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Modeling Students' Cognitive Load Profiles as a Diagnostic Framework for Adaptive Mathematics Instruction in Higher Education

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Abstract: This study addresses the growing need for cognitively responsive adaptive learning in higher education mathematics by examining students' cognitive load profiles as a diagnostic foundation for instructional design. While previous research has primarily treated cognitive load as an outcome variable, limited attention has been given to its configuration at the individual level. This study aims to model students' cognitive load profiles and explore their implications for adaptive mathematics instruction. A quantitative exploratory design was employed involving 180 undergraduate students selected through probability sampling. Data were collected using a validated Cognitive Load Questionnaire measuring intrinsic, extraneous, and germane cognitive load. A person-centered profiling approach was applied to identify distinct cognitive load configurations. The results revealed three profiles: overload (34.4%), unproductive load (27.2%), and optimal load (38.4%). High intrinsic and extraneous load combined with moderate germane load indicates suboptimal cognitive resource allocation. This study contributes theoretically by positioning cognitive load profiles as a diagnostic framework for adaptive learning design, and practically by informing cognitively responsive instructional strategies in mathematics education.

Keywords: cognitive load; cognitive load profile; adaptive learning; mathematics education; higher education.

Abstrak: Penelitian ini merespons kebutuhan yang semakin meningkat terhadap pembelajaran adaptif yang responsif secara kognitif dalam pendidikan matematika di perguruan tinggi dengan mengkaji profil beban kognitif mahasiswa sebagai dasar diagnostik dalam perancangan pembelajaran. Sementara penelitian sebelumnya umumnya memperlakukan beban kognitif sebagai variabel hasil, perhatian terhadap konfigurasi beban kognitif pada tingkat individu masih terbatas. Penelitian ini bertujuan untuk memodelkan profil beban kognitif mahasiswa serta mengeksplorasi implikasinya terhadap pembelajaran matematika adaptif. Penelitian ini menggunakan desain kuantitatif eksploratif dengan melibatkan 180 mahasiswa sarjana yang dipilih melalui teknik *probability sampling*. Data dikumpulkan menggunakan instrumen *Cognitive Load Questionnaire* yang telah tervalidasi, yang mengukur beban kognitif intrinsik, ekstraneous, dan germane. Pendekatan profiling berbasis individu (*person-centered*) digunakan untuk mengidentifikasi konfigurasi beban kognitif yang berbeda. Hasil penelitian mengungkapkan tiga profil utama, yaitu *overload* (34,4%), *unproductive load* (27,2%), dan *optimal load* (38,4%). Kombinasi beban kognitif intrinsik dan ekstraneous yang tinggi dengan beban germane yang sedang menunjukkan alokasi sumber daya kognitif yang belum optimal. Penelitian ini memberikan kontribusi secara teoretis dengan memposisikan profil beban kognitif sebagai kerangka diagnostik dalam desain pembelajaran adaptif, serta secara praktis memberikan dasar bagi pengembangan strategi pembelajaran matematika yang lebih responsif terhadap kondisi kognitif mahasiswa.

Kata Kunci: beban kognitif; profil beban kognitif; pembelajaran adaptif; pendidikan matematika; pendidikan tinggi.

INTRODUCTION

Mathematics learning at university level requires students to have basic skills such as analytical reasoning, developing abstract thinking, symbolic representation and being able to apply logical reasoning in solving various complex problems to support the development of science and technology (Nurhajarurahmah, 2021; Nurhajarurahmah & Syarifuddin, 2025). It is undeniable that these numerous demands place a significant and varied cognitive load on working memory, especially when mathematical concepts are presented in a dense and unstructured manner. If left unchecked, students will struggle to develop meaningful conceptual understanding, even though they are procedurally able to correctly follow the steps to solving mathematical problems (Nurhajarurahmah & Mulbar, 2025; Sofroniou, 2025).

This phenomenon is explained in Cognitive Load Theory (CLT), which asserts that learning is constrained by limited working memory capacity (Clark & Kimmons, 2023; Sweller, 2011). CLT distinguishes cognitive load into three main components: intrinsic cognitive load (ICL), extraneous cognitive load (ECL), and germane cognitive load (GCL). These three components interact to determine the quality of conceptual understanding and the formation of knowledge schemas in long-term memory. Proportional management of ICL, reduction of ECL, and strengthening of GCL are key prerequisites for effective mathematics learning (Blegur, 2020; Putra & Nuryadi, 2020).

