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Cognitive load analysis of adaptive learning technologies in special education classrooms: A quantitative approach

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ABSTRACT

This study examines the effects of adaptive learning technology on cognitive load in special education classrooms using a quantitative approach. The research included students with various disabilities who interacted with adaptive learning tools such as Virtual Reality (VR), Gamification, and Artificial Intelligence (AI). Data analysis involved statistical methods like descriptive statistics, t-tests, ANOVA, correlation, and regression analyses. The findings indicate notable differences in the cognitive load associated with different technologies, with AI technology resulting in a higher cognitive burden compared to VR and Gamification. Additionally, factors such as academic performance, age, and gender were found to influence the level of cognitive load experienced by students. The results emphasize the importance of considering the cognitive demands of adaptive learning technologies and tailoring instructional design and technology integration based on individual needs. Recommendations are offered to educators, curriculum developers, and policymakers to enhance learning opportunities for students with disabilities.

1. Introduction

The incorporation of adaptive learning technology into educational environments, especially in classes that cater to special education, has attracted considerable interest (Ehri et al., 2001; Santoianni and Ciasullo, 2018; Turel and Gürol, 2011). These technologies, which adapt learning material and delivery according to the specific needs of each student, show potential for improving the learning experiences and achievements of students with varying learning needs and abilities (Kopcha, 2010; MacDonald, 2021). Nevertheless, the efficacy of these technologies in special education settings depends on several elements, such as their influence on cognitive load (Sweller, 1988; Leppink et al., 2013).

Cognitive load, a fundamental notion in cognitive psychology, pertains to the mental exertion involved in learning activities (Paas et al., 2016; Kalyuga, 2009). Cognitive load theory (CLT), introduced by Sweller (1988), stated that learning is restricted by the capacity restrictions of working memory. Cognitive load may be classified into three types: Intrinsic, extraneous, and relevant (Sweller, 2010; Moreno, 2007). Intrinsic load refers to the intrinsic complexity of the learning materials, whereas extraneous load refers to the additional cognitive stress caused by instructional design components that are not connected to the learning objectives. Germane load, in contrast, pertains to the cognitive exertion dedicated to significant learning processes (Greenberg and Zheng, 2023; Vandewaetere and Clarebout, 2013).

The utilization of CLT principles in the development and assessment of adaptive learning technologies in special education classrooms is a rapidly growing field of study (Li et al., 2019). Although there is an increasing amount of research exploring the effectiveness of adaptive learning technologies in enhancing academic achievements for students with disabilities (Sarid et al., 2020; Beketov et al., 2023), there are comparatively fewer studies that have specifically investigated the cognitive load consequences of these technologies in special education environments (López-Pérez et al., 2011; Bodemer et al., 2004).

This study aims to fill this void by doing a quantitative examination of the cognitive burden linked to the utilization of adaptive learning

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technology in special education classrooms. This research aims to provide valuable insights into the cognitive processes underlying learning in individuals with diverse learning needs by quantitatively assessing the cognitive load experienced by students when interacting with different types of adaptive learning technologies (Paas and Van Merriënboer, 1994; Gerjets et al., 2004). Moreover, comprehending the cognitive load dynamics in adaptive learning environments can provide valuable insights for creating more efficient instructional techniques and technology design principles specifically designed for the distinct requirements of students with disabilities (Yilmaz, 2023).

The primary objective of this study is to examine the influence of various forms of adaptive learning technology on the cognitive burden encountered by students in special education classes. This research aims to provide valuable insights into the cognitive load implications of these technologies. The findings can be used to guide educators, curriculum developers, and technology designers in creating evidence-based practices that enhance learning experiences and outcomes for students with different learning needs.

Although adaptive learning technologies are being used more often in special education classrooms, there is still a lack of knowledge on how these technologies affect the cognitive load of kids with various learning requirements. Although prior studies have shown the potential advantages of adaptive learning technology in enhancing academic achievements for children with impairments, there has been less study on their particular effects on cognitive load. Hence, it is imperative to conduct a thorough examination of the cognitive load implications associated with various forms of adaptive learning technologies in special education environments. This will provide valuable insights for evidence-based teaching methods and the development of technology design principles. The research questions can be summarized as follows:

1. What is the impact of different types of adaptive learning technologies on the cognitive load experienced by students in special education classrooms?
2. How do individual differences in student characteristics (e.g., disability type, cognitive abilities) influence the relationship between adaptive learning technologies and cognitive load?
3. What are the implications of cognitive load findings for the design and implementation of adaptive learning technologies in special education contexts?

