reshaping education by aligning technological tools with cognitive science (Santoro & Monin, 2023). Central to this evolution is Cognitive Load Theory (CLT), which emphasises managing finite working memory to prevent overload (Koc-Januchta et al., 2022). AI-driven solutions, such as Intelligent Tutoring Systems, optimise this by automating processes and increasing Germane Cognitive Load through adaptive, structured feedback (Luo et al., 2022). These systems address traditional CLT limitations by supporting self-directed learning and tailoring content to individual cognitive styles in real time (Benabou et al., 2024; Johnson et al., 2020).In integrated science education, particularly Biology, these tools must align with Self-Determination Theory (SDT) to be effective. Educators should use AI to support autonomy, competence, and relatedness (Gkintoni et al., 2023). Autonomy-supportive instruction encourages self-paced, student-directed learning (Tedre et al., 2021), whereas competence support entails explicit expectations and constructive feedback, which have been shown to enhance science performance (Suryani et al., 2024). Furthermore, relatedness, fostered through strong teacher-student relationships remains a critical driver of engagement (Ghafouri, 2023). While AI can enhance involvement, poor technical execution can weaken a student's sense of ownership (Jeon, 2024). Current research often neglects the teacher's role in these settings (Xia et al., 2023). Therefore, further investigation is required to determine how teachers and GenAI can collaboratively foster supportive environments that maximise student engagement (Reeve, 2013).

Teacher Instructional Strategies and Gender Differences

Recent advancements in AI are reshaping human sectors, yet their integration reveals critical concerns regarding data privacy, ethics, and equity (Grassini, 2023). Biassed word embeddings often hinder gender-neutral AI applications, according to research (Bolukbasi et al., 2016; Hall & Ellis, 2023). Furthermore, long-term studies on justice and real-world efficacy are necessary due to persistent disparities in AI access across demographics. Teaching methods significantly impact student engagement and achievement (Duruji et al., 2014; Inayat & Ali, 2020). Beyond test scores, researchers must consider cognitive processes and gender-specific responses to instruction. Idris and Rajuddin (2012) found substantial performance variations based on instructional methods, while others note that men and women possess inherent cognitive differences in technological learning (Määttä & Uusiautti, 2020). These differences contribute to a persistent gender imbalance in technology education (Campos & Scherer, 2024; Niiranen, 2017). While boys often favour physically active learning (UNDP, 2014), girls may thrive in relational settings (Osarenren-Osaghae et al., 2019). Some AI-driven tools have shown that male students may use these resources less frequently than females (Leo, 2022). Given these complexities and democratic participation trends (Mitchell, 2019), traditional teaching approaches must be carefully reviewed before integrating AI instruments (Santilli, 2025).

Identified Research Gap

As previously noted, with AI-tutor growing more popular in science education, it is vital to explore how students' cognitive load management in science learning with them are enhanced (Koc-Januchta et al., 2022), however, factors affecting student cognitive load in learning science concepts in this AI-tutor context are less understood. Related studies have confirmed the effectiveness of teaching strategies support in fostering student cognitive load reduction, retention and performance in science concepts in non-AI contexts, however, limited attention has been paid to such relationships in the AI-tutor context particularly in the northeast, Nigeria.

Moreover**,** although these AI-driven education tools are helpful, they require considerable training data to perform optimally. Access to AI enhanced learning remains uneven across gender, race, age, and geographical divides; thus, there is a need for research into equity and fairness in AI applications.

The present study

This study aims to investigate the impact of AI-tutor individualized learning on students' cognitive load (intrinsic, extraneous, and germane) in genetics concepts learning in AI-tutor learning environment.

The relationship is showed in the proposed research model, see Fig. 1.

Accordingly, the two main research questions and hypotheses are:

RQ1: What is the difference between the cognitive load of integrated science students exposed to AI-tutor individualized learning and those exposed to lecture method?

RQ2: What is the difference between the cognitive loads of male and female students exposed to AI-tutor individualized learning and those exposed to lecture method?

Ho_1: There is no significant difference between the cognitive load of integrated science students exposed to AI-tutor individualized learning and those exposed to lecture method

Ho_2: There is no significant difference between the cognitive loads of male and female integrated science exposed to AI-tutor individualized learning and those exposed to lecture method