Current mathematics learning practices in higher education still tend to focus on delivering material in a uniform manner, with limited attention to the diversity of students' cognitive characteristics (Jayasree Krishnan et al., n.d.; McCormick et al., 2020; Pacheco et al., 2019; Richland et al., 2020; Ridho & Dasari, 2023). This approach is generally based on the assumption that students' learning capacities are homogeneous, even though empirically students demonstrate significant differences in prior knowledge, information processing speed, and metacognitive regulation abilities.

These conditions cause students participating in the same learning process to experience different cognitive loads. Some students experience high extraneous cognitive loads due to ineffective learning designs, such as unstructured presentation of material or fragmented concept representations (Curum & Khedo, 2021; Ozogul et al., 2012; Phan & Ngu, 2021). On the other hand, some students do not allocate their extraneous cognitive load optimally to build in-depth conceptual understanding (Angeli et al., 2009; Curum & Khedo, 2021; Hery Murtianto et al., 2022). This suggests that the experience of cognitive load is individual and cannot be treated as a uniform phenomenon.

As research on cognitive load in mathematics education develops, most studies still focus on the correlation between cognitive load and learning outcomes, or on testing the effectiveness of specific learning strategies. Recent studies in mathematics education have extensively examined cognitive load from various perspectives, particularly focusing on its relationship with learning outcomes and the effectiveness of instructional strategies. Prior research has demonstrated that managing intrinsic load through task complexity adjustment, reducing extraneous load through improved instructional design, and enhancing germane load through meaningful learning activities are essential for optimizing learning performance (Curum & Khedo, 2021; Ginns et al., 2020; Phan & Ngu, 2021).

Furthermore, several studies have explored the role of instructional interventions, such as worked examples, multimedia learning environments, and technology-enhanced learning systems, in regulating cognitive load to improve students' conceptual understanding (Angeli et al., 2009; Ozogul et al., 2012; Richland et al., 2020). With the advancement of digital learning, recent research has also begun to integrate artificial intelligence and adaptive learning systems to personalize instruction based on learners' performance indicators (Cosentino, Anton, Sharma, & ..., 2025; Liu et al., 2019; Xie et al., 2019; Xu et al., 2025). However, despite these advancements, existing studies predominantly adopt a variable-centered approach, treating cognitive load as an isolated construct rather than examining its configuration as an integrated system at the individual level.

Research that systematically maps students' cognitive load profiles as a basis for developing adaptive learning is still relatively limited. Despite extensive research on cognitive load, little is known about how its multidimensional configuration operates at the individual level to inform adaptive instructional design. This gap indicates that existing studies remain predominantly variable-centered and have not adequately captured the complexity of cognitive load interactions within individuals. Therefore, a person-centered approach is needed to capture the dynamic configuration of cognitive load components as a diagnostic basis for adaptive learning design. This lack of understanding of the interactions between intrinsic, extraneous, and intrinsic cognitive load at the individual level has the potential to lead to generalized learning adaptations that are less responsive to students' cognitive needs.

The limitations of studies focused on mapping cognitive load profiles indicate a gap between theoretical understanding of students' cognitive processes and their implementation in learning design. Without a diagnostic framework capable of capturing the dynamics of cognitive load interactions at the individual level, efforts to develop adaptive learning have the potential to lack a strong conceptual foundation. As a result, developed learning innovations, including those based on technology, tend to emphasize visible learning outcomes rather than underlying cognitive processes.

Digital transformation is driving the development of adaptive learning systems and artificial intelligence-based tutors. However, most of these systems still rely on observable performance indicators, such as answer accuracy, response time, or error rates, without explicitly considering students' cognitive load (Chen et al., 2025; Cosentino, Anton, Sharma, Gelsomini, et al., 2025; Jadhav et al., 2025). This approach risks producing adaptive decisions that focus solely on task difficulty, while ignoring cognitive stress and unproductive mental effort.

Therefore, mapping students' cognitive load profiles is not merely an analytical endeavor but a critical requirement for advancing adaptive mathematics learning in higher education. Without a diagnostic framework that captures the configuration of cognitive load at the individual level, instructional design risks remaining generalized and misaligned with students' cognitive capacities. This misalignment may lead to inefficient learning processes, increased cognitive overload, and suboptimal conceptual understanding.