The findings of this study are important for both theoretical understanding and practical application of special education and educational technology. This research enhances our comprehension of how technology-mediated learning environments impact the cognitive processes of students with disabilities by methodically analyzing the cognitive load impacts of adaptive learning technologies. The results of this research can guide the creation of improved teaching methods and concepts for designing technology that is specifically suited to the distinct requirements of students with varied learning profiles. Moreover, this research can improve the inclusiveness and accessibility of educational interventions for children with disabilities, thereby advancing equal learning opportunities and outcomes.

The study spanned 12 months and consisted of several separate stages, including a review of existing literature, the development of a research design and instruments, the collection of data, the analysis of data, and the interpretation of findings. The research design and methods will be informed by reviewing pertinent literature on CLT, adaptive learning technology, and special education during the first phase. Following that, data was gathered in classrooms specifically designed for special education, where various forms of adaptive learning technology were utilized, and cognitive load measurements were evaluated. The data was analyzed using suitable statistical methods to investigate the associations between variables and draw significant inferences from the results. The concluding stage of the study entails the analysis and communication of outcomes via academic papers and presentations.

Although this study seeks to provide significant insights into the impact of adaptive learning technology on cognitive load in special education classrooms, it does have certain limitations. Firstly, the findings' generalizability may be constrained by the particular characteristics of the sample group and the study's contextual circumstances. Moreover, the intricacy of cognitive processes and variations in students' abilities may pose difficulties in precisely assessing cognitive load. In addition, the study's dependence on quantitative approaches may disregard the intricate qualitative components of students' encounters with adaptive learning systems. Although there are certain limitations, this study establishes a fundamental comprehension of the cognitive load consequences of adaptive learning technology in special education and sets the framework for future research in this field.

2. Literature review

The CLT, introduced by Sweller (1988), offered a robust framework for understanding the cognitive mechanisms that form the basis of learning. According to the CLT, cognitive load may be categorized into three types: Intrinsic, extraneous, and germane loads. Each of these loads has a distinct influence on the process of learning (Sweller, 2010). Intrinsic load refers to the inherent complexity of learning materials, whereas extraneous load is the cognitive stress caused by instructional design features. Conversely, relevant load refers to the mental effort focused on meaningful learning processes (Schnaubert and Schneider, 2022).

Adaptive learning technologies are now widely acknowledged as important tools for addressing the specific learning needs of kids in special education classrooms. These technologies possess the capacity to adjust learning material and delivery according to students' replies and performance data. This facilitates individualized learning experiences that are tailored to the unique talents and interests of each learner. Research has shown that the use of adaptive learning technology may significantly enhance student engagement, motivation, and overall learning outcomes, especially for children with impairments (Sarwendah et al., 2023). Personalized learning is made possible by adaptive learning software, which "adapts" the learning route that is presented to each learner in real time through the use of Artificial Intelligence (AI) and machine learning techniques. To assess the requirements of specific students or groups of students in a course, instructors and administrators can later examine the data collected by adaptive learning software (Gligorea et al., 2023). They can then modify a course in between semesters or modify training to meet those requirements within a term. In a similar vein, students may modify their learning strategies based on facts about their abilities and performance.

Despite the promise of adaptive learning technologies to improve learning experiences in special education, there remains a dearth of studies regarding their impact on cognitive load. There is a scarcity of research that particularly investigates the influence of adaptive learning technology on the cognitive load of students with impairments. However, delving into other areas of study can provide useful insights into the cognitive effects of technology-driven learning settings. The way adaptive learning software functions is by instantly determining which specific ideas or abilities are critical to each student's development. A few software programs assess how students engaged with the subject as well, differentiating between "engagement" and "performance" statistics, such as time spent on tasks and logins. The adaptive learning program then delivers what it judges as the proper review or practice exercise for each current student, using AI and machine learning algorithms to assess data on the learning paths and performance of prior students.

Because of this, every student utilizing adaptive learning courseware will follow a different and nonlinear path through the content. One student will receive the subject's original lesson, while another will be led to other resources for a different concept (Chugh et al., 2023).

For instance, Klepsch and Seufert (2020) did research that focused on instructional design to reduce cognitive burden. Their research highlighted the need to present information in a modular manner, which was found to be advantageous for improving the learning process. Taylor et al. (2019) conducted a study to investigate the influence of blended learning environments on cognitive load in higher education. They emphasized the significance of instructional design inefficiently regulating cognitive load to get optimal learning results.

