Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index

Vol. 11, No. 4 : December 2025
E-ISSN: 2442-7667
pp. 1347-1358
Email: jklppm@undikma.ac.id

Examining The Effects of Task Complexity and Task Difficulty on Students' Knowledge Retention: A Cognitive Load Theory Perspective

Arief Yulianto[1*], Suwito Eko Pramono[2], Angga Pandu Wijaya[3], Slamet Lestari[4], Lennora Putit[5]

[1*]Department of Educational Administration, [2]Department of Educational Management, Postgraduate School, [3]Department of Management, Faculty of Economics and Business, Universitas Negeri Semarang, Indonesia.

[4]Department of Educational Management, Faculty of Education, Universitas Negeri Yogyakarta, Indonesia.

[5]Faculty of Business and Management, Universiti Teknologi MARA, Shah Alam, Malaysia.

*****Corresponding Author. Email: ariefyulianto@mail.unnes.ac.id

Abstract: This study aims to analyze the effect of task complexity and task difficulty on knowledge retention through cognitive load. Previous studies have been largely outcome-oriented, focusing on student performance without examining long-term knowledge, thus leaving a gap for research that specifically elaborates on knowledge retention. A quantitative approach with a cross-sectional research design was employed. Using the Slovin formula with a 5% margin of error, the study involved 246 undergraduate students majoring in financial management from public universities located in Semarang, Surakarta, and Purwokerto, selected through purposive sampling. Data were analyzed using the variance-based structural equation modeling (VB-SEM) approach. The results reveal that cognitive load has a negative and significant effect on knowledge retention ($\beta = -0.492$, $t = 4.167$, $p = 0.000$). Task complexity shows a positive and significant effect on cognitive load ($\beta = 0.300$, $t = 4.326$, $p = 0.000$), but its direct effect on knowledge retention is not significant. Similarly, task difficulty has a positive and significant effect on cognitive load ($\beta = 0.341$, $t = 4.628$, $p = 0.000$), yet it does not directly affect knowledge retention. The findings indicate that both task complexity and task difficulty have negative and significant indirect effects on knowledge retention through cognitive load. These results demonstrate the importance of proportional instructional design, particularly the segmentation of complex content into smaller units to manage cognitive load. The use of educational technology is recommended to design tasks and instructional materials that align with students' cognitive capacities, thereby enhancing knowledge retention.

Article History
Received: 11-10-2025
Revised: 14-11-2025
Accepted: 30-11-2025
Published: 25-12-2025

Key Words:
Task complexity; Task Difficulty; Cognitive Load; Knowledge Retention.

How to Cite: Yulianto, A., Pramono, S. E., Wijaya, A. P., Lestari, S., & Putit, L. (2025). Examining The Effects of Task Complexity and Task Difficulty on Students' Knowledge Retention: A Cognitive Load Theory Perspective. *Jurnal Kependidikan : Jurnal Hasil Penelitian Dan Kajian Kepustakaan Di Bidang Pendidikan, Pengajaran, Dan Pembelajaran*, *11*(4), 1347-1358. https://doi.org/10.33394/jk.v11i4.18326

https://doi.org/10.33394/jk.v11i4.18326

Introduction

Research on the effectiveness of learning processes has been extensively conducted using various approaches and measurement methods. One of the most commonly used indicators is student performance, which generally reflects the degree of learners' success in achieving learning objectives, as demonstrated in studies by Osabutey et al., (2024) and Zheng & Li (2024). The concept of student performance encompasses cognitive, affective, and psychomotor domains, representing an evaluation of learners' ability to comprehend learning materials in accordance with expected competencies (Li et al., 2023). Previous studies, such as

Vol. 11, No. 4 : December 2025
E-ISSN: 2442-7667
pp. 1347-1358
Email: jklppm@undikma.ac.id

Youssef et al., (2022), have employed student performance as a primary component in assessing learning outcomes by measuring achievement levels through assessment scores.

Limited research has specifically focused on learners' ability to retain knowledge after the completion of the learning process. This limitation is supported by the studies of Spiegel & Nivette (2023), which examine the characteristics of student assignments, and Alhamad & Agha (2023), which explore the role of technology in learning processes. Specifically, these studies have not addressed the processes, mechanisms, or factors that contribute to the development of knowledge retention. In fact, the capacity to store and recall learned information is a crucial element of genuine learning effectiveness (Udu et al., 2022). Evaluation methods that rely solely on test results or short-term performance often fail to capture the depth of conceptual understanding over time. Knowledge retention thus becomes a critical dimension to be considered in learning evaluation, as the ability to retain knowledge forms a fundamental component of student performance and long-term memory capability.