In the context of rapidly evolving digital and AI-driven learning environments, the absence of cognitively grounded diagnostic data further limits the effectiveness of adaptive systems, which may rely solely on performance indicators without understanding underlying cognitive processes. Consequently, developing a cognitive load–based profiling approach becomes essential to ensure that adaptive learning is not only personalized but also cognitively meaningful and effective. This study responds to this critical gap by proposing a person-centered cognitive load profiling approach as a diagnostic foundation for adaptive mathematics instruction.

THEORETICAL STUDY

1. Cognitive Load Theory in Higher Education Mathematics Learning

Learning mathematics at the university level requires students to understand abstract concepts, symbols, and reasoning in a hierarchical and complex manner. Mathematical problems presented to students are constructed by involving the interrelationships between definitions, theorems, symbol manipulation, and conceptual reasoning. When these demands exceed their working memory capacity, the learning process becomes inefficient (Lovell & Sherrington, 2020; Sweller, 1988; Van Merriënboer & Sweller, 2010). When this occurs, this condition is understood to result from a mismatch between the complexity of the material and the student's cognitive capacity, not simply from individual limitations.

CLT distinguishes cognitive load into three components: intrinsic, extraneous, and germane. Intrinsic load relates to the level of material complexity and the number of elements that must be processed simultaneously. Extraneous load arises from inappropriate presentation methods, such as unstructured explanations or the use of confusing representations. Meanwhile, cognitive load reflects the mental effort that supports the formation of understanding and the development of knowledge schemas. Effective learning does not aim to reduce all cognitive load, but rather to manage all three components in a balanced manner (Larmuseau et al., 2019; Nursit, 2015). Reducing extra cognitive load and regulating intrinsic load allows for increased cognitive load, allowing students to develop deeper understanding and transfer knowledge to new situations.

Despite its strong theoretical foundation, the application of CLT to mathematics learning in higher education is still often used to explain learning outcomes after the learning process has taken place, rather than as a basis for designing learning from the outset. Furthermore, each student's experience of cognitive load varies, influenced by prior knowledge, learning strategies, and information processing methods. This situation suggests that cognitive load needs to be positioned as a foundation in learning design, rather than simply as an explanatory variable. With this approach, mathematics learning can be designed more in line with students' cognitive needs and more effectively build sustainable conceptual understanding.

2. Student Cognitive Load Profile as an Initial Diagnostic Perspective for Adaptive Learning

The student cognitive load profile can be positioned as a systematic initial diagnostic perspective in determining instructional design in mathematics learning. Furthermore, cognitive load not only represents the level of material difficulty but also provides an initial overview of how content complexity, the quality of the instructional design, and student cognitive engagement contribute to the learning process before instructional strategies are established (de Bruin & van Merriënboer, 2017; Koomen, 2016; Orosco et al., 2025; Smith & Suzuki, 2015).

As a diagnostic tool, this approach allows for more accurate identification of the sources of student learning difficulties. High intrinsic load is not always the primary cause of learning barriers if the instructional design is able to suppress extraneous load while simultaneously facilitating intrinsic load (Davenport, 2019; Hawthorne et al., 2019). Conversely, unstructured instructional design, the use of inappropriate representations, or the presentation of excessive information can actually increase extraneous load and hinder the process of knowledge construction. The literature shows that reducing extraneous load through strategies such as worked examples, material segmentation, and multimodality management plays a crucial role in creating space for enhanced cognitive processing, which supports deeper conceptual understanding (Davenport, 2019; Ginns et al., 2020; Hawthorne et al., 2019; Yu & Xue, 2025).

The primary implication of using cognitive load profiles as an initial diagnostic perspective is that they can provide insight and guide adaptive, student-centered instructional design. Lecturers can structure materials progressively to manage intrinsic load, simplify presentations to minimize extraneous load, and design learning activities that encourage deep cognitive engagement to optimize cognitive load, such as meaningful problem-solving and conceptual reflection. This approach is also relevant in diverse learning environments, including digital and inclusive learning, where variations in format and student characteristics influence the distribution of cognitive load differently. Thus, cognitive load profiles serve not only as an analytical tool but also as a practical foundation for designing effective, efficient, and sustainable mathematics learning.

