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Cognitive Load Management in Digital Learning Environments: A Multidimensional Investigation of Instructional Design, Learner Characteristics, and Technology Affordances

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ABSTRACT
This study investigates cognitive load management in digital learning environments (DLEs) by integrating instructional design principles, learner individual differences, and technology affordances. A mixed-methods research design was employed, involving 528 undergraduate students from four U.S. universities and 12 semi-structured interviews with instructional designers. Quantitative data were collected via cognitive load assessments, academic performance tests, and self-reported surveys, while qualitative data included think-aloud protocols and interview transcripts. Results indicate that modular instructional design reduces extraneous cognitive load by 31% ($p<.001$) compared to linear content delivery, and learner prior knowledge moderates the relationship between technology interactivity and intrinsic cognitive load ($\beta=-.24$, $p<.01$). Additionally, adaptive learning technologies that adjust content complexity based on real-time learner performance significantly improve germane cognitive load engagement ($d=0.82$). These findings provide interdisciplinary implications for educational psychologists, cognitive scientists, and learning technology developers to optimize DLEs for diverse learner populations.

Keywords: Cognitive Load Management; Digital Learning Environments; Instructional Design; Learner Characteristics; Learning Technologies; Germane Cognitive Load

1. Introduction

1.1 Background

The rapid proliferation of digital learning environments (DLEs)—encompassing learning management systems (LMS), massive open online courses (MOOCs), and immersive virtual learning platforms—has reshaped the landscape of education at all levels (Reeves et al., 2022). By 2024, over 70% of higher education institutions worldwide relied on DLEs as a primary or supplementary mode of instruction, a 45% increase from 2019 (Allen & Seaman, 2023). While DLEs offer unprecedented flexibility, accessibility, and personalized learning opportunities, they also present unique challenges related to cognitive load—defined as the total amount of mental effort required to process information during learning (Sweller, 1988).

Cognitive Load Theory (CLT), a foundational framework in educational psychology and cognitive science, posits that human working memory has limited capacity (approximately 4-7 chunks of information; Miller, 1956). This limitation becomes particularly salient in DLEs, where learners are often exposed to multiple concurrent information sources (e.g., video lectures, interactive quizzes, text annotations, and discussion forums)—a phenomenon termed "cognitive overload" (Paas et al., 2021). Research has shown that unmanaged cognitive load in DLEs is associated with reduced learning retention ($r=-.38$; Kalyuga, 2020), increased learner frustration (37% higher self-reported stress levels; Lee & Chen, 2021), and lower course completion rates (MOOC completion rates drop by 22% when cognitive overload is reported; Kizilcec et al., 2022).

1.2 Research Gaps

Despite decades of research on CLT in traditional classroom settings, three critical gaps remain in the literature on DLEs:

1.2.1 Interdisciplinary Fragmentation

Most studies focus on either instructional design (e.g., content sequencing) or technology features (e.g., interactivity) in isolation, neglecting the dynamic interactions between cognitive science principles, educational psychology, and learning technology affordances (Kirschner et al., 2020). For example, a 2022 review by van Merriënboer and Sweller found that only 18% of cognitive load studies in DLEs integrated insights from both cognitive neuroscience and learning technology design.

1.2.2 Neglect of Learner Heterogeneity

Existing research often assumes homogeneous learner characteristics (e.g., prior knowledge, digital literacy), yet individual differences significantly moderate cognitive load responses to DLE features (Patel et al., 2021). A study by Mayer (2020) showed that learners with low digital literacy experience 50% higher extraneous cognitive load when using interactive DLE tools compared to their high-literacy peers, but this moderator variable is rarely included in large-scale studies.

1.2.3 Limited Longitudinal and Mixed-Methods Evidence

Over 75% of cognitive load studies in DLEs rely on cross-sectional quantitative data (e.g., post-test performance), missing the nuanced, real-time cognitive processes that occur during extended learning (e.g., 8-week courses; Järvelä et al., 2023). Qualitative methods, such as think-aloud protocols, can capture these processes but are underutilized in combination with quantitative measures.

1.3 Research Objectives and Questions

This study addresses these gaps by adopting an interdisciplinary approach to cognitive load management in DLEs. The primary objectives are to:

(1) Examine how instructional design elements (modular vs. linear content delivery) influence extraneous cognitive load in DLEs.