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue XII December 2025

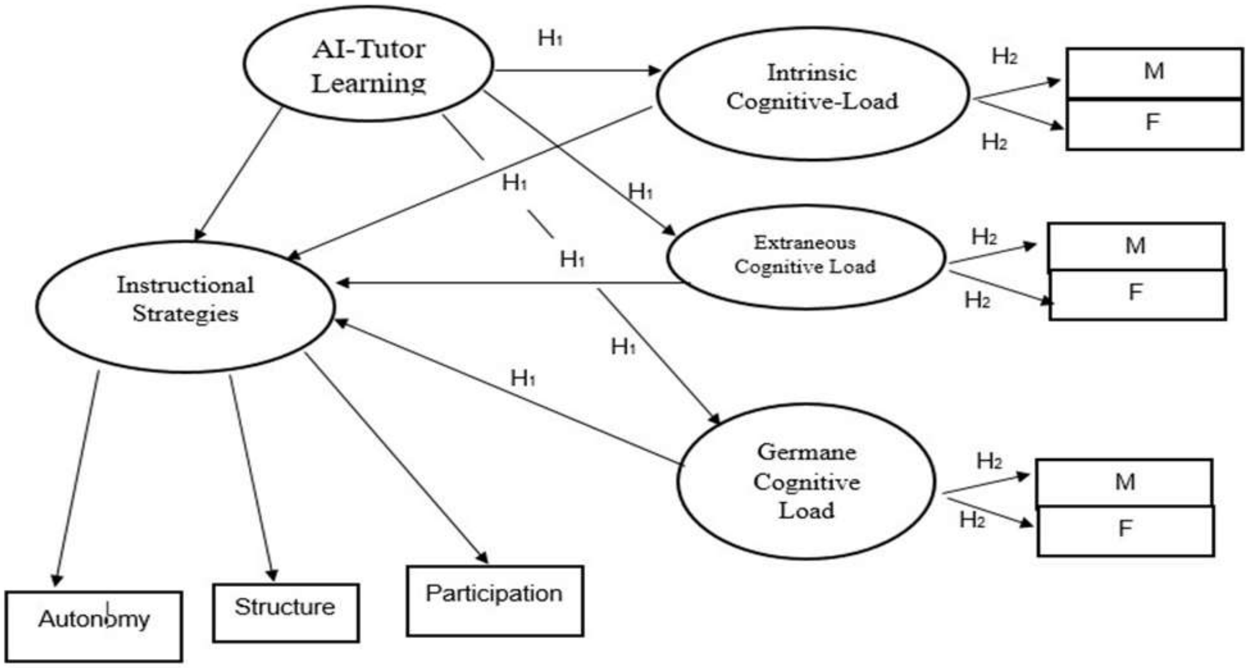

Fig. 1 Research Model

Participants and procedure

Participants were 55 learners from 300 level in two Federal universities that run integrated science education in Northeastern Nigeria, with 25 male (38%) and 30 female (62%) registered for SED 3213; titled General Biology for Integrated Science II in Integrated Science education. They registered for an integrated science course titled: General Biology for Integrated Science II in integrated science education programme aiming to develop and enhance understanding of concepts of genetics, heredity, cell divisions, among others for integrated science undergraduate students. All the students that enrolled for the course were purposely selected for the study because of the small population size. Ten integrated education course lecturers participated in the study, 5 from each of the two universities from the Northeast that run integrated science education programme, and they serve as research assistants. The study adopted mix method research approach design. A quasi experimental-control group design with intact class involving pretest, post-test with one experimental group and one control group and qualitative-interpretive research approach design. Qualitative research comprises the collection of extensive narrative data (non-numeric data on variables over a period to gain insight into discourse of impact of AI-tutor individualized learning on students' cognitive load management in integrated science education in Northeast Nigeria. Students in both experimental group and control groups were pre-tested after which only experimental group received treatment (AI-tutor individualized learning) while control group received no treatment as they were taught with lecture method. The experimental group was introduced to the AI-tutor learning platform, which the researchers had developed. The study lasted for fourteen weeks during the first semester.

The AI-tutor learning platform is a sophisticated content delivery system. It personalises lessons and lectures based on each student's abilities and available time. It also includes multimedia elements, such as videos, diagrams, and quizzes, to keep students engaged and help them learn. The platform spaces lessons, adjusts difficulty levels, and changes question formats based on how students interact with it, including their response times and errors. Students accessed the platform by creating user accounts with their email addresses and passwords.

Students can study each lesson at their own pace and in their own space. After each topic, they're given a set of ten quiz questions. The questions get harder depending on how well the student does. The platform also has an analytics feature. It immediately shows students how they did on the quiz and points out areas where they might need to review the material. Once all the topics are finished, there's a final quiz with thirty questions that cover

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue XII December 2025

everything. To prevent cheating, the platform has a security feature. If a student minimises the application or leaves it inactive for thirty seconds, the quiz will be submitted automatically.

Pedagogical practice: The teacher instruction included three dimensions: autonomy, structure, and involvement.