Knowledge retention represents an essential aspect of the learning process because it reflects how well the acquired knowledge is stored and later applied by learners within a certain period (Palacios et al., 2021). Nevertheless, the extensive amount of material that learners are required to master often exceeds memory capacity, preventing optimal retention of all information. Knowledge retention is closely related to the function of working memory, which serves as a short-term memory system responsible for temporarily storing and processing information during learning (Ellah et al., 2019). The limited capacity of working memory makes it difficult for learners to retain all received information, particularly when cognitive load is excessive (Hanham et al., 2023). Consequently, students may experience difficulty in optimally storing knowledge due to irrelevant learning burdens unrelated to core competencies. This condition can hinder the internalization of concepts within the cognitive domain and reduce the overall effectiveness of learning, ultimately leading to problems in knowledge retention.

In the learning process, learners possess limited cognitive capacity; therefore, when confronted with excessive tasks and explanations, the learners' focus becomes fragmented and diverted from the core competencies (Siregar, 2023). This study emphasizes a contradiction: while tasks and explanations play an essential role in evaluating and elaborating on the material, such components can simultaneously overload students' working memory. This condition poses a challenge for knowledge retention, as an abundance of information, instructions, and learning activities may distort the understanding of fundamental concepts. Unstructured learning materials or overly complex tasks tend to increase cognitive load during the learning process (Alzayed & Alzamel, 2023). When cognitive load exceeds the processing capacity of working memory, the storage of long-term knowledge becomes hindered (Chen et al., 2018). Consequently, the acquired information becomes difficult to recall or apply in different contexts, leading to suboptimal achievement of learning objectives.

Essentially, although knowledge retention constitutes an important aspect of learning, only a limited number of studies have explicitly linked it to cognitive load. Complex instructions and tasks that are misaligned with learners' cognitive capacity can serve as key contributors to excessive cognitive load (Mundy et al., 2023). When this occurs, learners' ability to process, store, and retrieve information diminishes significantly. Managing cognitive load through the design of effective instructional materials and tasks is, therefore, crucial to support knowledge retention and ensure that acquired knowledge endures over time.

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan
di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index
Vol. 11, No. 4 : December 2025
E-ISSN: 2442-7667
pp. 1347-1358
Email: jklppm@undikma.ac.id

In relation to instructional and task design, previous studies have shown that cognitive load is closely associated with task complexity, defined as the degree to which a task is characterized by multiple constituent elements, extensive informational demands, and interdependent procedural components that must be processed and coordinated to achieve completion (Krawitz et al., 2024). The more complex a task is, the greater the cognitive demands placed on learners in completing it. Task complexity in online learning environments has been found to influence student behavior, where higher complexity tends to decrease academic performance compared to tasks with lower complexity (Sun & Kim, 2023). When task complexity exceeds learners' cognitive capacity, cognitive load increases, thereby impeding the learning process. Under such complex learning conditions, learners often struggle to identify essential information and maintain long-term comprehension (Chen et al., 2023). Hence, an imbalance between the level of task complexity and learners' cognitive abilities can negatively affect learning effectiveness and, consequently, hinder knowledge retention.

The classroom learning process is also associated with task difficulty, which plays a significant role in shaping students' cognitive load. Task difficulty refers to the perceived level of challenge learners experience when completing a task (Pavlov et al., 2023). It influences the formation of cognitive load by generating internal difficulties that burden the learner's cognitive system. When a task is perceived as demanding, a learner's mental focus and cognitive resources are directed toward figuring out the task, leaving limited capacity for building conceptual understanding (Seyderhelm & Blackmore, 2023). This condition may hinder knowledge construction and reduce the ability to retain information over the long term. Nevertheless, limited research has directly linked task difficulty to cognitive load. Xie et al., (2017) conducted a meta-analysis that identified factors that reduce cognitive load, among which is task difficulty, thereby lowering the level of challenge presented to learners. The meta-analysis indicating that empirical evidence on task difficulty and cognitive load remains limited is further supported by Lin et al., (2024), who provided a more detailed and comprehensive mapping of the mechanisms through which knowledge retention can be enhanced by reducing counterproductive levels in the learning process, thereby alleviating cognitive load. When tasks are perceived as excessively difficult, learners tend to experience cognitive stress that increases internal cognitive load, thereby reducing concentration and learning engagement (Nihalani & Robinson, 2022). As a result, information processing becomes shallow, and the retained knowledge is short-lived. Conversely, when the level of task difficulty is aligned with learners' abilities or zone of proximal development, a balance is achieved between challenge and competence, which encourages active learning engagement. This study affirms that task complexity refers to the objective structure of a task involving its elements and interrelations, whereas task difficulty reflects the learner's subjective perception of how demanding the task feels.

Cognitive Load Theory (CLT), first introduced by Sweller (1988), provides a foundational framework for understanding how individuals process information during learning and how excessive cognitive load can affect knowledge retention. CLT posits that humans possess a limited capacity in working memory, a short-term memory system responsible for temporarily holding and processing information (Hanham et al., 2023). When cognitive load exceeds this capacity, information processing becomes inefficient, and the transfer of new information to long-term memory, where knowledge is permanently stored, becomes obstructed (Duran et al., 2022).

