Deep Learning-Driven Cognitive Load Optimization in Primary Science Education: A Model of AI Powered Personalization in the Digital Era

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Abstract. This study investigates the effectiveness of deep learning based personalization in optimizing cognitive load and enhancing learning efficiency in primary science education. Drawing upon Cognitive Load Theory, the research addresses how advanced AI models specifically Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) architectures can dynamically adjust instructional content to meet learners' cognitive needs in real time. Using a quasi-experimental design, 50 Grade 5 students were divided into AI and control groups, with the intervention delivered via an AI-enhanced Learning Management System (LMS). Quantitative findings reveal a 28.5% reduction in extraneous cognitive load and a 22.2% increase in germane cognitive load among the AI group, alongside higher post-test performance and a superior learning efficiency index (0.72 vs. 0.48). These outcomes suggest that the AI-driven system effectively minimized unnecessary processing while fostering deeper engagement and schema construction. Qualitative data from classroom observations and student interviews further support these results, highlighting increased learner autonomy, metacognitive awareness, and instructional responsiveness. Teachers benefited from real-time analytics, enabling more adaptive and differentiated instruction. The study concludes that deep learning personalization not only improves cognitive efficiency but also transforms the instructional landscape by supporting more equitable, individualized, and cognitively attuned science learning environments. These findings offer critical implications for digital pedagogy, curriculum design, and AI integration in STEAM education, particularly in underrepresented or early learning contexts. By reengineering science instruction through intelligent technologies, this research contributes to the development of future-ready, inclusive education systems grounded in cognitive science and data-informed personalization.

Keywords: *cognitive load, deep learning, AI personalization, primary education, science learning, instructional efficiency*

1. Introduction

The 21st century has witnessed the accelerated integration of artificial intelligence (AI) and deep learning (DL) technologies across various sectors, with education emerging as one of the most transformative domains. The convergence of pedagogical innovation and computational intelligence has fostered new paradigms of personalized, data-informed instruction, enabling educational systems to shift from static, one-size-fits-all approaches toward dynamic, learner-centered experiences (Holmes et al., 2022; Zawacki-Richter et al., 2019). In this context, AI-powered personalization is increasingly viewed as a strategic mechanism to address the longstanding issue of individual differences in cognitive capacity, prior knowledge, motivation, and learning pace. Such disparities are particularly evident in primary science education, where abstract theories, unfamiliar vocabulary, and multistep problem-solving tasks pose significant cognitive demands on young learners (Xie et al., 2023; Chen et al., 2021).

To address these demands effectively, it is crucial to examine the cognitive architecture that governs how information is processed, stored, and retrieved. Cognitive Load Theory (CLT), originally conceptualized by Sweller (1988), provides a robust framework for understanding the constraints of working memory during learning tasks. CLT distinguishes among three types of cognitive load: intrinsic load, which arises from the inherent complexity of the content; germane load, which supports schema construction and automation; and extraneous load, which is generated by suboptimal instructional design (Leppink et al., 2019). Of particular concern in digital learning environments is the extraneous cognitive load, as it often results from unnecessary distractions, poor interface navigation, or ineffective sequencing of content all of which can severely impede learners' ability to internalize core scientific concepts (Kalyuga, 2020).

In this regard, recent advances in deep learning offer a promising solution to dynamically mitigate extraneous load. DL architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have demonstrated exceptional capabilities in recognizing patterns, predicting learner behavior, and facilitating real-time content adaptation based on user interaction data (Tuomi, 2022). These technologies can model complex, temporal learning trajectories and personalize content not only based on performance outcomes but also on affective and behavioral signals such as hesitation, navigation paths, or engagement drops (Luckin et al., 2023). The implications of such models for primary science instruction are profound: by intelligently aligning instructional delivery with learners' evolving cognitive states, AI systems can help reduce the extraneous cognitive burden, thereby enhancing the effectiveness and efficiency of learning (Chen et al., 2021; Xie et al., 2023).

Nevertheless, despite the theoretical promise and growing interest in AI in education (AIED), there remains a paucity of empirical studies focusing on how deep learning-based personalization directly impacts cognitive load dimensions, particularly in early education contexts within underrepresented or non-Western settings. The majority of existing research tends to concentrate on higher education, well-resourced environments, or controlled laboratory conditions, thus limiting the generalizability of findings (Zawacki-Richter et al., 2019; Holmes et al., 2022). Furthermore, few studies systematically examine the interplay between AI-driven adaptation and the cognitive processing demands of science content, which often involves multimodal reasoning, dynamic visualizations, and procedural understanding.