Table 1: Teaching Strategy in learning genetics in biology for integrated II with AI-Tutor Based learning

Teacher's task	Description	Autonomy	Structure	Involvement
Teacher explains the teaching objectives clearly	The Teacher explain to the students the objective of using AI-Based learning in genetics concepts and how lesson are arranged chronologically for easier understanding.	X	X	
Present prior knowledge	The first lesson on the AI-Based learning platform gives a background on genetics and its importance as an area of study.	X	X	
Encouraging students to interact with AI-Based learning.	The teacher encourage student to interact with AI-Based learning platform to read, view diagrams and videos to generate more ideas about the genetics concepts and relate the ideas with their previous knowledge.		X	X
Provide help when needed	The teacher communicates with the students and provide useful information on AI-Based learning platform, solve technical problems and encourages students to perform their tasks.		X	X
Feedback	Teacher check students' performance and discuss areas of weakness, to support the students to improve.		X	X
Encourage self-assessment	Teacher encourage the students to take quiz at the end of each lesson and the general quiz at the end of all the lessons.		X	X

Note: X indicate that Teaching strategy falls in the corresponding of teacher instruction

Measuring Instrument

Following ethical approval from our institution and the acquisition of consent from all participants, a questionnaire was administered. After fourteen weeks of instruction, during which participants engaged with AI-tutor-led genetics concepts (120 minutes per week, with teacher supervision), they completed the Integrated Science Students Cognitive Load Questionnaire (ISSCLQ). This questionnaire, developed by the researchers, was administered in class for a duration of 20 minutes. Each item on the questionnaire was rated on a 5-point scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument's validity was confirmed by peer experts within the Faculty of Education at Federal University of Kashere, Gombe State, and its reliability was determined using Cronbach's alpha. A reliability index of 0.894 was obtained, indicating the instrument's reliability and its suitability for the study.

Data Analysis

The ordinal data derived from the ISSCLQ was subjected to inferential non-parametric tests, specifically the Mann-Whitney and Kruskal-Wallis tests, to evaluate the null hypotheses. Descriptive statistics, including median and mean ranks, were employed to address the research questions. The findings from the data analysis are detailed in Tables 1 through 6.

RESULTS

Descriptive Statistics

RQ1: What distinguishes the cognitive load experienced by integrated science students who engage with AI-tutor individualised learning from those who are taught via the lecture method?

Table 2: Mean Rank, Sum of Ranks and Median of Cognitive Loads of Integrated Science Students Exposed to AI-tutor Individualized Learning and Those Exposed to Lecture Method

Variable	N	Mean Rank	Sum of Ranks	Median	Remark
Experimental	18	19.11	344	2	Difference Exists
Control	37	32.32	1196	3	

Table 2 indicates that mean rank, sum of ranks and median of integrated science students cognitive load exposed to lecture method (experimental group) are 19.11, 344, and 2 respectively. On the other side cognitive load mean rank, sum of ranks and median those of students exposed to lecture method (control group) are 32.32, 1196 and 3 respectively. This shows that difference exists between the cognitive loads of students exposed to AI-tutor individualized learning and those exposed to lecture method in favour of those exposed to lecture method (control group)

RQ2: What is the difference between the cognitive loads of male and female students exposed to AI-tutor individualized learning and those exposed to lecture method?

Table 3: Mean Rank and Median of Male and Female Integrated Science Students Cognitive Loads Exposed to Individualized Learning and Those Exposed to Lecture Method

Variable	N	Mean Rank	Median	Remark
Male Experimental	6	22.17	2	
Female Experimental	12	17.58	2	Differences Exist
Male Control	19	34.79	3	
Female	18	29.72	2	

Table 3 reveals that mean ranks and median of cognitive load of male experimental, female experimental, male control and female control are 22.17, 2; 17.58, 2; 34.79, 3 and 29.72, 2 respectively. This shows that differences exist among the groups in favour of male students exposed to lecture method

Ho_1: There is no significant difference between the cognitive load of integrated science students exposed to AI-tutor individualized learning and those exposed to lecture method

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XII Issue XII December 2025

Table 4: Mann- Whitney of Integrated Science Students Cognitive Loads Exposed to Individualized Learning and Those Exposed to Lecture Method

Variable	N	Mean Rank	Sum of Ranks	U-value	P. value	Remark
Experimental	18	19.11	344	173	0.002	S
Control	37	32.32	1196			

Table 4 shows that U = 173, P = 0.002. At P≤ 0.05, this indicates significant difference between the cognitive loads of integrated science students exposed to individualized learning and those exposed to lecture method. Hence, null hypothesis 1 which says that there is no significant difference between the cognitive load of integrated science students exposed to individualized learning and those exposed to lecture method is rejected.

Ho_2: There is no significant difference between the cognitive loads of male and female integrated science exposed to AI-tutor individualized learning and those exposed to lecture method

Table 5: Kruskal- Wallis of Male and Female Integrated Science Cognitive Loads Exposed to Individualized Learning and Those Exposed to Lecture Method

Variable	N	Mean Rank	H. value	Df	P. value	Remark
Male Experimental	6	22.17				
Female Experimental	12	17.58	10.64	3	0.014	S
Male Control	19	34.79				
Female Control	18	29.72				

Table 5 indicates that H (3) = 10.64, P = 0.014. At P≤ 0.05, this shows that significant difference exists among the cognitive loads of male and female integrated science students. As such, null hypothesis 2 which says that there is no significant difference among the cognitive loads of male and female integrated science exposed to individualized learning and those exposed to lecture method is rejected.