CLT emphasizes the importance of managing cognitive load to enable learners to process information effectively. As classified by Sweller et al., (1998), cognitive load consists

Vol. 11, No. 4 : December 2025
E-ISSN: 2442-7667
pp. 1347-1358
Email: jklppm@undikma.ac.id

of three types: intrinsic load, which arises from the inherent complexity of the material; extraneous load, which results from ineffective information presentation; and germane load, which refers to the mental effort devoted to constructing and reinforcing knowledge. Effective instruction aims to reduce extraneous load, balance intrinsic load, and simultaneously enhance germane load, thereby allowing the cognitive resources of learners to focus on developing deep conceptual understanding.

Previous studies have predominantly focused on learning outcomes by measuring student performance, which generally reflects short-term achievement, while the learning process associated with efforts to retain knowledge has received relatively little attention. In fact, genuine learning success is achieved when learners are able to retain knowledge over the long term. The limited understanding of classroom learning processes generates cognitive load and contributes to the inability to maintain knowledge represents a significant research gap. The state of the art of this study lies in examining classroom learning processes by assessing academic load and its implications for students' ability to retain knowledge. Focusing on classroom learning processes is considered essential, as the interaction among tasks, instructional methods, and learning environments shapes and influences the cognitive load experienced by learners (Sweller, 2022). This research is grounded in CLT, which serves as the primary framework for understanding how cognitive load is formed during learning and how it affects knowledge retention. The study seeks to explain how task complexity and task difficulty contribute to the development of cognitive load and to measure the impact of cognitive load on knowledge retention.

Research Method

This study employed a quantitative approach with a causal research design. The quantitative method enables the collection of measurable and objective data, allowing for statistical analysis and interpretation of results (Seeber, 2020). A causal research design was adopted to explain the cause-and-effect relationship between independent and dependent variables (Korsgaard, 2020). The study involved undergraduate students enrolled in financial management courses. The selection of this field was based on its relevance to the research variables, as the nature of financial management materials requires conceptual understanding and involves tasks that are both complex and progressively difficult. This aligns with the core variables examined in the study, task complexity and task difficulty. Financial management students are expected to retain knowledge over the long term since financial concepts are hierarchical and interrelated.

The sample size was determined using the Slovin formula with a 95% confidence level, a 5% margin of error. The total population consisted of 639 students majoring in financial management, and the calculation resulted in a sample of 246 respondents. The sample was drawn from public universities located in Central Java, specifically in the cities of Semarang, Surakarta, and Purwokerto. The study applied a non-probability purposive sampling technique, with specific criteria established to ensure that participants possessed characteristics relevant to the research variables. The criteria were: (a) students concentrating in financial management who had reached the fifth semester, and (b) students enrolled at a public university.

Data were collected using a structured questionnaire designed to capture respondents' perceptions based on the study indicators. The questionnaire items were adapted from validated instruments used in previous research. This study adopted indicators from previous research to ensure validity and avoid research bias. The measurement of knowledge retention was adapted from Saleh (2011), which evaluates students' ability to retain acquired

Vol. 11, No. 4 : December 2025
E-ISSN: 2442-7667
pp. 1347-1358
Email: jklppm@undikma.ac.id

knowledge using four indicators. Cognitive load was measured based on the scales developed by Leppink et al., (2013) and Ouwehand et al., (2021), with four indicators used to assess the ability to retain knowledge. Task complexity and task difficulty were measured using indicators derived from Robinson (2001), with three indicators for each construct. Moreover, the study employed a Likert scale to represent the range of responses from participants.

The collected data were analyzed using Variance-Based Structural Equation Modeling (VB-SEM) to examine the relationships among variables. VB-SEM is a structural equation modeling approach that explains variance among latent constructs through outer and inner models (Schamberger, 2023). This study analyzed the collected data using SmartPLS, a software tool required for conducting variance-based structural equation modeling, including measurement model assessment and structural model evaluation. The outer model was used to evaluate the relationship between latent constructs and the corresponding indicators, including assessments of convergent validity, discriminant validity, and construct reliability. Meanwhile, the inner model was applied to test the causal relationships among latent constructs within the structural framework.

Results and Discussion

This study employed a two-stage model analysis in Partial Least Squares Structural Equation Modeling (PLS-SEM), consisting of the outer model and the inner model. In the outer model assessment stage, validity and reliability tests were conducted to evaluate the extent to which the indicators represented the respective latent constructs. Validity was assessed using loading factor values and Average Variance Extracted (AVE), while construct reliability was measured through Composite Reliability (CR) and Cronbach's Alpha values.

The inner model testing stage aimed to examine the causal relationships among latent variables that had met the eligibility criteria established in the previous stage. This evaluation included analyzing the R-square values to determine the explanatory power of independent variables toward dependent variables, as well as assessing path coefficients and t-statistics or p-values to identify the significance of the relationships among variables.