RESEARCH METHODS

The research population included all students in the Mathematics Education Study Program at Makassar State University. The sample size was 180 students selected using probability sampling with simple random sampling to ensure representativeness of the sample within the population. The sample consisted of students from the classes of 2023, 2024, and 2025. The research instrument was the Cognitive Load Questionnaire (CLQ), developed based on the Cognitive Load Theory framework. This instrument measures three main constructs: (1) Intrinsic Cognitive Load (ICL), (2) Extraneous Cognitive Load (ECL), and (3) Germane Cognitive Load (GCL). Each construct was operationalized using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

To ensure the quality of the instrument, content validity was tested using expert judgment, and construct validity was tested using exploratory factor analysis (EFA). Furthermore, internal reliability was measured using Cronbach's Alpha coefficient, with an $\alpha \geq 0.70$ as an indicator of acceptable reliability.

Data collection was conducted online and offline, adhering to ethical research principles. All participants were explained the purpose of the study and asked to provide informed consent. Data collected was kept confidential, and participation was voluntary and anonymous.

Data analysis was conducted in two stages. First, descriptive statistical analysis was used to describe the distribution and trends of each cognitive load component through mean values, standard deviations, and score categorization. Second, pattern-based profiling analysis was conducted using a clustering approach to identify the relative configurations of ICL, ECL, and GCL in each individual. This technique allows for the classification of students into several cognitive load profiles, such as overload, unproductive load, and optimal load, thus providing a stronger empirical basis for developing adaptive mathematics learning.

RESULTS

Reliability of the Cognitive Load Instrument

Internal reliability testing was conducted using the Cronbach's Alpha coefficient for each construct in the Cognitive Load Questionnaire, developed based on the CLT framework. The analysis showed that all constructs had a good to excellent level of internal consistency. The following presents the internal reliability data for the instruments used**.**

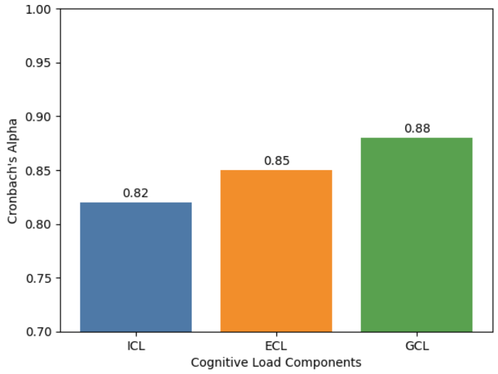

Figure 1. Reliability of the CLQ Instrument

The Cronbach's Alpha value for each construct was above the recommended threshold ($\alpha \geq 0.70$), indicating that the instrument has adequate internal consistency. The total reliability value of 0.91 indicates that the instrument has excellent measurement stability and is suitable for use in higher education research contexts. Methodologically, these results strengthen the validity of the cognitive load construct measurement as a complex psychometric variable.

Descriptive Statistics of Student Cognitive Load

Descriptive statistical analysis was conducted to illustrate the distribution of scores for each component of student cognitive load (N = 180). The results are presented visually in Figure 2, which displays the mean and standard deviation (SD) for each component.

Based on the visualization in Figure 2, the mean scores for each cognitive load component are as follows: Intrinsic Cognitive Load (ICL) = 3.87 (SD = 0.62), Extraneous Cognitive Load (ECL) = 3.42 (SD = 0.71), and Germane Cognitive Load (GCL) = 3.15 (SD = 0.68). Based on the predefined Likert scale categorization (1.00–2.60 = low; 2.61–3.40 = moderate; 3.41–5.00 = high), both ICL and ECL fall within the high category, whereas GCL is categorized as moderate.