Post- Hoc test in form of Bonferroni Adjusted Level of significance at P≤ 0.05 was used to determine where the significant differences exist among the six groups as presented in Table 6

Table 6: Bonferroni Adjusted Level of Significance of Male and Female Integrated Science Cognitive Loads Exposed to AI-tutor Individualized Learning and Those Exposed to Lecture Method

Variables		P. value	Remark
ME	**FE**	0.62	**NS**
	MC	0.04	**NS**
	FC	0.42	**NS**
FE	**MC**	0.001*	**S**
	FC	0.07	**NS**
MC	**FC**	0.45	**NS**

P≤ 0.008

KEY:

ME: male students in the experimental group
FE: female students in the experimental group
MC: male students in the control group
FC: female students in the control group

Table 6 shows that at $P \leq 0.008$, there is no significant difference between the cognitive loads of male students exposed to AI-tutor individualized learning and female students exposed to AI-tutor individualized learning, male students exposed to individualized learning and female students exposed to female students exposed to control, female students exposed to individualized learning and those exposed to lecture method, male students exposed to lecture method and female students exposed to lecture method and also between male students exposed to individualized learning and male students exposed to lecture method. However, there is significant difference between female students exposed to individualized learning and male students exposed to lecture method.

Interviews with lecturers reveal that AI-tutor individualized learning significantly reduces students' cognitive load compared to the Conventional Lecture Learning Approach (CLLA). The Key Findings includes

AI-Tutor Impact: Students using AI tutors experienced enhanced understanding, reduced mental effort, and lower stress. The ability to learn at an individualized pace and review materials frequently allowed for better engagement and problem-solving.

Conventional Limitations: Conversely, CLLA resulted in higher cognitive burdens. Lecturers noted that students found concepts overwhelming, struggled with a fixed pace, and felt bored or stressed, hindering their ability to apply knowledge.

Gender Disparity: The study found that male students managed cognitive loads more effectively than females, particularly in technology-driven environments, showing higher confidence and independence.

Overall, the findings align with existing research suggesting that AI-driven tools optimize learning by streamlining content, while traditional methods may limit cognitive offloading and academic growth in science education.

DISCUSSIONS

This study aims to examine the impact of AI-tutor based individualized learning on students' cognitive load management in genetics concepts in integrated science education in Northeast Nigeria. The findings provide four empirical implications and three practical suggestions for teachers and researchers to better facilitate students' learning with AI-tutor based learning.

AI-tutor based individualized learning positively and significantly enhanced students' cognitive load reduction in genetic concepts in integrated science education biology course in class. This finding is consistent with previous studies of, Dong, et. al. (2020) who found out that AI-driven tools have helped optimize cognitive load management through complex problem-solving tasks that automate processes, streamline instructional content, and offer just-in-time feedback. Similarly, the finding corroborates the finding of Luo, et. al. (2022) who discovered that Intelligent Tutoring Systems powered by AI significantly enhance students' ability to retain complex concepts by reducing extraneous load and reinforcing Germane Cognitive Load through scaffolded feedback loops. Also agree with the finding is Brachten, et. al. (2024) who reported that AI-driven platforms can model students' metacognitive abilities and suggest personalized strategies for improving retention and comprehension. However, the impact of AI-driven tools in previous studies were mostly conducted in non-educational courses context, and this study provides evidence of using AI-tutor individualized learning to significantly reduce students' cognitive load in learning genetics concepts in biology in integrated science education in the universities in the northeast, Nigeria.

The findings revealed that there was no significant difference among the cognitive load management of male and female students exposed to AI-tutor individualized method and those exposed to lecture method based on gender, except between female students in the experimental group and male students in the Control group. This finding corroborates the findings of Leo (2022) and Mitchell (2019) which reiterated that male children had significantly lower odds of attending school, the use of AI-driven educational tools and cognitive load compared to female children, warranting careful consideration against existing literature that often highlights girls' heightened vulnerability due to factors like safety concerns and gender norms.

Theatrical contributions

First, the empirical implications of this study contribute to SDT-based research by examining the relationship between perceived teacher support, needs satisfaction, and four dimensions of student engagement in a new technology-supported context (AI-tutor-individualized learning). Our findings echo the SDT founders' call about enriching SDT research in a technological environment (Ryan and Deci, 2020). In addition, this study specially specified how needs satisfaction affected student engagement and mediated the relationship between teacher support and student engagement in AI-tutor genetic learning. Needs satisfaction and cognitive offload in the AI-tutor context were less understood (Xia et al., 2023) and SDT-based research on science education was limited (Wang & Xue, 2024; Xia et al., 2023). Therefore, this study provided more evidence on how needs satisfaction and cognitive load management were enhanced under the AI-tutor individualised context within the genetic concepts in biology in science education.Second, this study enriches technological pedagogical content knowledge (TPACK) research by providing teaching strategies in the AI-tutor individualised learning environment. Teachers in this study acted as knowledge presenters, designers, facilitators, assessors, and resource providers. They provided both technology and content knowledge to students and incorporated genetic concepts into learning materials as AI-tutor in the teaching process to support the pedagogy, which could contribute to TPACK (Rosenberg & Koehler, 2015).