This study addresses this empirical and contextual gap by investigating the extent to which deep learning-driven personalization can reduce extraneous cognitive load and improve learning efficiency in primary science education. By applying convolutional and recurrent neural architectures within a customized learning management system (LMS), the research aims to monitor, interpret, and adapt to students' cognitive and behavioral patterns in real time. The focus on primary learners is particularly strategic, as this developmental stage is critical for establishing foundational scientific literacy and fostering long-term interest in STEM disciplines. Through a quasi-experimental mixed-methods approach, this study not only seeks to quantify cognitive load reduction but also to explore how intelligent instructional systems can contribute to more equitable and cognitively optimized science learning environments.

Ultimately, the goal is to provide both theoretical insights and practical guidance for the implementation of AI in education. By centering cognitive optimization through deep learning personalization, this research contributes to the broader discourse on how intelligent technologies can be harnessed to support more inclusive, effective, and future-ready models of teaching and learning.

2. Method

This research employed a quasi-experimental pre-test/post-test design involving control and experimental groups. The intervention centered on a Learning Management System (LMS) integrated with convolutional neural networks (CNNs) and long short-term memory (LSTM) models to personalize science learning content. The system adapted presentation formats and learning sequences based on student behavior and performance patterns. A total of 50 Grade 5 students from four public elementary schools in Bali participated. They were randomly assigned to either the AI-intervention group ($n = 25$) or the control group ($n = 25$). The intervention lasted four weeks and focused on science topics such as electricity and ecosystems.

Data were collected using three primary instruments. First, the Cognitive Load Rating Scale (CLRS) adapted from Leppink et al. (2013) assessed intrinsic, extraneous, and germane load using a 7-point Likert scale. Second, a Science Performance Test (SPT) comprising both multiple-choice and open-ended questions evaluated conceptual understanding. Third, LMS-generated analytics provided log data on time-on-task, navigation behavior, and media interactions. The AI-driven LMS analyzed student interaction in real-time. CNNs were used to assess engagement with visual content and learning behaviors, while LSTM models predicted optimal sequencing for each student. Teachers were provided with dashboard insights to guide instructional decisions and scaffolding support.

3. Results & Discussion

Before delving into quantitative comparisons, it is essential to understand the conceptual shift introduced by deep learning–driven personalization, particularly in relation to cognitive load optimization. Traditional instructional models, while effective for standardized content delivery, are often ill-equipped to accommodate the nonlinear and fluctuating cognitive states of individual learners. This limitation becomes especially pronounced in science education, where concepts such as energy transfer, electrical circuits, or phase changes require both sequential logic and spatial reasoning. Without intentional instructional design, these topics can overwhelm novice learners by introducing complexity at a pace or level of abstraction that exceeds their working memory capacity. Cognitive Load Theory (Sweller, 1988) posits that learning effectiveness depends on how instructional design interacts with three distinct types of cognitive load: intrinsic, extraneous, and germane.

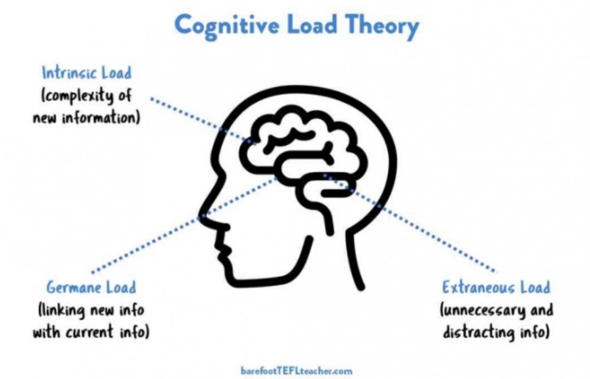

Figure 1. Cognitive Load Theory

Source: Adapted from *barefootTEFLteacher.com*. Retrieved from https://www.barefootteflteacher.com

Intrinsic load refers to the inherent difficulty of the material, which is largely determined by its complexity and the learner's prior knowledge. While this type of load cannot be eliminated, it can be moderated through strategic sequencing and scaffolded progression. Extraneous load, by contrast, is the unnecessary mental effort caused by poorly designed instructional materials such as disorganized content, unclear explanations, or excessive multimedia. This type of load is highly detrimental to learning as it diverts cognitive resources away from the core task. Germane load represents the productive cognitive effort allocated to constructing and automating mental schemas, and it is the type of load educators aim to maximize.