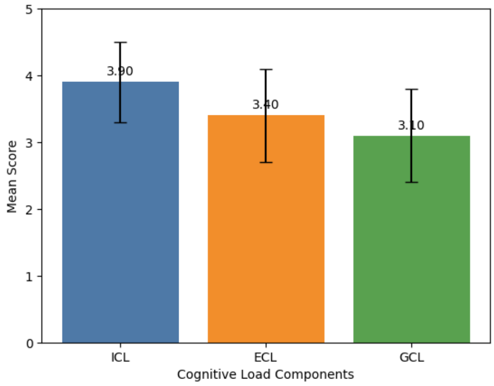

Figure 2. Descriptive Statistics of Student Cognitive Load (Mean ± SD)

This pattern suggests an imbalance in cognitive load distribution, where high processing demands are not accompanied by sufficient productive cognitive engagement. While the high intrinsic load reflects the inherent complexity of mathematical content, the similarly high extraneous load indicates potential inefficiencies in instructional design that may impose unnecessary cognitive burden. In contrast, the moderate level of germane cognitive load suggests that students' cognitive resources are not optimally allocated toward schema construction and meaningful understanding.

Furthermore, the variability indicated by the error bars reveals heterogeneity in students' cognitive experiences, particularly in how they respond to instructional design and allocate cognitive resources during learning. Notably, the greater dispersion observed in ECL and GCL implies that instructional factors and individual engagement differ substantially across students. This finding highlights the limitation of aggregate descriptive analysis and underscores the need for a person-centered profiling approach to capture the underlying configuration of cognitive load at the individual level.

Student Cognitive Load Profile

To gain a more comprehensive understanding, a pattern-based profiling analysis was conducted by grouping students based on their relative configurations of ICL, ECL, and GCL. The classification results revealed three main profiles.

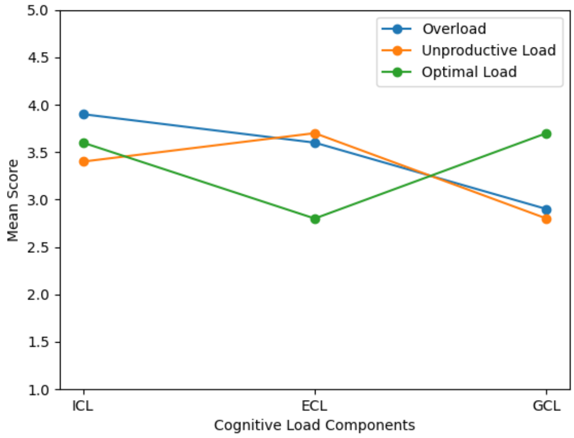

Figure 3. Cluster Plot of Student Cognitive Load Profiles

The diagram shows the differences in patterns between three cognitive load profiles: overload, unproductive load, and optimal load, based on the relative configurations of ICL, ECL, and GCL. Figure 3 shows the differences in cognitive load configuration patterns across student groups. The overload profile is characterized by high ICL and ECL, accompanied by low GCL. The unproductive load profile shows a predominance of high ECL and low GCL. Meanwhile, the optimal load profile shows a more balanced pattern, with lower ECL and relatively high GCL.

This visualization confirms the heterogeneity of students' cognitive experiences and reinforces the finding that not all students experience optimal cognitive load. Thus, a pattern-based profiling approach provides a stronger foundation for understanding cognitive load dynamics than purely descriptive analysis.

DISCUSSION

The findings of this study provide important insights into the dynamic interaction of cognitive load components in higher education mathematics learning. Rather than merely indicating high levels of intrinsic and extraneous load, the results reveal a structural imbalance in cognitive load distribution, where excessive unproductive load limits students' capacity to engage in meaningful cognitive processing. This finding suggests that cognitive load should not be interpreted as isolated components, but as an interdependent system that collectively shapes learning effectiveness.

Conceptually, the high level of ICL in this study can be explained by the inherent complexity of college-level mathematics material, which requires high element interactivity. However, the assumption that high ICL is the primary factor in learning difficulties requires more critical examination. The findings of this study actually indicate that despite high ICL, the primary problem lies in the high level of unproductive ECL. This indicates that students' learning difficulties stem not solely from the complexity of the material, but also from the way it is presented. Thus, these findings challenge the tendency in educational practice to simplify learning problems as a matter of "material difficulty," without considering the dimensions of instructional design.