The first stage of model testing focused on assessing validity to ensure that each indicator accurately and consistently represented the construct being measured. An indicator was considered valid if it had a loading factor value of ≥ 0.70, indicating a strong correlation with its associated construct. The AVE value was used to determine the extent to which the variance of the indicators could be explained by the latent construct. An AVE value of ≥ 0.50 indicates that more than half of the indicator variance is explained by the construct, thereby fulfilling the criteria for convergent validity (Hair et al., 2014). The results of the validity testing are presented in Table 1.

Table 1. Validity Test Result

Variable	Indicator	Loading Factor	Average Variance Extracted (AVE)
Cognitive Load	CL1	0.635	0.563
	CL2	0.615	
	CL3	0.627	
	CL4	0.624	
Knowledge Retention	KR1	0.685	0.685
	KR2	0.691	
	KR3	0.692	
	KR4	0.690	
Task Complexity	TC1	0.653	0.617

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan
di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index

Vol. 11, No. 4 : December 2025
E-ISSN: 2442-7667
pp. 1347-1358
Email: jklppm@undikma.ac.id

	TC2	0.647	
	TC3	0.663	
Task Difficulty	TD1	0.662	0.635
	TD2	0.669	
	TD3	0.662	

Based on the results presented in Table 1, all indicators in this study demonstrated loading factor and AVE values above the minimum threshold. Therefore, it can be concluded that the constructs used in this research adequately meet the criteria for convergent validity. The next stage involved reliability testing to assess the internal consistency of each construct employed in the study. Reliability was evaluated using two main parameters: Cronbach's alpha and composite reliability. According to the established criteria, both Cronbach's alpha and composite reliability values should be≥0.70, while a satisfactory rho_A value should be ≥0.70 for the construct to be considered reliable (Hair et al., 2019).

As shown in Table 2, all constructs exhibited Cronbach's Alpha and Composite Reliability values above the required threshold, indicating that all constructs in this study fulfill the reliability criteria.

Table 2. Reliability Test Result

Variable	Cronbach's Alpha	rho_A	Composite Reliability
Cognitive Load	0.640	0.642	0.656
Knowledge Retention	0.691	0.691	0.692
Task Complexity	0.651	0.652	0.667
Task Difficulty	0.663	0.663	0.674

This study successfully validated the outer model, confirming that all constructs met the established criteria for validity and reliability. Following this stage, the analysis proceeded with the evaluation of the inner model to assess the overall model fit and determine the adequacy of the proposed research model.

Table 3. Model Fit Result

Model Fit	Saturated Model
SRMR	0.054
d_ULS	0.2125
d_G	0.375
Chi-Square	430.007
NFI	0.921

The results of the model fit test presented in Table 3 indicate that both the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI) meet the recommended criteria. The SRMR value was found to be ≤ 0.08, suggesting that the model demonstrates a good level of fit. Additionally, the NFI value was ≥ 0.90, indicating that the structural model shows an adequate degree of congruence between the empirical data and the theoretical model.

Table 4. Coefficient of Determination Results

Variable	R Square	R Square Adjusted
Cognitive Load	0.556	0.549
Knowledge Retention	0.777	0.597

The results of the Coefficient of Determination test presented in Table 4 show the R-Square values, which represent the proportion of variance in the dependent variables explained by the independent variables in the research model. The R-Square value indicates that 55.6% of the variance in cognitive load is explained by its predictors, while the model

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index
Vol. 11, No. 4 : December 2025
E-ISSN: 2442-7667
pp. 1347-1358
Email: jklppm@undikma.ac.id

accounts for 77.7% of the variance in knowledge retention. These findings suggest that the model exhibits strong explanatory power, particularly in predicting knowledge retention.
The subsequent results are illustrated in Figure 1, which presents the research model, providing a visual representation of the direction and strength of the relationships among the constructs examined in this study.