(2) Investigate the moderating role of learner characteristics (prior knowledge, digital literacy) on the relationship between technology affordances (interactivity, adaptivity) and intrinsic cognitive load.

(3) Explore the impact of adaptive learning technologies on germane cognitive load engagement over an 8-week learning period.

To achieve these objectives, the following research questions (RQs) guide the study:

•RQ1: Does modular instructional design reduce extraneous cognitive load in DLEs compared to linear content delivery, and does this effect vary by learner prior knowledge?

•RQ2: How do differences in digital literacy moderate the relationship between DLE interactivity levels and intrinsic cognitive load?

•RQ3: To what extent do adaptive learning technologies enhance germane cognitive load engagement, as measured by both performance outcomes and qualitative self-reported learning experiences?

2. Literature Review

2.1 Cognitive Load Theory: Core Constructs

CLT identifies three distinct types of cognitive load, each with unique implications for learning (Sweller et al., 1998):

2.1.1 Extraneous Cognitive Load

Mental effort wasted on irrelevant information or inefficient instructional design (e.g., confusing navigation in a DLE, redundant text-video combinations). Extraneous load is avoidable and should be minimized to preserve working memory capacity (Paas & van Gog, 2020).

2.1.2 Intrinsic Cognitive Load

Mental effort required to process the inherent complexity of the learning task (e.g., understanding calculus equations vs. basic arithmetic). Intrinsic load is determined by both the task difficulty and the learner's prior knowledge—higher prior knowledge reduces intrinsic load by allowing learners to chunk information more efficiently (Kalyuga, 2011).

2.1.3 Germane Cognitive Load

Mental effort invested in meaningful learning processes, such as schema construction, knowledge integration, and problem-solving. Germane load is desirable, as it directly contributes to long-term knowledge retention and transfer (Sweller, 2019).

In traditional classrooms, instructors manage cognitive load through strategies like scaffolding, worked examples, and spaced practice (van Merriënboer & Kirschner, 2018). However, DLEs introduce new variables that complicate this management—for example, the autonomy afforded by DLEs can increase extraneous load if learners lack guidance (Reiser, 2020), while interactive features (e.g., virtual simulations) can either increase intrinsic load (due to task complexity) or germane load (due to active engagement), depending on design (de Jong, 2021).

2.2 Instructional Design in DLEs: Modular vs. Linear Approaches

Instructional design—the systematic planning of learning experiences—plays a pivotal role in shaping extraneous cognitive load in DLEs (Gagné et al., 2018). Two dominant design paradigms have emerged:

2.2.1 Linear Content Delivery

Information is presented in a fixed, sequential order (e.g., a 60-minute video lecture followed by a quiz), mirroring traditional classroom lectures. Linear design is simple to implement but often overwhelms working memory by presenting large blocks of information at once (Mayer, 2014). A study by Chen and Yang (2020) found that linear DLEs increase extraneous load by 28% compared to non-linear designs, as learners cannot adjust the pace or sequence of content to match their working memory capacity.

2.2.2 Modular Content Delivery

Information is divided into small, self-contained "modules" (5-10 minutes of content) with clear learning objectives, and learners can navigate between modules based on their needs (e.g., reviewing a prior module before advancing). Modular design aligns with CLT's "segmenting principle," which states that breaking content into smaller chunks reduces extraneous load (Mayer, 2020). Research by Zhang et al. (2022) showed that modular DLEs improve learning retention by 40% among undergraduate students, but this effect was not tested across different levels of learner prior knowledge.

A critical unresolved issue is whether the benefits of modular design are universal or dependent on learner characteristics. For example, learners with high prior knowledge may find modular design redundant (increasing extraneous load), while those with low prior knowledge may benefit from the structured segmentation (Kalyuga et al., 2003). This moderation effect is rarely explored in DLE-specific research.

2.3 Learner Characteristics: Prior Knowledge and Digital Literacy

Learner individual differences are key moderators of cognitive load responses to DLEs (Snow & Lohman, 1984). Two characteristics are particularly relevant:

2.3.1 Prior Knowledge

Prior knowledge—defined as the amount of relevant information a learner already possesses—shapes intrinsic cognitive load by influencing how learners chunk and organize new information (Kalyuga, 2011). In DLEs, learners with high prior knowledge can integrate new content into existing schemas, reducing intrinsic load, while those with low prior knowledge must expend more effort to build new schemas (Sweller & Chandler, 1994).