CONCLUSION

In conclusion, the efficacy of AI-tutor individualized learning on students' cognitive load management in genetic concepts learning in integrated science education in the universities, Northeast, Nigeria has been underscored, with a focus on students' cognitive offload. The study affirms that AI-tutor individualized learning applications, coupled with teachers' guidance, contribute significantly to the enhancement of students' cognitive load reduction in genetic concepts learning. The efficacy of AI-tutor individualized learning environment further emphasizes the need for professional development opportunities, highlighting the crucial role of ongoing training in harnessing the full potential of AI tools in teaching science concepts in the universities. Furthermore, the findings indicate that significant differences do not exist between male and female participants exposed to AI-tutor learning environment and the conventional traditional lecture method, except between female students in the experimental group and male students in the Control group. This suggest that pedagogical practices should carefully take care of gender issues and properly attend to them irrespective of teacher's instructions. However, this study relied on a self-report questionnaire and in-depth interview. More methods (e.g. recording, observation, etc.) can be used to make data collected more comprehensive and objective.

Practical suggestions

This study provided insights for teachers on how to better facilitate student cognitive offload in scientific concepts particularly genetic concepts engagement in AI-tutor individualized learning environment.

1 Teachers should try to enhance students' cognitive offload to encourage their participation in science concepts learning, and teachers should take many factors (e.g., AI-tutor's functions and affordances, students' interest, engagement, anxiety, etc.) into account when trying to improve students' emotional engagement in the AI-tutor learning context.

2 Teachers should carefully incorporate AI-tutor individualized learning in their instructional design (i.e., not just let students to use AI-tutor individualized learning without guidance). Hence, teachers should enrich their technological knowledge in addition to pedagogy knowledge (PK) and content knowledge to better instruct students' learning.

3 Teachers should be more engaged in professional development sessions and receive training on AI technology. This technology is emerging, which requires teachers to keep progressing to enhance their AI competency and teacher instruction in an AI learning context.

Limitations and Future Directions

This study has three limitations. First, this study comprised a sample size of 55 participants from the only two universities that run integrated science education in Northeast Nigeria; Second, the study adopted quantitative and qualitative approaches over a short period; a longitudinal design could be adopted in the future to track the interactions between the variables. Third, this study relied on a self-report questionnaire and in-depth interview; more methods (e.g., recording, observation, etc.) can be used to make data collected more comprehensive. Fourth, this study was conducted in a university; it could be a different picture for secondary school education. Future studies are suggested to investigate the mediating effect in different educational contexts.

Acknowledgements: The authors thank all the students and lecturers who participated in this study

Funding: This research was funded by the TETFund Institutional Based Research grant (IBR)

Data availability: The datasets used in this study are available from the corresponding author upon request.

Declarations

Ethics approval: for this study was obtained by the author's university**.**

Conflicts of interest: There is no conflict of interests between the author and participants

REFERENCES

1. Alam, A. & Mohanty, A. (2023). Educational technology: Exploring the convergence of technology and pedagogy through mobility, interactivity, AI, and learning tools. Cogent Engineering. 10, 2283282.
2. Alneyadi, S., & Wardat, Y. J. C. E. T. (2023). ChatGPT: Revolutionizing student achievement in the elec tronic magnetism unit for eleventh-grade students in Emirates schools. Contemporary Educational Technology, 15(4), ep448. https://doi.org/10.30935/cedtech/13417.
3. Al-Obaydi, L. H., Shakki, F., Tawafak, R. M., Pikhart, M., & Ugla, R. L. (2023). What I know, what I want to know, what I learned: Activating EFL college students' cognitive, behavioral, and emotional engagement through structured feedback in an online environment. Frontiers in Psychology, 13, 1083673. https://doi.org/10.3389/fpsyg.2022.1083673
4. AlShaikh, R.; Al-Malki, N. & Almasre, M. (2024). The implementation of the cognitive theory of multimedia learning in the design and evaluation of an AI educational video assistant utilizing large language models. Heliyon 10, e25361.
5. Bai, L.; Liu, X. & Su, J. (2023). ChatGPT: The cognitive effects on learning and memory. Brain-X, 1, e30.
6. Barshay, J. (2024). Kids Who Use ChatGPT as a Study Assistant do Worse on Tests. The Hechinger Report. http://hechingerreport.org/kids-chatgpt worse-on-tests/.
7. Benabou, A.; Touhami, F. & Demraoui, L. (2024). Artificial Intelligence and the Future of Human Resource Management. In Proceedings of the 2024 International Conference on Intelligent Systems and Computer Vision (ISCV), Fez, Morocco, 1–8.
8. Bolukbasi, T., Chang, K.-W., Zou, J.Y., Saligrama, V., Kalai, A.T. (2016). Man is to computer programmer as woman is to homemaker? debiasing word embeddings. Advances in neural information processing systems, 29
9. Brachten, F.; Brünker, F.; Frick, N.R.; Ross, B. (2020). Stieglitz, S. On the ability of virtual agents to decrease cognitive load: An experimental study. Information System E-Business Management, 18, 187–207.
10. Campos, D.G., & Scherer, R. (2024). Digital gender gaps in students' knowledge, attitudes and skills: An integrative data analysis across 32 Countries. Education Information Technology, 29, 655–693. https://doi.org/10.1007/s10639-023-12272-9