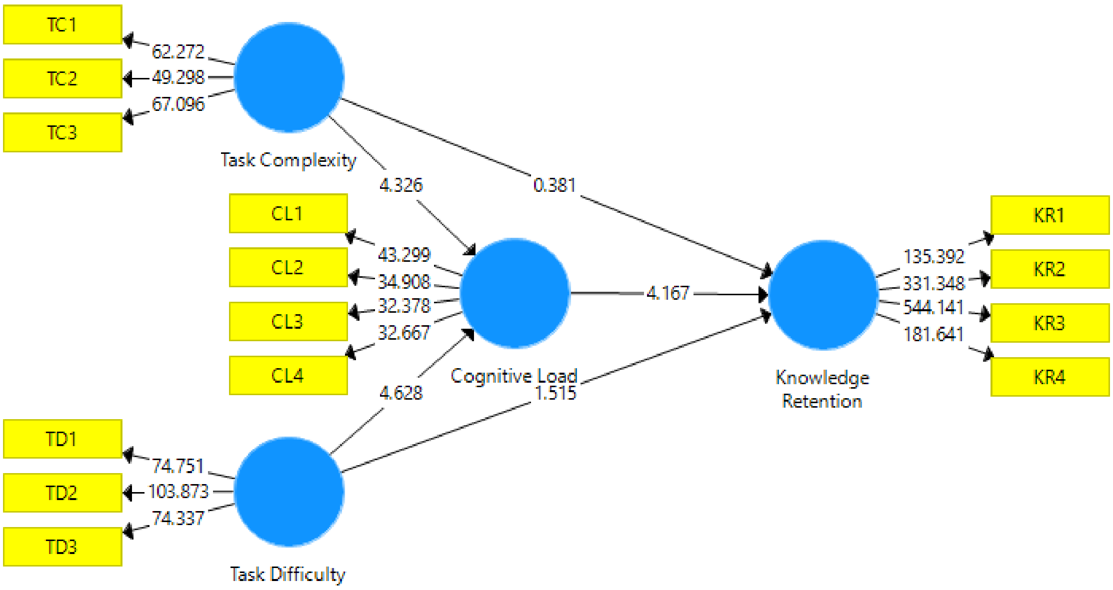

Figure 1. Reseach Framework

In greater detail, the results of the relationship testing among variables are presented in Table 5, which shows the direct effects of the independent variables on the dependent variables. Meanwhile, Table 6 presents the indirect effects, illustrating the mediating role of specific variables in the relationships among constructs within the research model.

Table 5. Direct Effect Results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Cognitive Load → Knowledge Retention	-0.492	-0.484	0.082	4.167	0.000
Task Complexity → Cognitive Load	0.300	0.310	0.069	4.326	0.000
Task Complexity → Knowledge Retention	0.063	0.059	0.115	0.264	0.489
Task Difficulty → Cognitive Load	0.341	0.332	0.074	4.628	0.000
Task Difficulty → Knowledge Retention	0.157	0.155	0.103	1.515	0.090

The results indicate that Cognitive Load has a negative and significant effect on Knowledge Retention ($\beta = -0.492$, $t = 4.167$, $p = 0.000$). This finding suggests that an increased cognitive load contributes to a reduced ability to retain knowledge. Furthermore, Task Complexity has a positive and significant effect on Cognitive Load ($\beta = 0.300$, $t = 4.326$, $p = 0.000$), indicating that higher task complexity leads to greater cognitive load. However, the direct effect of Task Complexity on Knowledge Retention is found to be insignificant ($\beta = 0.063$, $t = 0.264$, $p = 0.489$). Similarly, Task Difficulty also shows a positive and significant effect on Cognitive Load ($\beta = 0.341$, $t = 4.628$, $p = 0.000$), implying that more difficult tasks increase learners' cognitive load. Nonetheless, the direct effect of Task Difficulty on Knowledge Retention is not significant ($\beta = 0.157$, $t = 1.515$, $p = 0.090$).

Jurnal Kependidikan:
Jurnal Hasil Penelitian dan Kajian Kepustakaan di Bidang Pendidikan, Pengajaran dan Pembelajaran
https://e-journal.undikma.ac.id/index.php/jurnalkependidikan/index

Vol. 11, No. 4 : December 2025
E-ISSN: 2442-7667
pp. 1347-1358
Email: jklppm@undikma.ac.id

Table 6. Indirect Effect Results

Result	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Task Difficulty → Cognitive Load → Knowledge Retention	-0.241	-0.233	0.082	2.942	0.003
Task Complexity → Cognitive Load → Knowledge Retention	-0.213	-0.214	0.067	3.168	0.002

The results reveal that Task Difficulty, through Cognitive Load, has a negative and significant effect on Knowledge Retention (β = -0.241, t = 2.942, p = 0.003). This indicates that task difficulty generates cognitive load, which in turn adversely affects the ability to retain knowledge. The study also demonstrates that Task Complexity, mediated by Cognitive Load, has a negative and significant impact on Knowledge Retention (β = -0.213, t = 3.168, p = 0.002). These findings suggest that when tasks become excessively complex or demanding, such tasks increase cognitive load and subsequently hinder students' ability to store and recall learned knowledge.

Discussion

The findings indicate that cognitive load has a negative and significant effect on knowledge retention. This suggests that an increased cognitive burden leads to difficulties in maintaining long-term knowledge. Such a condition arises because the limited capacity of working memory restricts the efficient processing of information into long-term memory, thereby hindering the storage and retrieval of learned knowledge (Chen et al., 2018). This result aligns with the Cognitive Load Theory (CLT), which posits that excessive cognitive load disrupts the learning process as mental resources are consumed by processing irrelevant information rather than constructing meaningful understanding. The present study supports the findings of Leppink et al. (2013), who reported that high extraneous load negatively affects learning effectiveness and diminishes knowledge retention.