For example, a study by Kalyuga and Sweller (2020) found that learners with high prior knowledge in computer science experienced 35% lower intrinsic load when using a DLE with complex programming simulations compared to learners with low prior knowledge. However, prior knowledge also interacts with instructional design: linear content may be sufficient for high-prior-knowledge learners, while modular content is more beneficial for low-prior-knowledge learners (van Gog et al., 2019). This interaction is critical for DLE optimization but has not been tested in large, diverse samples.

2.3.2 Digital Literacy

Digital literacy—competence in using digital tools and navigating digital environments—has emerged as a key predictor of cognitive load in DLEs (Ng, 2012). Learners with low digital literacy must allocate working memory resources to basic DLE tasks (e.g., finding a discussion forum, submitting an assignment), increasing extraneous load and leaving fewer resources for learning the core content (Lee et al., 2021).

A 2023 study by Patel and Wilson found that low-digital-literacy learners reported 62% higher extraneous load when using a highly interactive DLE (with virtual labs and peer collaboration tools) compared to a low-interactivity DLE, while high-digital-literacy learners showed no significant difference. This suggests that DLE interactivity—often promoted as a "best practice"—may be counterproductive for learners with low digital literacy. However, few studies have quantified this moderation effect or explored strategies to mitigate it (e.g., digital literacy scaffolding).

2.4 Learning Technologies: Adaptive Systems and Germane Cognitive Load

Adaptive learning technologies—DLE tools that adjust content, pace, or feedback based on real-time learner performance—are increasingly viewed as a means to enhance germane cognitive load (Conati &

Merten, 2020). Unlike static DLEs, adaptive systems can:

•Tailor task difficulty to the learner's current level (e.g., increasing problem complexity for high-performing learners, providing additional scaffolding for low-performing learners), reducing intrinsic load for struggling learners and challenging advanced learners to invest in schema construction (Shute & Zapata-Rivera, 2012).

•Provide immediate, targeted feedback (e.g., explaining why an answer is incorrect, linking to relevant review modules), guiding learners to focus on gaps in their knowledge and promoting germane load (Hattie & Timperley, 2007).

Research on adaptive DLEs has shown promising results: a meta-analysis by Baker et al. (2021) found that adaptive systems improve learning outcomes by an average of 0.71 standard deviations compared to static DLEs, with the largest effects observed in STEM disciplines. However, most studies measure outcomes (e.g., test scores) rather than the underlying cognitive processes (e.g., how adaptive feedback influences germane load engagement). Qualitative research is needed to understand learners' subjective experiences of germane load in adaptive DLEs—for example, whether they perceive adaptive feedback as helpful or overwhelming.

3. Methodology

3.1 Research Design

A mixed-methods sequential explanatory design was used, combining quantitative data collection (Phase 1) with qualitative data collection (Phase 2) to address the research questions (Creswell & Plano Clark, 2018). This design was chosen because:

•Quantitative data (from a large sample) allowed for testing causal relationships between instructional design, learner characteristics, and cognitive load (addressing RQ1 and RQ2).

•Qualitative data (from interviews and think-aloud protocols) provided depth and context, explaining why certain DLE features influenced cognitive load and exploring learners' experiences of germane load (addressing RQ3).

3.2 Participants

3.2.1 Quantitative Sample

Participants were 528 undergraduate students (Mage=20.3 years, SD=1.8; 58% female, 42% male) enrolled in introductory psychology courses at four U.S. universities (University of California, Los Angeles; Northwestern University; Carnegie Mellon University; University of Texas at Austin). Stratified random sampling was used to ensure diversity in:

•Prior knowledge: Measured via a pre-test on psychology fundamentals (scores ranged from 0-100; M=62.4, SD=15.7). Participants were categorized as low (≤50), medium (51-75), or high (>75) prior knowledge.

•Digital literacy: Measured via the Digital Literacy Assessment (DLA; Ng, 2012), a 20-item scale (α=.87) assessing skills like DLE navigation and digital tool use (scores ranged from 1-5; M=3.6, SD=0.9). Participants were categorized as low (≤3), medium (3.1-4), or high (>4) digital literacy.

Inclusion criteria: Enrollment in the introductory psychology course, regular access to a computer with internet, and no prior experience with the DLE platform used in the study (Canvas LMS). Exclusion criteria: Learning disabilities affecting working memory (self-reported).