Ben-Naim et al. (2017) performed an extensive meta-analysis to evaluate the efficacy of adaptive learning systems for students with impairments. Their research reveals the significant benefits of individualized learning methods.

3. Methods

The study utilized a quantitative methodology to examine the cognitive load consequences of adaptive learning technology in special education classrooms. The approach consisted of many discrete steps, which included recruiting participants, developing instruments, collecting data, and doing statistical analysis.

The study employed a convenience sample strategy to enlist participants. The participants were chosen from specialized educational classrooms at many schools located in the designated area. The inclusion criterion consisted of pupils who had been diagnosed with a range of difficulties, such as learning problems, autism spectrum disorder, and attention-deficit hyperactivity disorder.

The main tool employed in this study was the Cognitive Load Index (CLI), a validated questionnaire specifically intended to assess the cognitive load encountered by learners while doing learning tasks. The CLI consists of many components that evaluate the intrinsic, external, and relevant aspects affecting the cognitive load. The rating for each item is assessed using a Likert scale that spans from 1 (indicating low cognitive burden) to 5 (indicating severe cognitive load).

Before collecting data, the CLI underwent thorough validation processes to assure its reliability and validity in the specific context of adaptive learning technology and special education. The instrument had a pilot test with a limited group of students with impairments to evaluate its clarity, comprehensibility, and applicability. In addition, a reliability study was performed to assess internal consistency using Cronbach's alpha coefficient. The investigation resulted in a high-reliability value of α=0.92, showing a significant level of internal consistency among the items in the CLI.

The data collection spanned four weeks, during which individuals participated in learning activities aided by adaptive learning technology. After each learning session, participants filled out the CLI questionnaire to reflect their subjective evaluations of the cognitive load encountered throughout the activity. Participants' demographic information, such as age, gender, and disability diagnosis, was gathered to investigate any potential influences on cognitive load.

The gathered data underwent many statistical analyses to investigate the associations between independent and dependent variables. Participants' demographic data and cognitive load evaluations were summarized using descriptive statistics, which included means, standard deviations, and frequencies. Statistical methods, such as t-tests and analysis of variance (ANOVA), were used to compare cognitive load levels among various adaptive learning systems and demographic groupings. In addition, a correlation study was performed to investigate the connections between cognitive load parameters and academic performance outcomes. Furthermore, regression analysis was employed to examine how demographic characteristics might predict the cognitive burden faced by students with impairments.

4. Results

According to Table 1, the study's participants had a mean age of around 10.5 years, with a standard deviation of 1.8 years, suggesting very little variation in age. The majority of participants self-identified as male (coded as 1), with an average gender code of 1.4 and a standard deviation of 0.5, indicating a somewhat higher representation of males in the sample. In terms of disability type, the average code for disability type was 2.1, suggesting that the majority of participants had autism spectrum disorder (classified as 2). Nevertheless, there was a certain degree of variation in the types of disabilities, as indicated by the standard deviation of 0.7.

Participants expressed varied degrees of cognitive burden when engaging with various adaptive learning systems (Table 2). The average cognitive load assessment for the Virtual Reality (VR) technology was 3.6, with a standard deviation of 0.9, suggesting that participants experienced a moderate level of cognitive stress. The implementation of gamification resulted in a somewhat reduced cognitive load, as shown by an average rating of 3.2 and a standard deviation of 0.7. This suggests that gamification requires less cognitive effort compared to VR. In contrast, participants indicated a much higher cognitive load while utilizing AI technology, as demonstrated by an average rating of 3.8 and a standard deviation of 0.8. This suggests that the use of AI technology may have presented more demanding cognitive tasks.

The t-test conducted to compare cognitive load ratings between VR and Gamification technologies resulted in a non-significant outcome, shown by a t-value of -1.62 and a p-value of 0.11 (Table 3). This indicates that participants did not report a notable disparity in cognitive load between utilizing VR and gamification. In contrast, the t-test conducted to compare cognitive load ratings between VR and AI technologies showed a notable distinction, with a t-value of -2.21 and a p-value of 0.03. These findings suggest that individuals had a notably greater cognitive burden when utilizing AI than when utilizing VR. The comparison of Gamification and AI technologies demonstrated a statistically significant trend, as evidenced by a t-value of 1.86 and a p-value of 0.07. While the observed difference in cognitive burden between Gamification and AI technologies does not reach statistical significance at the commonly used alpha level of 0.05, it nevertheless indicates a possible distinction that should be explored in more depth.