A positive and significant effect of task complexity on cognitive load was observed, suggesting that task complexity increases the cognitive demands on learners. Task complexity requires the processing of larger quantities of interrelated information, demanding higher coordination among dependent elements. It also encourages students to employ more sophisticated cognitive strategies (Tremblay et al., 2023). This outcome is consistent with CLT, which emphasizes that an increase in the complexity of information elements contributes to greater intrinsic load. The finding supports Lee (2019), who stated that as the number and interdependence of informational elements increase, working memory capacity becomes more heavily taxed. Consequently, learners must exert greater effort to integrate new information with existing knowledge. Assigning tasks that are overly complex may reduce learning effectiveness by introducing excessive, nonessential material.

Evidence suggests knowledge retention does not respond significantly to changes in task complexity. This implies that the level of task complexity alone does not determine learners' ability to retain knowledge. Although complex tasks may stimulate higher cognitive engagement, the impact on retention depends largely on the learners' capacity for comprehension. This finding corroborates Haji et al. (2016), who found that task complexity does not influence knowledge retention, as performance during the retention phase remained stable. However, task complexity does affect the initial learning process by increasing cognitive load, which may impede knowledge formation if not properly managed. Supporting this, Bouwmeester et al. (2019) reported that while higher learning activity complexity in a

Vol. 11, No. 4 : December 2025
E-ISSN: 2442-7667
pp. 1347-1358
Email: jklppm@undikma.ac.id

flipped classroom setting can enhance learning experiences and self-efficacy, it does not necessarily translate into improved knowledge retention compared to traditional learning methods.

The findings reveal that task difficulty has a positive and significant effect on cognitive load, indicating that the perceived difficulty of a task influences learners' cognitive burden. Task difficulty, shaped by individual characteristics, represents the learner's personal perception of the demands involved in completing a task. This result is consistent with Seyderhelm and Blackmore (2023), who found that tasks perceived as difficult tend to increase learners' effort, thereby heightening cognitive load. Similarly, the result aligns with Gupta and Zheng (2020), who demonstrated that perceptions of task difficulty are directly associated with increased cognitive load in problem-based learning contexts.

Results show that task difficulty does not significantly influence knowledge retention. These findings imply that learners' retention of prior knowledge is not solely determined by the level of task difficulty. When tasks are perceived as excessively difficult, learners are likely to experience cognitive overload, which hinders the transfer of information into long-term memory. Conversely, tasks that are too simple fail to sufficiently stimulate the deep cognitive processing necessary for effective retention. Achieving a balance between task difficulty and cognitive capacity is thus essential for optimizing learning effectiveness. This finding supports Gasparič et al. (2024), who emphasized that it is not the degree of difficulty itself that determines knowledge retention, but rather the instructional design that allows learners to meaningfully process conceptual knowledge. In line with this, Estaiteyeh and DeCoito (2024) found that knowledge retention improves when learning activities are designed around contextual and relevant tasks, rather than those that are merely difficult. Task difficulty without opportunities for reflection and feedback may instead hinder the ability to sustain knowledge over time.

The findings reveal that task difficulty, through cognitive load, exerts a negative and significant effect on knowledge retention. This suggests that difficult tasks generate cognitive strain among students, ultimately diminishing the students' ability to retain knowledge over time. Similarly, task complexity, when mediated by cognitive load, also shows a negative and significant impact on knowledge retention. This indicates that as the complexity of a task increases, the cognitive burden it imposes can hinder learners' capacity to store and retrieve information effectively. These findings are particularly noteworthy amid the widespread adoption of educational technology, which increasingly provides interactive learning tasks and exercises (Alam & Mohanty, 2023). Educational technology fosters dynamic interaction between learners and facilitators, whether teachers or lecturers. Chen et al. (2023) emphasized that higher element interactivity, combined with lower prior knowledge, intensifies cognitive load, an important consideration for effective instructional design. The emergence of gamification as an alternative instructional method further illustrates this dynamic. While gamified tasks often heighten task complexity and task difficulty, Tang et al. (2021) found that such tasks can still enhance student enjoyment, suggesting that gamification remains effective when the instructional design is well-balanced and goal-oriented. This study reinforces the view that although complex tasks can stimulate cognitive engagement, the effect on knowledge retention becomes negative when the resulting cognitive load exceeds students' optimal processing capacity. Consistent with Cognitive Load Theory, this occurs when task complexity surpasses individual cognitive capacity, disrupting the transfer of information from working memory to long-term memory, and thereby weakening the retention of learned material.

Conclusion

The findings reveal that both task complexity and task difficulty significantly increase cognitive load, indicating that complex and difficult tasks place greater mental demands on learners. However, their direct effects on knowledge retention were found to be insignificant. Conversely, cognitive load demonstrated a negative and significant effect on knowledge retention, suggesting that excessive cognitive demand impairs students' ability to retain learned knowledge over time. The findings highlight that the ability to retain knowledge depends less on task complexity or difficulty and more on the effective management of cognitive load during the learning process.