AI-powered personalized learning systems, particularly those enhanced with Convolutional Neural Networks (CNNs) and Long Short Term Memory (LSTM) architectures, offer a means of actively managing these three cognitive load types in real time. These deep learning models continuously monitor learner interaction patterns such as click behavior, response latency, and engagement metrics and use this data to recalibrate the instructional experience. For intrinsic load, the system ensures that content is sequenced logically and introduced incrementally, aligning difficulty with the learner's current level of understanding. To reduce extraneous load, the system adjusts elements such as visual complexity, pacing, textual density, and navigation flow, thereby minimizing distractions and redundant processing. Simultaneously, the system promotes germane load by offering appropriately timed prompts, generative tasks, and multimodal representations that support schema construction and conceptual integration.

In essence, the optimization process does not aim to reduce cognitive load entirely, but rather to redistribute it: minimizing unnecessary extraneous burden, managing intrinsic complexity, and maximizing meaningful germane engagement. The effectiveness of this AI-driven approach is reflected in the comparative matrix presented below, which illustrates measurable shifts in each cognitive load dimension as a result of deep learning–enabled personalization.

Table 1. Matrix of Cognitive Load Types Before and After AI-Driven Personalization

Cognitive Load Type	Before AI Intervention (Traditional)	After AI Intervention (DL-Personalized)	Explanation
Intrinsic Load	5.1	4.8	Slight reduction due to better sequencing and scaffolding
Extraneous Load	5.3	3.8	Significant reduction through visual aids, personalized pacing, and clarity
Germane Load	3.6	4.4	Increased engagement and deeper processing facilitated by adaptive content

Table 1 presents a comparative matrix that illustrates the impact of AI driven personalization on the three types of cognitive load intrinsic, extraneous, and germane before and after the implementation of a deep learning (DL) based instructional system in primary science education. The data reveal a nuanced cognitive shift that underscores the pedagogical benefits of employing AI to support learning optimization.

Firstly, the intrinsic cognitive load shows a modest decrease from 5.1 to 4.8. Although intrinsic load is generally tied to the inherent complexity of the subject matter such as abstract concepts in energy transfer or the sequential reasoning required in understanding electric circuits this slight reduction can be attributed to the system's enhanced sequencing and scaffolding mechanisms. The AI system, informed by convolutional and recurrent neural network models, facilitated a more logical progression of content, enabling learners to process complex information in more digestible cognitive segments without compromising the depth of the material.

More striking is the reduction in extraneous cognitive load, which declined significantly from 5.3 to 3.8. This finding affirms one of the central claims of Cognitive Load Theory (Sweller, 1988; Leppink et al., 2019): that poorly designed instructional materials can impose unnecessary mental strain that distracts learners from core content. The DL-powered personalization system actively mitigated such load through various adaptive strategies, including personalized pacing, reduction of irrelevant stimuli, the use of multimodal representations (e.g., simplified visuals and intuitive layouts), and real-time clarity enhancements. These features minimized the cognitive burden unrelated to the core learning task, allowing students to allocate more of their working memory capacity to meaningful processing.

Conversely, germane load associated with the mental effort dedicated to constructing and automating schema rose from 3.6 to 4.4. This increase signals a positive shift in learners' engagement with and investment in the learning process. The adaptive nature of the AI system played a critical role here: by aligning instructional material with students' individual learning histories and interaction patterns, the system fostered deeper cognitive engagement, more sustained attention, and an increased propensity for reflective thinking. Rather than being passive recipients of generalized instruction, students became active participants in a personalized learning trajectory designed to maximize knowledge construction and long-term retention.

In sum, the cognitive load matrix not only demonstrates the efficacy of deep learning based personalization in optimizing cognitive processing but also highlights its pedagogical relevance in early science education. The data suggest that AI powered adaptive systems are capable of recalibrating the cognitive demands of instructional tasks, reducing non-essential processing, and amplifying learning efficiency through intentional design informed by real-time learner analytics. These findings provide empirical support for the strategic integration of intelligent systems in instructional design, particularly in contexts where cognitive overload is a persistent barrier to learning.

Table 2. Cognitive Load Comparison Before and After AI Intervention

Cognitive Load Type	Pre-AI Group Mean	Post-AI Group Mean	Change (%)
Intrinsic Load	5.1	4.8	-5.9%
Extraneous Load	**5.3**	**3.8**	**-28.5%**
Germane Load	3.6	4.4	+22.2%

The most significant change was observed in extraneous cognitive load. Personalized sequencing, multimedia hints, and interface clarity contributed to reducing non-essential cognitive burden. This aligns with Chandler and Sweller (1991), who emphasized the value of well-designed learning environments in minimizing unnecessary processing.