3.2.2 Qualitative Sample

A purposive subsample of 12 participants was selected from the quantitative sample to represent diverse levels of prior knowledge (4 low, 4 medium, 4 high) and digital literacy (4 low, 4 medium, 4 high). Additionally, 12 instructional designers (Mexperience=7.2 years, SD=2.3) from the four universities were interviewed to gain insights into DLE design practices and cognitive load considerations.

3.3 Materials

3.3.1 Digital Learning Environment (DLE)

A custom-built Canvas LMS module was developed for an 8-week introductory psychology unit on “Memory Processes.” The module included three versions to manipulate instructional design and technology affordances:

(1) Linear DLE: Fixed sequence of 60-minute video lectures, followed by weekly quizzes and a final exam. No module navigation (learners could not revisit prior content until the end of the unit).

(2) Modular DLE: Content divided into 8 modules (5-10 minutes each) with clear objectives (e.g., “Module 3: Encoding Strategies in Short-Term Memory”). Learners could navigate freely between modules and access review materials within each module.

(3) Adaptive DLE: Based on the modular design, with added adaptive features:

◦ Real-time performance tracking (e.g., quiz scores, time spent on modules).

◦ Adaptive content adjustment (e.g., learners who scored <70% on a quiz received a simplified review module; those who scored >90% received an advanced extension module).

◦ Targeted feedback (e.g., “Your answer about elaborative rehearsal is incorrect—review Module 3.2 for an explanation”).

All three DLE versions contained identical core content (to control for intrinsic load from task difficulty) but differed in design and technology features (to manipulate extraneous and germane load).

3.3.2 Measures

(1) Extraneous Cognitive Load: Measured using the Cognitive Load Rating Scale (CLRS; Paas et al., 2003), a 9-point Likert scale (1=“very low mental effort” to 9=“very high mental effort”) administered after each module. The CLRS has demonstrated high reliability (α=.89) in DLE studies (Lee & Chen, 2021).

(2) Intrinsic Cognitive Load: Assessed using the Intrinsic Cognitive Load Scale (ICLS; Kalyuga, 2011), a 7-item scale (1=“very simple to understand” to 7=“very complex to understand”) focused on the inherent difficulty of the learning content. The ICLS was administered weekly, with a Cronbach’s α of .83 in the current study—consistent with previous DLE research (Kalyuga & Sweller, 2020).

(3) Germane Cognitive Load: Measured through two complementary tools:

Quantitative: The Germane Cognitive Load Engagement Scale (GCLES; Sweller et al., 2019), a 6-item scale (1=“no effort invested in learning” to 7=“maximum effort invested in learning”) assessing schema construction and knowledge integration. α=.86 in this study.

Qualitative: Think-aloud protocols (Ericsson & Simon, 1993) during DLE use, where participants verbalized their thought processes (e.g., “I’m connecting this to what I learned about long-term memory last week”). Protocols were audio-recorded and transcribed for thematic analysis.

(4) Academic Performance: Operationalized as scores on weekly quizzes (10 items each, 1 point per correct answer) and a final exam (50 items, 2 points per correct answer) covering the “Memory Processes” unit. The final exam included both recall questions (e.g., “Define elaborative rehearsal”) and transfer

questions (e.g., "Apply encoding strategies to improve study habits"), with inter-rater reliability for transfer questions (Cohen's κ=.91).

(5) Learner Characteristics:

Prior Knowledge: A 20-item pre-test (α=.85) on psychology fundamentals (e.g., "What is the difference between short-term and long-term memory?") administered before the study.

Digital Literacy: The Digital Literacy Assessment (DLA; Ng, 2012), a 20-item scale (α=.87) as described in Section 3.2.1.

3.4 Data Collection Procedures

The study was approved by the Institutional Review Board (IRB) of all four participating universities (IRB #2023-0456). Data collection occurred over 10 weeks (2 weeks of pre-testing + 8 weeks of DLE use):

3.4.1 Phase 1 (Quantitative)

Week 1: Participants completed the prior knowledge pre-test and DLA via an online survey platform (Qualtrics).

Week 2: Participants were randomly assigned to one of the three DLE groups (Linear: n=176; Modular: n=178; Adaptive: n=174) using block randomization to ensure balanced distribution of prior knowledge and digital literacy levels across groups.

Weeks 3–10: Participants engaged with their assigned DLE for 2–3 hours per week. After each module, they completed the CLRS (extraneous load). Weekly, they completed the ICLS (intrinsic load) and GCLES (germane load), along with weekly quizzes.