A key contribution of this study lies in demonstrating the competitive relationship between extraneous and germane cognitive load. While prior studies have acknowledged the negative impact of extraneous load, this study provides further evidence that high extraneous load not only reduces learning efficiency but also systematically suppresses germane cognitive processes. This indicates that cognitive resources are not merely limited but are dynamically reallocated, where inefficient instructional design directly constrains students' capacity to construct meaningful understanding (Curum & Khedo, 2021; Ginns et al., 2020) but this study further contributes by demonstrating that ECL not only results in decreased performance but also systematically inhibits the improvement of GCL. In other words, there is a competitive relationship in the allocation of cognitive resources, where increasing extraneous load directly reduces the capacity available for germane processing. This perspective strengthens the argument that ECL management is a key factor in improving learning quality, not merely a complement to ICL management.

Conversely, a moderate GCL indicates that students are not yet fully engaged in deep cognitive processing. However, interpreting GCL also requires caution. Most previous studies tend to treat GCL as a direct indicator of learning quality, without considering that GCL itself is influenced by both ICL and ECL conditions. Therefore, the low GCL in this study cannot be interpreted solely as a lack of student motivation or effort, but rather as a consequence of high extraneous load that hinders optimal allocation of cognitive resources.

The pattern-based profiling approach used in this study revealed significant heterogeneity in students' experiences of cognitive load. This finding fills an important gap in the literature, as most previous studies have focused on variable-centered analyses, such as correlation or regression, which tend to overlook individual variation. By adopting a person-centered approach, this study demonstrates that students differ not only in their levels of cognitive load but also in the configuration of interactions between its components.

Despite its contributions, this study has several limitations. The use of a descriptive profiling approach without advanced model-based techniques such as Latent Profile Analysis (LPA) may limit the precision of classification. Additionally, the reliance on self-reported data introduces potential bias, including perceptual and social desirability bias. Furthermore, the cross-sectional design restricts the ability to capture the dynamic nature of cognitive load over time. Future research should employ more robust statistical modeling approaches and integrate additional variables such as prior knowledge, metacognitive skills, and affective factors to provide a more comprehensive understanding of cognitive load dynamics.

Furthermore, this study has not explicitly integrated other variables that could potentially moderate cognitive load, such as prior knowledge, metacognitive abilities, and affective factors like motivation and math anxiety. The absence of these variables limits the study's ability to comprehensively explain the mechanisms underlying variations in students' cognitive load profiles.

Nevertheless, this study advances the existing body of knowledge by shifting the perspective of cognitive load from a variable-centered construct to a person-centered diagnostic framework. Unlike traditional approaches that examine cognitive load in isolation, this study demonstrates that the configuration of cognitive load components at the individual level provides a more meaningful basis for understanding learning processes. This person-centered perspective enables a more precise identification of students' cognitive conditions, thereby offering a stronger foundation for adaptive instructional design.

This finding has significant implications for the development of adaptive learning systems, particularly in the context of artificial intelligence–supported education. Current adaptive systems predominantly rely on observable performance indicators, such as accuracy and response time, which may not fully capture learners' internal cognitive states. By incorporating cognitive load profiles as a diagnostic input, adaptive systems can be designed to respond not only to performance outcomes but also to learners' cognitive conditions, thereby enabling more cognitively responsive and personalized learning experiences.

The practical implications of these findings call for a reorientation in mathematics learning design in higher education. Uniform learning approaches need to be replaced with more adaptive strategies that consider the diversity of students' cognitive profiles. In this regard, reducing ECL through improved instructional design is a top priority, followed by strategies to increase GCL through activities that encourage deep processing. Furthermore, the integration of artificial intelligence-based learning technology has great potential for implementing real-time adaptive approaches, utilizing cognitive load profile data as a basis for decision-making. The findings of this study confirm that the main problem in mathematics learning lies not only in the complexity of the material, but also in the mismatch between learning design and students' cognitive capacities.

Therefore, an approach oriented towards systematically mapping and managing cognitive load is crucial to improving the effectiveness of mathematics learning. Furthermore, further research is needed to adopt more robust analysis methods, such as the Achievement Assessment (LPA), and to integrate other cognitive and affective variables to gain a more comprehensive understanding of the dynamics of cognitive load in mathematics learning.

CONCLUSION

This study shows that most students are not yet at an optimal cognitive load, characterized by an imbalance between intrinsic, extraneous, and germane cognitive loads. High intrinsic and extraneous loads, not accompanied by optimal germane loads, indicate that students' cognitive resources have not been allocated effectively to support the development of in-depth conceptual understanding. This situation emphasizes the need for systematic cognitive load management through more adaptive and efficient learning designs.

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