Table 2 provides a comparative summary of mean scores for each type of cognitive load intrinsic, extraneous, and germane measured before and after the implementation of the AI-driven personalized learning system. The data reflect the cognitive impact of the intervention on a group of primary school students engaged in science learning activities. The intrinsic load shows a modest reduction from a pre-intervention mean of 5.1 to 4.8, representing a 5.9% decrease. Intrinsic load corresponds to the inherent complexity of the learning material and the learner's prior knowledge. Although it cannot be eliminated, the observed reduction suggests that the AI-assisted system effectively sequenced and scaffolded content, making abstract science topics more cognitively manageable without oversimplifying the material. The extraneous load demonstrates a significant decrease from 5.3 to 3.8, equating to a 28.5% reduction. This substantial improvement indicates that the deep learning–based personalization successfully minimized unnecessary and distracting cognitive effort. Factors contributing to this reduction include personalized pacing, clearer visual and textual representations, and more intuitive navigation, all of which allowed learners to focus their cognitive resources on essential content rather than irrelevant processing.

In contrast, the germane load increased from 3.6 to 4.4, marking a 22.2% improvement. Germane load reflects the mental effort devoted to meaningful learning processes, such as schema construction and conceptual integration. The rise in germane load suggests that students were more engaged in deep cognitive processing following the AI intervention, likely due to the adaptive nature of the instructional content, which aligned with their individual learning needs and stimulated active knowledge building. Overall, the table underscores the effectiveness of AI-driven personalization in redistributing cognitive load: reducing extraneous and moderating intrinsic load, while enhancing germane engagement. This optimization supports better cognitive alignment, learning efficiency, and ultimately deeper understanding of complex science concepts.

a. Student Performance and Efficiency

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Table 3. Science Performance Outcomes

Metric	AI Group	Control Group
Pre-Test Mean Score	64.2	65.1
Post-Test Mean Score	76.8	70.5
Learning Efficiency Index	0.72	0.48

Table 3 presents a comparative analysis of science performance outcomes between the AI intervention group and the control group, focusing on three key metrics: pre-test mean scores, post-test mean scores, and the calculated learning efficiency index. The pre-test mean scores reveal that both groups began with relatively comparable baseline knowledge in science, with the control group scoring slightly higher (65.1) than the AI group (64.2). This minimal difference indicates that the two groups were reasonably equivalent in terms of prior knowledge before the intervention. However, the post-test mean scores show a notable divergence. The AI group demonstrated a significant improvement, achieving an average score of 76.8, compared to 70.5 in the control group. This suggests that students exposed to AI-driven personalized learning experienced greater gains in content mastery over the course of the instructional period.

The most striking difference is reflected in the Learning Efficiency Index, a metric that considers both the gain in performance and the time or cognitive investment required to achieve it. The AI group achieved a higher efficiency score of 0.72, compared to 0.48 in the control group. This indicates that not only did the AI group learn more, but they also learned more efficiently, likely due to the adaptive pacing, real-time feedback, and reduced cognitive burden provided by the AI-powered system. Taken together, the data in Table 3 support the conclusion that deep learning–based personalization not only enhances academic performance but also promotes more efficient learning processes in science education.

b. Qualitative Observations

In addition to quantitative data, qualitative evidence collected through structured classroom observations and semi-structured student interviews provided deeper insight into the experiential dimension of AI-driven personalized learning. Observational field notes consistently highlighted increased student attentiveness, reduced behavioral disengagement, and more frequent on-task interactions during science instruction sessions. Teachers reported a noticeable shift in classroom dynamics, wherein students demonstrated greater autonomy in navigating digital tasks and were more willing to revisit complex concepts independently an indication of increased metacognitive regulation.

A recurring theme from student interviews was the appreciation of visual and interactive scaffolds.