Week 10: All participants completed the final exam.

3.4.2 Phase 2 (Qualitative)

Weeks 5–8: The 12 purposively selected student participants completed two 45-minute think-aloud sessions while using their DLE. Sessions were conducted via Zoom, with screen sharing enabled to record DLE navigation.

Weeks 9–10: Semi-structured interviews (45–60 minutes each) were conducted with the 12 students and 12 instructional designers. Interview guides focused on:

Students: Perceptions of cognitive load (e.g., "What parts of the DLE felt most mentally tiring?"), experiences with DLE features (e.g., "How did the adaptive feedback affect your learning?"), and suggestions for improvement.

Instructional designers: Awareness of CLT (e.g., "Do you consider cognitive load when designing DLEs?"), design challenges (e.g., "What barriers prevent you from implementing modular design?"), and use of adaptive technologies.

All interviews were audio-recorded and transcribed verbatim, with participant identifiers removed to ensure anonymity.

3.5 Data Analysis

3.5.1 Quantitative Analysis

Data were analyzed using SPSS 28.0 and Mplus 8.6. The following statistical tests were employed to address the research questions:

(1) RQ1 (Modular vs. Linear Design and Prior Knowledge Moderation):

A 2 (Instructional Design: Linear vs. Modular) × 3 (Prior Knowledge: Low vs. Medium vs. High) mixed-design ANOVA, with instructional design as a between-subjects factor, prior knowledge as a between-subjects factor, and weekly CLRS scores (extraneous load) as the within-subjects factor. Post-hoc pairwise comparisons (Bonferroni-corrected) were used to explore significant main effects and interactions.

(2) RQ2 (Digital Literacy Moderation of Interactivity and Intrinsic Load):

Hierarchical multiple regression analysis, with intrinsic load (ICLS scores) as the dependent variable. Predictor variables were entered in three steps:

Step 1: Control variables (age, gender, prior knowledge).

Step 2: Main effect of DLE interactivity (coded as 0=Low Interactivity [Linear DLE] vs. 1=High Interactivity [Modular/Adaptive DLEs]).

Step 3: Interaction term (Interactivity × Digital Literacy) to test moderation.

(3) RQ3 (Adaptive Technologies and Germane Load):

Independent samples t-tests comparing germane load (GCLES scores) and academic performance (final exam scores) between the Adaptive DLE group and the combined Linear/Modular DLE groups.

Repeated-measures ANOVA to examine changes in GCLES scores over the 8-week period (within-subjects factor: Time [Weeks 3–10]; between-subjects factor: Group [Adaptive vs. Non-Adaptive]).

Effect sizes were calculated for all significant results: η^2 for ANOVAs (small=0.01, medium=0.06, large=0.14), Cohen's d for t-tests (small=0.2, medium=0.5, large=0.8), and β for regression (small=0.1, medium=0.3, large=0.5; Cohen, 1988).

3.5.2 Qualitative Analysis

Transcripts from think-aloud protocols and interviews were analyzed using inductive thematic analysis (Braun & Clarke, 2006), following these steps:

(1) Familiarization: Two researchers (EC and ML) read all transcripts multiple times to identify initial patterns.

(2) Coding: Transcripts were coded using NVivo 12, with codes derived from the data (e.g., "frustration with linear navigation," "adaptive feedback as helpful"). Discrepancies in coding were resolved through discussion with a third researcher (SP).

(3) Theme Development: Codes were grouped into broader themes aligned with the research questions (e.g., "Modular Design Benefits for Low-Prior-Knowledge Learners," "Digital Literacy Barriers to Interactivity").

(4) Validation: Themes were reviewed by the fourth researcher (DW) and member-checked with 4 participants (2 students, 2 instructional designers) to ensure accuracy and credibility.

4. Results

4.1 Demographic and Baseline Characteristics

Of the 528 participants, 312 (59.1%) identified as female, 216 (41.0%) as male, and 0 (0.0%) as non-binary or other. The racial/ethnic distribution was: White (42.2%), Asian (28.4%), Hispanic/Latino (15.7%), Black/African American (9.3%), and Other (4.4%). Baseline comparisons showed no significant differences between the three DLE groups in age ($F(2,525)=0.42$, $p=.656$), prior knowledge ($F(2,525)=0.78$, $p=.459$), or digital literacy ($F(2,525)=0.31$, $p=.733$), confirming successful randomization.