11. Chen,O.; Paas, F. & Sweller, J. (2021). Spacing and interleaving effects require distinct theoretical bases: A systematic review testing the cognitive load and discriminative-contrast hypotheses. Educational Psychology Review., 33, 1499–1522.
12. Chiu. T. K. F. (2021). Computers in Human Behavior.Digital support for student engagement in blended learning based on Self-determination Theory. Computers in Human Behavior, 124, 106909 https://doi.org/10.1016/j.chb.2021.106909
13. Derry, J. A. (2020). Problem for Cognitive Load Theory-the Distinctively Human Life-form. Journal of Philosophy of Education, 54, 5–22.
14. Dong, Y.; Hou, J.; Zhang, N. & Zhang, M. (2020). Research on how human intelligence, consciousness, and cognitive computing affect the development of artificial intelligence. Complexity, 2020, 1680845.
15. Dou, L. (2019). A cold thinking on the development of STEM education. In 2019 International Joint Conference on Information, Media and Engineering (IJCIME) (pp. 88–92). https://doi.org/10.1109/IJCIME49369.2019.00027
16. Du,X.; Dai, M.; Tang, H.; Hung, J.-L.; Li, H. & Zheng, J. (2022). A multimodal analysis of college students' collaborative problem solving in virtual experimentation activities: A perspective of cognitive load. J. Comput. High. Educ., 35, 272–295.
17. Duruji, M., Azuh, D., Segun, J., Olanrewaju, I. P., & Okorie, U. (2014). Teaching method and assimilation of students in tertiary institutions: A study of Covenant University, Nigeria. Proceedings of EDULEARN14 Conference 7th-9th July 2014 (Barcelona, Spain).
18. Fombona, J.; Pascual, M.A. & Ferra, M.P. (2020). Analysis of the educational impact of M-Learning and related scientific research. Journal of New Approaches Education Research. 9, 167–180.
19. Ghafouri, M. (2023). ChatGPT: The catalyst for teacher-student rapport and grit development in L2 class. System, 120. https://doi.org/10.1016/j.system.2023.103209
20. Gkintoni, E.; Dimakos, I.; Halkiopoulos, C. & Antonopoulou, H. (2023). Contributions of Neuroscience to Educational Praxis: A Systematic Review. Emerging Science Journal, 7, 146–158.
21. Grassini, S. (2023). Shaping the future of education: Exploring the potential and consequences of AI and ChatGPT in educational settings. Educ. Sci., 13, 692.
22. Halkiopoulos, C. & Gkintoni, E. (2024). Leveraging AI in e-learning: Personalized learning and adaptive assessment through cognitive neuropsychology—A systematic analysis. Electronics, 13, 3762.
23. Hall, P., & Ellis, D. (2023). A systematic review of socio-technical gender bias in ai algorithms. Online Information Review,
24. Haryana, M.R.A.; Warsono, S.; Achjari, D. & Nahartyo, E. (2022). Virtual reality learning media with innovative learning materials to enhance individual learning outcomes based on cognitive load theory. International Journal of Management in Education, 20, 100657.
25. Idris, A. & Rajuddin, M. R. (2012). The influence of teaching approaches among technical and vocational education teachers towards the acquisition of technical skills in Kano State Nigeria. Journal of Education and Practice, 3(16), 160-166.
26. Inayat, A. & Ali, A. Z. (2020). Influence of teaching style on students' engagement, curiosity and exploration in the classroom. Journal of Education and Educational Development, (1), 87-102. http://dx.doi.org/10.22555/joeed.v7i1.2736
27. Jeon, J., Lee, S., & Choe, H. (2023). Beyond ChatGPT: A conceptual framework and systematic review of speech-recognition chatbots for Language learning. Computers & Education, 206, 21, 104898. https://doi.org/10.1016/j.compedu.2023.104898
28. Jiang, D.; Chen, Z.; Liu, T.; Zhu, H.; Wang, S. & Chen, Q. (2022). Individual creativity in digital transformation enterprises: Knowledge and ability, which is more important? Frontier Psychology., 12, 734941.
29. Johnson, O.W.; Han JY, C.; Knight, A.L.; Mortensen, S.; Aung, M.T.; Boyland, M. & Resurrección, B.P. (2020). Intersectionality and energy transitions: A review of gender, social equity and low-carbon energy. Energy Res. Soc. Sci., 70, 101774.
30. Kayan-Fadlelmula, F., Sellami, A., Abdelkader, N., & Umer, S. (2022). A systematic review of STEM education research in the GCC countries: Trends, gaps and barriers. International Journal of STEM Education, 9 (2). https://doi.org/10.1186/s40594-021-00319-7
31. Kennedy, M.J. & Romig, J.E. (2021). Cognitive load theory: An applied reintroduction for special and general educators. Teach. Except. Child., 56, 440–451.