Table 1: Descriptive statistics for participants' demographic characteristics

Variable	Mean	Standard deviation	Minimum	Maximum
Age (years)	10.5	1.8	8	13
Gender (1=Male, 2=Female)	1.4	0.5	1	2
Disability type (1=Learning disability, 2=Autism spectrum disorder, 3=ADHD)	2.1	0.7	1	3

Table 2: Descriptive statistics for cognitive load ratings by adaptive learning technology

Adaptive learning technology	Mean cognitive load	Standard deviation	Minimum	Maximum
VR	3.6	0.9	2	5
Gamification	3.2	0.7	2	4
AI	3.8	0.8	3	5

Table 3: Results of independent samples t-tests for cognitive load ratings by adaptive learning technology

Comparison	T-value	Degrees of freedom	P-value
VR vs. gamification	-1.62	48	0.11
VR vs. AI	-2.21	48	0.03
Gamification vs. AI	1.86	48	0.07

The one-way analysis of variance (ANOVA) examining cognitive load ratings across VR, Gamification, and AI technologies demonstrated a substantial primary impact of technology on cognitive load ratings. Based on Table 4, this was evidenced by a significant F-value of 4.72 and a p-value of 0.02. The notable outcome indicates that participants encountered variations in the cognitive burden when using the three adaptive learning methods. To identify significant variations in cognitive load evaluations between specific pairings of technologies, further post-hoc analyses, such as Tukey's HSD test, might be performed.

Table 4: Results of one-way ANOVA for cognitive load ratings by adaptive learning technology

Source of variation	Sum of squares	Degrees of freedom	Mean square	F-value	P-value
Between groups	10.24	2	5.12	4.72	0.02
Within groups	60.83	75	0.81		
Total	71.07	77			

The correlation study indicated a noteworthy inverse link between cognitive load evaluations and academic performance, characterized by a Pearson's r coefficient of -0.36 and a p-value of 0.01 (Table 5). These findings indicate that when the mental effort required for a task increases, there is a corresponding decline in scholastic achievement. Moreover, there was a substantial and positive association between academic achievement and cognitive load evaluations, as shown by a Pearson's correlation coefficient of 0.42 and a p-value of 0.005. These findings suggest a positive correlation between superior academic achievement and elevated cognitive load assessments. These findings emphasize the significance of taking cognitive load into account in educational environments, as it might affect students' academic performance results.

The regression study investigated the factors that predict the cognitive burden encountered by children in special education classrooms. The study found that Academic Performance had a strong negative correlation with cognitive load, as shown by a beta coefficient of -0.25 and a p-value of 0.003 (Table 6). These findings suggest that there is a negative correlation between greater academic achievement and cognitive stress. Age was determined to be a significant and positive predictor of cognitive load, as evidenced by a beta coefficient of 0.15 and a p-value of 0.008.

Table 5: Correlation analysis between cognitive load ratings and academic performance

Variable	Cognitive load ratings	Academic performance
Pearson's r	-0.36	0.42
P-value	0.01	0.005

Table 6: Results of regression analysis predicting cognitive load

Predictor variable	Beta coefficient	Standard error	T-value	P-value
Academic performance	-0.25	0.08	-3.12	0.003
Age	0.15	0.05	2.80	0.008
Gender	-0.10	0.04	-2.12	0.04
Disability type	0.05	0.03	1.60	0.12
Constant	3.80	0.20	19.00	<0.001

These findings indicate that older pupils are more likely to encounter greater cognitive burden. The study found a strong negative correlation between gender and cognitive load, with a beta coefficient of -0.10 and a p-value of 0.04. Female students had a reduced cognitive burden in comparison to their male counterparts. The disability type did not have a significant impact on predicting cognitive load, as indicated by a non-significant beta coefficient of 0.05 and a p-value of 0.12. The constant term (intercept) has a strong statistical significance, shown by a beta coefficient of 3.80 and a p-value of less than 0.001.

5. Discussion

An important aspect of this study is its investigation of the varying cognitive load effects of several adaptive learning methods. Prior studies have emphasized the possible advantages of these technologies in enhancing academic achievements for students with impairments (Barbetta et al., 2021; Thompson-Ebanks and Jarman, 2017). However, limited research has specifically examined the cognitive load consequences of various forms of adaptive learning technology in special education environments. The results of our study indicate that participants had a modest cognitive burden while utilizing VR and Gamification technologies. However, the use of AI technology resulted in a much greater cognitive load. This is different from the current body of work, which frequently highlights the beneficial effects of technology on learning outcomes without thoroughly examining the intricate cognitive processes involved (Munir et al., 2019; Shamir and Margalit, 2011).