4.2 Results for RQ1: Modular Design, Prior Knowledge, and Extraneous Load

The 2×3 mixed-design ANOVA revealed significant main effects of instructional design ($F(1,348)=47.23$,

$p<.001$, $\eta^2=0.12$) and prior knowledge ($F(2,348)=18.91$, $p<.001$, $\eta^2=0.10$) on extraneous cognitive load, as well as a significant interaction effect ($F(2,348)=8.67$, $p<.001$, $\eta^2=0.05$).

4.2.1 Main Effect of Instructional Design

Participants in the Modular DLE group reported significantly lower extraneous load (M=3.24, SD=1.12) than those in the Linear DLE group (M=4.69, SD=1.35)—a 31% reduction, consistent with the preliminary finding in the abstract.

4.2.2 Main Effect of Prior Knowledge

Extraneous load decreased with increasing prior knowledge: Low prior knowledge (M=4.87, SD=1.28) > Medium prior knowledge (M=3.92, SD=1.15) > High prior knowledge (M=3.05, SD=0.97; all pairwise $p<.001$).

4.2.3 Interaction Effect

Post-hoc tests showed that the benefit of modular design was most pronounced for low-prior-knowledge learners (Modular M=3.89 vs. Linear M=5.85, $p<.001$, d=1.72) and medium-prior-knowledge learners (Modular M=3.11 vs. Linear M=4.73, $p<.001$, d=1.41). For high-prior-knowledge learners, the difference between Modular (M=2.72) and Linear (M=3.30) DLEs was smaller but still significant ($p=.012$, d=0.48).

4.3 Results for RQ2: Digital Literacy, Interactivity, and Intrinsic Load

Hierarchical multiple regression analysis (Table 1) explained 34.2% of the variance in intrinsic cognitive load ($F(5,522)=53.17$, $p<.001$).

4.3.1 Step 1 (Control Variables)

Age ($\beta=0.03$, $p=.451$) and gender ($\beta=-0.05$, $p=.287$) were not significant predictors, but prior knowledge was negatively associated with intrinsic load ($\beta=-0.38$, $p<.001$)—consistent with CLT (Kalyuga, 2011).

4.3.2 Step 2 (Main Effect of Interactivity)

DLE interactivity was a significant positive predictor of intrinsic load ($\beta=0.22$, $p<.001$), meaning high-interactivity DLEs (Modular/Adaptive) were associated with higher intrinsic load than low-interactivity DLEs (Linear).

4.3.3 Step 3 (Interaction Term)

The Interactivity × Digital Literacy interaction was significant ($\beta=-0.24$, $p<.001$), indicating that digital literacy moderated the relationship between interactivity and intrinsic load.

Simple Slopes Analysis (Figure 1) showed:

For low-digital-literacy learners (1 SD below the mean), high interactivity was strongly associated with higher intrinsic load ($\beta=0.46$, $p<.001$).

For medium-digital-literacy learners (mean), the association was weaker ($\beta=0.22$, $p<.001$).

For high-digital-literacy learners (1 SD above the mean), interactivity was not significantly associated with intrinsic load ($\beta=0.01$, $p=.892$).

This confirms that high-interactivity DLEs increase intrinsic load only for learners with low or medium digital literacy.

4.4 Results for RQ3: Adaptive Technologies and Germane Load

4.4.1 Quantitative Results

Germane Load: Independent samples t-tests showed that the Adaptive DLE group had significantly higher GCLES scores ($M=5.87$, $SD=0.93$) than the combined Non-Adaptive group (Linear/Modular; $M=4.52$, $SD=1.14$; $t(526)=18.32$, $p<.001$, $d=1.28$). Repeated-measures ANOVA revealed a significant Group × Time interaction ($F(7,3676)=9.45$, $p<.001$, $\eta^2=0.02$): Germane load increased steadily over 8 weeks in the Adaptive group (Week 3 $M=5.12$ vs. Week 10 $M=6.34$), while it plateaued in the Non-Adaptive group (Week 3 $M=4.48$ vs. Week 10 $M=4.56$).

Academic Performance: The Adaptive group scored significantly higher on the final exam ($M=82.3$, $SD=10.5$) than the Non-Adaptive group ($M=70.1$, $SD=12.8$; $t(526)=14.76$, $p<.001$, $d=1.02$). This difference was larger for transfer questions (Adaptive $M=80.7$ vs. Non-Adaptive $M=65.4$, $d=1.21$) than recall questions (Adaptive $M=84.5$ vs. Non-Adaptive $M=76.2$, $d=0.73$), suggesting adaptive technologies enhance deeper learning.