32. Ko´c-Januchta, M.M.; Schönborn, K.J.; Roehrig, C.; Chaudhri, V.K.; Tibell, L.A. & Heller, H.C. (2022). "Connecting concepts helps put main ideas together": Cognitive load and usability in learning biology with an AI-enriched textbook. International Journal of Educational Technology and Higher Education, 19, (11).
33. Leo, J. (2022). Early-Warning dropout visualization tool for secondary schools: Using machine learning, QR code, GIS and mobile application techniques. International Journal of Advanced Computer Sci ence and Applications, 13(11). https://doi.org/10.14569/ijacsa.2022.0131176
34. Lovell, O. & Sherrington, T. (2020). Sweller's Cognitive Load Theory in Action; John Catt: Woodbridge, UK.
35. Luo, G.; Yuan, Q.; Li, J.; Wang, S. & Yang, F. (2022). Artificial intelligence powered mobile networks: From cognition to decision. IEEE Netw., 36, 136–144.
36. Määttä K. & Uusiautti S. (2020). Nine contradictory observations about girls' and boys' upbringing and education – The strength-based approach as the way to eliminate the gender gap. Frontiers of Education, 5, 134. https://doi.org/10.3389/feduc.2020.00134
37. Mercer, S., & Dörnyei, Z. (2020). Engaging Language learners in contemporary classrooms. Cambridge University Press.
38. Mitchell, L. (2019). Policy Frameworks and Democratic Participation (pp. 125–143). https:/ /doi.org/10.1007/978-981-13-1793-_7
39. Murtaza, M.; Ahmed, Y.; Shamsi, J.A.; Sherwani, F. & Usman, M. (2022). AI-based personalized e-learning systems: Issues, challenges, and solutions. IEEE Access, 10, 81323–81342.
40. National Universities Commission (2017). Benchmark Minimum Academic Standards for Undergraduate Programmes in Nigerian Universities. Abuja, Nigeria.
41. Nazareno, L. & Schiff, D.S. (2021). The impact of automation and artificial intelligence on worker well-being. Technol. Soc., 67, 101679.
42. Niiranen, S. (2017). Gender and technology education. In de Vries, M. (Ed.), Handbook of technology education. Springer International Handbooks of Education. Springer, Cham. https://doi.org/10.1007/978-3-319-38889-2_61-1
43. Osarenren-Osaghae, R. I. Imhangbe1 O. S., & Irabo Q. O. (2019). Relationship between social challenges and the education of the girl-child as perceived by female academics in the tertiary institutions of Edo State, Nigeria. Educational Research and Reviews, 14(17), 625 638.
44. Paas, F. & van Merriënboer, J.J.G. (2020). Cognitive-load theory: Methods to manage working memory load in the learning of complex tasks. Curr. Dir. Psychol. Sci., 29, 394–398.
45. Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. Contemporary Educational Psychology, 61,101860. https://doi.org/10.1016/j.cedpsych.2020.101860
46. Rosenberg, J. M., & Koehler, M. J. (2015). Context and technological pedagogical content knowledge (TPACK): A systematic review. Journal of Research on Technology in Education, 47(3), 186–210.htps://doi.org/10.1080/15391523.2015.1052663
47. Reeve, J. (2013). How students create motivationally supportive learning environments for themselves: The concept of agentic engagement. Journal of Educational Psychology, 105(3), 579–595. https://doi.org/10.1037/a0032690
48. Santilli, T., Ceccacci, S., Mengoni, M & Giaconi, C. (2025). Virtual vs. traditional learning in higher education: A systematic review of comparative studies. Computers & Education, 227(2025) 1-31. doi.org/10.1016/j.compedu.2024.105214
49. Santoro, E. & Monin, B. (2023). The AI Effect: People rate distinctively human attributes as more essential to being human after learning about artificial intelligence advances. Journal of Experimental Social Psychology, 107, 104464.
50. Schnotz, W. & Rasch, T. (2005). Enabling, facilitating, and inhibiting effects of animations in multimedia learning: Why reduction of cognitive load can have negative results on learning. Educational Technology Research and Development, 53, 47–58.
51. Schöbel, S.; Saqr, M. & Janson, A. (2021). Two decades of game concepts in digital learning environments-A bibliometric study and research agenda. Computer Education., 173, 104296.