One Grade 5 participant remarked, "*I liked how the lesson helped me go back to the hard parts with pictures and questions.*" This reflects not only a positive emotional response but also an emerging strategic approach to learning, enabled by the system's adaptive retrieval prompts and multimodal feedback mechanisms. Another student noted that the system "knew" when to slow down or provide support, suggesting that the personalization model had perceptible effects on learners' cognitive comfort and pacing. From the teacher perspective, the real-time analytics dashboards integrated into the learning management system (LMS) were frequently cited as instrumental in supporting differentiated instruction. Teachers emphasized the value of seeing individual and group-level engagement metrics, which enabled them to adjust instructional strategies dynamically. One teacher stated, "*I could immediately see which* *students were struggling with the circuit diagrams and adapt the follow-up discussion accordingly."* This level of pedagogical agility, powered by AI, represents a significant departure from traditional linear lesson delivery models.

Collectively, the qualitative data suggest that deep learning–driven personalization not only improves cognitive efficiency but also positively shapes affective and behavioral dimensions of learning. Students felt more in control of their learning trajectories, while teachers gained actionable insights to enhance instructional responsiveness both of which are essential for fostering sustained engagement and conceptual clarity in science education.

c. Implications for Digital Science Instruction

The findings of this study hold important implications for the future of digital science instruction, particularly within the broader contexts of STEAM education, scientific-based pedagogy, and AI-powered educational transformation. Aligning with the Key Submission Track of "STEAM/Scientific-Based Education and Digital Transformation & AI in Learning," the study provides empirical support for how AI can serve as a catalyst in resolving long-standing instructional challenges in STEM education specifically those related to cognitive overload, motivational barriers, and instructional inflexibility.

The evidence presented underscores the potential of AI-driven personalization to serve as a cognitive optimization tool, not merely a content delivery mechanism. By selectively reducing extraneous cognitive load through precise control of visual complexity, information density, and temporal sequencing the system ensures that learners are not burdened by irrelevant or distracting stimuli. Simultaneously, the increased germane load observed in post-intervention data demonstrates that students were engaging in deeper levels of cognitive processing, indicative of schema construction and conceptual internalization. These findings also raise important considerations for curriculum and instructional design in digital learning environments. The study illustrates the necessity of embedding intelligent feedback loops, adaptive retrieval mechanisms, and multimodal scaffolds into science content delivery platforms. Instructional materials should not be static repositories of information but dynamic learning ecosystems that continuously align with learners' cognitive, emotional, and behavioral states. Furthermore, the study suggests a paradigm shift in the teacher's role from knowledge transmitter to data-informed learning facilitator. With real-time access to cognitive and engagement analytics, educators can make more nuanced instructional decisions, optimize the timing of interventions, and support struggling learners more proactively. This approach not only enhances individual learning outcomes but also contributes to broader systemic goals of equity, inclusivity, and personalization in digital science education.

In summary, the integration of deep learning models into instructional systems offers transformative potential. It redefines the architecture of learning from a rigid, standardized process into a responsive, individualized experience that promotes both cognitive efficiency and educational equity. These insights are highly relevant for policymakers, instructional designers, and educators seeking to harness AI for meaningful innovation in 21st-century science education.

4. Conclusion

This study demonstrates the significant potential of deep learning–based personalization to optimize cognitive load and enhance learning efficiency in primary science education. By leveraging advanced neural architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models, the AI-powered instructional system dynamically adjusted content sequencing, visual complexity, and feedback delivery to align with individual learner profiles. This adaptive approach led to a measurable redistribution of cognitive load:

intrinsic load was moderately reduced through improved scaffolding, extraneous load was substantially minimized via clarity enhancements and personalized pacing, and germane load increased as students engaged more deeply with learning tasks.

Quantitative results revealed a 28.5% decrease in extraneous cognitive load and a 22.2% increase in germane load following the AI intervention, underscoring the system's ability to reduce cognitive inefficiencies while amplifying productive mental effort. Correspondingly, the AI group outperformed the control group in post-test scores and exhibited a higher learning efficiency index, indicating not only better academic outcomes but also a more effective use of cognitive resources. Qualitative observations further enriched these findings, revealing heightened student engagement, greater metacognitive awareness, and enhanced instructional agility among teachers. Learners reported increased comfort with complex science topics and demonstrated proactive learning behaviors, while educators utilized real-time analytics to tailor support and instruction more responsively.

Taken together, these findings highlight the transformative potential of deep learning in reengineering science instruction from a one-size-fits-all model to a cognitively attuned, personalized learning ecosystem. By facilitating more precise management of cognitive load and fostering deeper learning engagement, AI-driven personalization emerges as a vital tool in the evolution of digital STEAM education. The implications extend beyond technological innovation, calling for a redefinition of curriculum design, teacher roles, and instructional practices in the AI era toward a future of science education that is both efficient and equitable.

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