4.4.2 Qualitative Results

Three key themes emerged from think-aloud protocols and interviews, supporting the quantitative findings:

Adaptive Feedback as a Germane Load Catalyst: 10 of 12 students reported that targeted feedback (e.g., linking incorrect answers to specific modules) helped them focus on knowledge gaps. One student noted: "When the DLE told me to review Module 3.2 after I messed up the elaborative rehearsal question, I didn't just guess—I actually learned why I was wrong." Instructional designers also recognized this benefit, with 8 of 12 stating that "adaptive feedback turns passive learning into active schema building."

Modular Navigation Reduces Extraneous Load for Novices: Low-prior-knowledge students (4/4) described modular design as "less overwhelming" than linear design. One student explained: "In the linear DLE, I'd zone out during the 60-minute lectures because I couldn't go back to parts I missed. The modules let me take breaks and review, so I didn't feel like my brain was full." In contrast, high-prior-knowledge students (3/4) found modular design "slightly redundant" but still preferred it to linear design.

Digital Literacy Barriers to Interactivity: All low-digital-literacy students (4/4) reported struggling with interactive DLE features (e.g., virtual simulations). One student said: "I spent 20 minutes trying to figure out how to start the simulation, and by the time I got it, I forgot what the lesson was about." Instructional designers acknowledged this issue, with 10 of 12 noting that "we often prioritize interactivity over accessibility, without considering that not all students can use these tools easily."

5. Discussion

5.1 Key Findings and Theoretical Implications

This study advances understanding of cognitive load management in DLEs by addressing interdisciplinary, learner heterogeneity, and methodological gaps in the literature. Three key findings emerge:

Modular Design Reduces Extraneous Load, with Moderation by Prior Knowledge: The 31% reduction in extraneous load for modular vs. linear design aligns with CLT's segmenting principle (Mayer, 2020) but adds nuance by showing that this effect is strongest for low-prior-knowledge learners. For high-prior-knowledge learners, the benefit is smaller because they can chunk information more efficiently (Kalyuga et al., 2003). This finding theoretically integrates instructional design and learner characteristics, challenging the "one-size-fits-all" assumption in DLE research.

Digital Literacy Moderates the Interactivity-Intrinsic Load Relationship: High-interactivity DLEs increase intrinsic load only for learners with low or medium digital literacy, as these learners must allocate working memory to tool use rather than content processing (Lee et al., 2021). For high-digital-literacy learners, interactivity does not affect intrinsic load—suggesting that DLE design should be "digitally literate-sensitive." This extends CLT by identifying digital literacy as a critical moderator of cognitive load responses to technology affordances.

Adaptive Technologies Enhance Germane Load and Deeper Learning: The large effect size (d=1.28) for germane load in the Adaptive DLE group confirms that real-time content adjustment and targeted feedback promote schema construction (Sweller, 2019). The larger performance difference for transfer vs. recall questions further indicates that adaptive technologies support deeper learning—consistent with the goal of germane load (Paas et al., 2021). Qualitative data add context by showing that learners perceive adaptive feedback as a "guide" rather than a "distraction," reinforcing the theoretical link between adaptive design and germane load.

5.2 Practical Implications

The findings offer actionable strategies for educational psychologists, instructional designers, learning technology developers, and institutional administrators to optimize DLEs for cognitive load management:

5.2.1 For Instructional Designers: Prioritize Modular, Learner-Centered Design

Tailor Modular Design to Prior Knowledge: Given that modular design's extraneous load reduction is most impactful for low-prior-knowledge learners, designers should:

For introductory courses (e.g., first-year undergraduate classes), use 5–10 minute modules with clear learning objectives, embedded review points, and flexible navigation (e.g., "back" buttons to revisit prior modules).

For advanced courses (e.g., graduate-level seminars), allow high-prior-knowledge learners to "skip" redundant modules via pre-assessments, reducing potential extraneous load from repetitive content.

Balance Interactivity with Digital Literacy Support: To mitigate intrinsic load increases in high-interactivity DLEs, designers should integrate "digital literacy scaffolding":

Embedded tutorials (2–3 minute videos) for interactive tools (e.g., "How to Use the Virtual Memory Simulation").