52. Schueller, S. M., Tomasino, K. N. & Mohr, D. C. (2017). Integrating Human Support into Behavioral Intervention Technologies: The Efficiency Model of Support. Clinical Psychology: Science and Practice, 24(1), 27-45. doi:10.1111/cpsp.12173
53. Shanmugasundaram, M. & Tamilarasu, A. (2023). The impact of digital technology, social media, and artificial intelligence on cognitive functions: A review. Frontier in Cognitive., 2, 1203077.
54. Sierens, E., Vansteenkiste, M., Goossens, L., Soenens, B., & Dochy, F. (2009). The synergistic relation ship of perceived autonomy support and structure in the prediction of self-regulated learning. British Journal of Educational Psychology, 79, 57–68. https://doi.org/10.1348/000709908x304398
55. Struyf, A., De Loof, H., Boeve-de Pauw, J., & Van Petegem, P. (2019). Students' engagement in different STEM learning environments: Integrated STEM education as promising practice? International Journal of Science Education, 41(10), 1387–1407. https://doi.org/10.1080/09500693.2019.1607983
56. Suryani, M.; Sensuse, D.I.; Santoso, H.B.; Aji, R.F.; Hadi, S.; Suryono, R.R. & Kautsarina. (2024). An initial user model design for adaptive interface development in learning management system based on cognitive load. Cogn. Technol. Work. 26, 653–672.
57. Sweller, J. (2019). Cognitive load theory and educational technology. Educational Technology Research and Development, 68, 1–16.
58. Tai, T. Y., & Chen, H. H. J. (2022). The impact of intelligent personal assistants on adolescent EFL learn ers' listening comprehension. Computer Assisted Language Learning, 37(3), 433–460. https://doi.org/10.1080/09588221.2022.2040536
59. Tao, Y., Meng, Y., Gao, Z. Y., & Yang, X. D. (2022). Perceived teacher support, student engagement, and academic achievement: A meta-analysis. Educational Psychology, 42(4), 401–420. https://doi.org/10.1080/01443410.2022.2033168
60. Tedre, M.; Toivonen, T.; Kahila, J.; Vartiainen, H.; Valtonen, T.; Jormanainen, I.; Pears, A. (2021). Teaching machine learning in K-12 classroom: Pedagogical and technological trajectories for artificial intelligence education. IEEE Access, 9, 110558–110572.
61. UNPD (2014). Gender and poverty reduction. http://www.undp.org/content/undp/en/home/ourwork/povertyreduction/focus_areas/focus_gender_and_poverty/
62. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.
63. Wahono, B., Lin, P.-L., & Chang, C.-Y. (2020). Evidence of STEM enactment effectiveness in Asian student learning outcomes. International Journal of STEM Education, 7(1), 1–18. https://doi.org/10.1186/s40594-020-00236-1
64. Wang, Y., & Xue, L. (2024). Using AI-driven chatbots to foster Chinese EFL students' academic engage ment: An intervention study. Computers in Human Behavior, 159, 108353. https://doi.org/10.1016/j.chb.2024.108353
65. Wang, Y., & Xue, L. (2024). Using AI-driven chatbots to foster Chinese EFL students' academic engage ment: An intervention study. Computers in Human Behavior, 159, 108353. ht tps://doi.org/10.1016/j.chb.2024.108353
66. Wang,J.; Antonenko, P.; Keil, A. & Dawson, K. (2020). Converging subjective and psychophysiological measures of cognitive load to study the effects of instructor-present video. Mind Brain Education, 14, 279–291.
67. Wirth, J.; Stebner, F.; Trypke, M.; Schuster, C. & Leutner, D. (2020). An interactive layers model of self-regulated learning and cognitive load. Educational Psychology Review, 32, 1127–1149.
68. Wu,C.-H.; Liu, C.-H. & Huang, Y.-M. (2022). The exploration of continuous learning intention in STEAM education through attitude, motivation, and cognitive load. International Journal of Stem Education, 9 (35).
69. Xia, Q., Chiu, T. K. F., Chai, C. S., & Xie, K. (2023). The mediating effects of needs satisfaction on the relationships between prior knowledge and self-regulated learning through artificial intelligence chat bot. British Journal of Educational Technology, 54(4), 967–986. https://doi.org/10.1111/bjet.13305
70. Yang, F. Y., & Xu, J. Z. (2019). A psychometric evaluation of teacher homework involvement scale in online learning environments. Current Psychology, 38(6), 1713–1720. https://doi.org/10.1007/s12144-017-9734–1