Recommendation

Practically, the growing availability of educational technology, particularly internet-based platforms, can be leveraged to design proportionate and cognitively balanced learning tasks that promote knowledge retention. Educators are encouraged to design instructional activities that align with students' academic abilities and cognitive capacities. Examples include breaking complex material into smaller learning units, giving guided steps for more challenging parts, using adaptive task sequences that match the learner's current level, and providing interactive feedback features to help monitor understanding during the activity. A well-calibrated instructional design can minimize extraneous load while strengthening germane load, enabling learners to process information more efficiently and sustain knowledge in the long term.

Acknowledgment

The author expresses sincere gratitude for the completion of this research, which was funded by the Budget Implementation Document (DPA) of the Graduate School, Universitas Negeri Semarang, No. DPA 139.03.2.693449/2025.09, under the Research Implementation Agreement of the Graduate School DPA Fund, Universitas Negeri Semarang, Year 2025, No. 27.17.4/UN37/PPK.09/2025.

References

Alhamad, B. R., & Agha, S. (2023). Comparing Knowledge Acquisition and Retention Between Mobile Learning and Traditional Learning in Teaching Respiratory Therapy Students: A Randomized Control Trial. *Advances in Medical Education and Practice*, *14*. https://doi.org/10.2147/AMEP.S390794

Alzayed, M. A., & Alzamel, D. (2023). Assertion-Evidence versus Traditional PowerPoint: An Investigation of the Impact of Slide Structure on Engineering Students' Cognitive load, Motivation, and Performance. *Journal of Engineering Research (Kuwait)*, *11*(1). https://doi.org/10.36909/jer.16963

Chen, O., Castro-Alonso, J. C., Paas, F., & Sweller, J. (2018). Extending Cognitive Load Theory to Incorporate Working Memory Resource Depletion: Evidence from the Spacing Effect. *Educational Psychology Review*, *30*(2). https://doi.org/10.1007/s10648-017-9426-2

Chen, O., Paas, F., & Sweller, J. (2023). A Cognitive Load Theory Approach to Defining and Measuring Task Complexity Through Element Interactivity. In *Educational Psychology Review* (Vol. 35, Issue 2). https://doi.org/10.1007/s10648-023-09782-w

Duran, R., Zavgorodniaia, A., & Sorva, J. (2022). Cognitive Load Theory in Computing Education Research: A Review. *ACM Transactions on Computing Education*, *22*(4). https://doi.org/10.1145/3483843

Ellah, B. O., Achor, E. E., & Enemarie, V. (2019). Problem-solving skills as correlates of attention span and working memory of low ability level students in senior secondary schools. *Journal of Education and E-Learning Research*, *6*(3). https://doi.org/10.20448/journal.509.2019.63.135.141

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). Multivariate Data Analysis Seventh Edition. In *Pearson New International*. https://doi.org/10.1007/978-3-319-01517-0_3

Hanham, J., Castro-Alonso, J. C., & Chen, O. (2023). Integrating cognitive load theory with other theories, within and beyond educational psychology. *British Journal of Educational Psychology*, *93*(S2). https://doi.org/10.1111/bjep.12612

Korsgaard, M. T. (2020). Exemplarity and education: Retuning educational research. *British Educational Research Journal*, *46*(6). https://doi.org/10.1002/berj.3636

Krawitz, J., Hartmann, L., & Schukajlow, S. (2024). Do task variables of self-generated problems influence interest? Authenticity, openness, complexity, and students' interest in solving self-generated modelling problems. *Journal of Mathematical Behavior*, *73*. https://doi.org/10.1016/j.jmathb.2024.101129

Leppink, J., Paas, F., Van der Vleuten, C. P. M., Van Gog, T., & Van Merriënboer, J. J. G. (2013). Development of an instrument for measuring different types of cognitive load. *Behavior Research Methods*, *45*(4). https://doi.org/10.3758/s13428-013-0334-1

Li, J., Xue, E., Li, C., & He, Y. (2023). Investigating Latent Interactions between Students' Affective Cognition and Learning Performance: Meta-Analysis of Affective and Cognitive Factors. *Behavioral Sciences*, *13*(7). https://doi.org/10.3390/bs13070555

Lin, L., Lin, X., Zhang, X., & Ginns, P. (2024). The Personalized Learning by Interest Effect on Interest, Cognitive Load, Retention, and Transfer: A Meta-Analysis. *Educational Psychology Review 2024 36:3*, *36*(3), 88-. https://doi.org/10.1007/S10648-024-09933-7

Mundy, C. E., Potgieter, M., & Seery, M. K. (2023). A design-based research approach to improving pedagogy in the teaching laboratory. *Chemistry Education Research and Practice*, *25*(1). https://doi.org/10.1039/d3rp00134b

Nihalani, P. K., & Robinson, D. H. (2022). Balancing Collaboration and Cognitive Load to Optimize Individual and Group Desirable Difficulties. *Journal of Educational Computing Research*, *60*(2). https://doi.org/10.1177/07356331211035188