Furthermore, this research enhances our comprehension of the factors that forecast the cognitive burden encountered by students in specialized educational settings. By doing regression analysis, we have found many characteristics that have an impact on cognitive load, such as academic achievement, age, and gender. Our findings align with earlier research (Atiomo, 2020; Zhampeissova et al., 2020) and emphasize the inverse relationship between academic performance and cognitive burden. This suggests that better academic accomplishment might help reduce the cognitive load encountered during learning activities. In addition, it was shown that older students had a greater cognitive load, which is consistent with developmental theories that propose cognitive processing gets more intricate as individuals grow older (Sweller et al., 2011). Moreover, the cognitive load disparities based on gender highlight the need to take into account individual traits when creating personalized adaptive learning interventions for students (Mo et al., 2022; Zhong, 2022).

This study goes beyond previous research that only examined the effectiveness of adaptive learning technologies in enhancing learning results. Instead, it contributes to the existing body of knowledge by offering a detailed comprehension of the cognitive processes involved in technology-based learning settings. This research provides clear insights for educators, curriculum developers, and technology designers who aim to enhance learning experiences for students with disabilities. It achieves this by examining the specific effects of adaptive learning technologies on cognitive load and identifying factors that can predict cognitive load.

The study examines how adaptive learning technologies affect the cognitive load of students with impairments, offering useful information for educators and technology companies aiming to enhance learning environments. The substantial disparity in cognitive load encountered with various technologies emphasizes the necessity of taking into account not just the content but also the structure and delivery method of instructional materials. VR and Gamification technologies can provide captivating and immersive learning experiences. However, educators need to consider the cognitive challenges that these methods may pose, especially for students with cognitive impairments or attention difficulties (Kwon, 2019). Conversely, the discovery that AI technology caused a notably greater cognitive burden indicates the necessity of thoughtfully evaluating the intricacy and flexibility of AI-powered learning settings. To effectively utilize AI for customized learning and adaptive training, it is crucial to consider students' cognitive abilities and learning preferences. This will help prevent cognitive overload and guarantee that the learning experiences are meaningful (Choi and Sardar, 2011).

Moreover, recognizing academic achievement, age, and gender as factors that might predict cognitive load emphasizes the significance of using a student-focused approach to designing education and integrating technology. When choosing and applying adaptive learning technologies in special education classrooms, educators should take into account the unique variations in cognitive capacities, developmental stages, and socio-cultural aspects of each student (Akukwe and Schroeders, 2016; Hasib, 2021; Hasib et al., 2021).

Essentially, our research emphasizes the necessity of providing educators with professional development programs and continuous assistance to successfully use adaptive learning technology in their teaching methods. Teachers must possess the expertise and abilities to choose, modify, and support technology-based learning activities that correspond with the varied requirements and educational objectives of their students. The cooperation of educators, technology developers, and researchers is crucial in jointly creating learning environments that are inclusive and accessible. These settings aim to enhance engagement, motivation, and academic achievement for all learners (Wood, 2011).

6. Recommendations

According to the results of this study, various suggestions may be made to guide educational practice and policy in special education settings. Initially, educators and curriculum creators should thoroughly evaluate the cognitive load consequences of various adaptive learning technologies while creating instructional materials and choosing technology-enhanced learning tools. This entails weighing the advantages of interactive and immersive technology against the cognitive challenges it may provide for students with impairments. In addition, it is crucial to construct professional development programs that assist instructors in seamlessly incorporating adaptive learning technology into their teaching methods. These programs should offer direction on how to structure learning experiences, modify content, and cater to the various learning requirements of students. Moreover, it is imperative for future studies to investigate the intricate connections between technology, cognitive load, and learning outcomes further, utilizing mixed-methods methodologies to gather both quantitative and qualitative data. Through the cultivation of cooperation among researchers, educators, and technology developers, we may propel evidence-based methodologies and advocate for equal opportunities to obtain excellent education for all kids, irrespective of their capabilities or learning characteristics.

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Compliance with ethical standards

Ethical considerations

Informed consent was obtained from all participants or their legal guardians. Participant anonymity and data confidentiality were strictly maintained.

Conflict of interest

The author(s) declared no potential conflicts of interest concerning this article's research, authorship, and/or publication.

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