Osabutey, E. L. C., Senyo, P. K., & Bempong, B. F. (2024). Evaluating the potential impact of online assessment on students' academic performance. *Information Technology and People*, *37*(1). https://doi.org/10.1108/ITP-05-2021-0377

Ouwehand, K., Kroef, A. van der, Wong, J., & Paas, F. (2021). Measuring Cognitive Load: Are There More Valid Alternatives to Likert Rating Scales? *Frontiers in Education*, *6*. https://doi.org/10.3389/feduc.2021.702616

Palacios, C. A., Reyes-Suárez, J. A., Bearzotti, L. A., Leiva, V., & Marchant, C. (2021). Knowledge discovery for higher education student retention based on data mining: Machine learning algorithms and case study in chile. *Entropy*, *23*(4). https://doi.org/10.3390/e23040485

Pavlov, A., Duhon, G., & Dawes, J. (2023). Examining the Impact of Task Difficulty on Student Engagement and Learning Rates. *Journal of Behavioral Education*, *32*(3). https://doi.org/10.1007/s10864-021-09465-y

Robinson, P. (2001). Task complexity, task difficulty, and task production: Exploring interactions in a componential framework. *Applied Linguistics*, *22*(1). https://doi.org/10.1093/applin/22.1.27

Saleh, Z. I. (2011). A framework to evaluate the likelihood of knowledge retention when college students obtain information from the internet. *International Journal of Education*

Vol. 11, No. 4 : December 2025
E-ISSN: 2442-7667
pp. 1347-1358
Email: jklppm@undikma.ac.id

Economics and Development, *2*(4). https://doi.org/10.1504/IJEED.2011.043832

Schamberger, T. (2023). Conducting Monte Carlo simulations with PLS-PM and other variance-based estimators for structural equation models: a tutorial using the R package cSEM. *Industrial Management and Data Systems*, *123*(6). https://doi.org/10.1108/IMDS-07-2022-0418

Seeber, M. (2020). Framework and operationalisation challenges for quantitative comparative research in higher education. *Higher Education Quarterly*, *74*(2). https://doi.org/10.1111/hequ.12245

Seyderhelm, A. J. A., & Blackmore, K. L. (2023). How Hard Is It Really? Assessing Game-Task Difficulty Through Real-Time Measures of Performance and Cognitive Load. *Simulation and Gaming*, *54*(3). https://doi.org/10.1177/10468781231169910

Siregar, N. R. (2023). Explicit Instruction and Executive Functioning Capacity: A New Direction in Cognitive Load Theory. *Journal of Education*, *203*(2). https://doi.org/10.1177/00220574211033256

Spiegel, T., & Nivette, A. (2023). The relative impact of in-class closed-book versus take-home open-book examination type on academic performance, student knowledge retention and wellbeing. *Assessment and Evaluation in Higher Education*, *48*(1). https://doi.org/10.1080/02602938.2021.2016607

Sun, T., & Kim, J. E. (2023). The Effects of Online Learning and Task Complexity on Students' Procrastination and Academic Performance. *International Journal of Human-Computer Interaction*, *39*(13). https://doi.org/10.1080/10447318.2022.2083462

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, *12*(2). https://doi.org/10.1016/0364-0213(88)90023-7

Sweller, J. (2022). The Role of Evolutionary Psychology in Our Understanding of Human Cognition: Consequences for Cognitive Load Theory and Instructional Procedures. *Educational Psychology Review*, *34*(4). https://doi.org/10.1007/s10648-021-09647-0

Sweller, J., Van Merrienboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive Architecture and Instructional Design. *Educational Psychology Review*, *10*(3). https://doi.org/10.1023/A:1022193728205

Udu, D. A., Nmadu, J., Uwaleke, C. C., Anudu, A. P., Okechineke, B. C., Attamah, P. C., Chukwuemeka, C. O., Nwalo, C. N., & Ogonna, O. C. (2022). Innovative Pedagogy and Improvement of Students' Knowledge Retention in Science Education: Learning Activity Package Instructional Approach. *Pertanika Journal of Social Sciences and Humanities*, *30*(3). https://doi.org/10.47836/pjssh.30.3.25

Xie, H., Wang, F., Hao, Y., Chen, J., An, J., Wang, Y., & Liu, H. (2017). The more total cognitive load is reduced by cues, the better retention and transfer of multimedia learning: A meta-analysis and two meta-regression analyses. *PLoS ONE*, *12*(8). https://doi.org/10.1371/journal.pone.0183884

Youssef, A. Ben, Dahmani, M., & Ragni, L. (2022). ICT Use, Digital Skills and Students' Academic Performance: Exploring the Digital Divide. *Information (Switzerland)*, *13*(3). https://doi.org/10.3390/info13030129

Zheng, X., & Li, C. (2024). Predicting Students' Academic Performance Through Machine Learning Classifiers: A Study Employing the Naive Bayes Classifier (NBC). *International Journal of Advanced Computer Science and Applications*, *15*(1). https://doi.org/10.14569/IJACSA.2024.0150199