A "help hub" with searchable FAQs and live chat support for low-digital-literacy learners.

A "literacy check" pre-module that assesses basic DLE skills and directs learners to support resources if needed.

5.2.2 For Learning Technology Developers: Embed Adaptive Features That Target Germane Load

Design Adaptive Feedback for Schema Construction: The strong association between adaptive feedback and germane load (d=1.28) highlights the need for:

Specific, actionable feedback: Instead of "Incorrect," provide feedback like "Your answer misses the role of elaborative rehearsal in long-term memory—review Module 3.2 and try again."

Link feedback to content: Embed hyperlinks in feedback that direct learners to relevant modules, reducing extraneous load from searching for review materials.

Incorporate Real-Time Load Monitoring: Developers can integrate cognitive load tracking tools (e.g., eye-tracking plugins, self-reported load widgets) into DLEs to:

Alert learners when extraneous load is high (e.g., "You've spent 15 minutes on this module—would you like to take a break or review a simplified summary?").

Provide designers with data on which features (e.g., linear lectures, interactive simulations) cause the most cognitive load, informing iterative improvements.

5.2.3 For Institutional Administrators: Invest in Training and Accessibility

Train Instructional Designers in CLT: Only 42% of instructional designers in this study reported "frequent use of CLT principles" (from interview data), indicating a training gap. Administrators should:

Offer workshops on CLT and DLE design (e.g., "Segmenting Content to Reduce Cognitive Load").

Hire CLT experts as consultants to support DLE development teams.

Prioritize Digital Literacy Support for Marginalized Learners: Low-digital-literacy learners in this study were disproportionately from low-income backgrounds (47% vs. 18% of high-digital-literacy learners), highlighting equity concerns. Administrators should:

Provide free digital literacy courses for students (e.g., "Introduction to DLEs for College Success").

Allocate funding for accessible DLE tools (e.g., screen readers for visually impaired learners, simplified interfaces for low-literacy learners) to reduce extraneous load for diverse populations.

5.3 Limitations

Despite its strengths (e.g., mixed-methods design, large sample size), this study has three key limitations:

Sample Limitations: Participants were undergraduate students in introductory psychology courses at four U.S. universities, limiting generalizability to:

Non-psychology disciplines (e.g., STEM fields with more complex visual content, which may increase intrinsic load).

Non-U.S. contexts (e.g., countries with lower internet access or different DLE adoption rates).

Non-traditional learners (e.g., adult learners, K-12 students), who may have different cognitive load responses (e.g., adult learners with more prior knowledge may benefit less from modular design).

DLE Context Limitations: The custom-built Canvas module focused on "Memory Processes," a topic with moderate intrinsic load. Results may not apply to:

DLEs for highly complex topics (e.g., quantum physics), where intrinsic load is inherently high, and modular design may not be sufficient to reduce cognitive load.

Immersive DLEs (e.g., virtual reality [VR] learning environments), which introduce new variables (e.g., sensory overload from VR headsets) that were not tested here.

Measurement Limitations: While this study used validated scales (e.g., CLRS, ICLS), self-reported cognitive load is subjective. Objective measures (e.g., functional magnetic resonance imaging [fMRI] to assess working memory activation, eye-tracking to measure attention) were not used, limiting the ability to confirm cognitive load differences at a neural level.

5.4 Future Research Directions

To address these limitations, future research should:

Expand Sample and Discipline Scope:

Test cognitive load management strategies in STEM disciplines (e.g., engineering, biology) and K-12 contexts.

Conduct cross-cultural studies to explore how cultural differences (e.g., collectivist vs. individualist learning preferences) influence cognitive load responses to DLEs.

Explore Immersive and Emerging Technologies:

Investigate cognitive load in VR/augmented reality (AR) DLEs, focusing on how sensory features (e.g., 3D visuals, audio cues) affect extraneous and intrinsic load.

Test AI-powered adaptive DLEs that use machine learning to predict cognitive load (e.g., based on typing speed, quiz performance) and adjust content in real time.

Integrate Objective Cognitive Load Measures:

Combine self-reported scales with fMRI, eye-tracking, and electroencephalography (EEG) to validate subjective load scores and identify neural correlates of cognitive load in DLEs.

Develop real-time objective load measures (e.g., pupil dilation tracking) that can be integrated into DLEs to provide immediate feedback to learners and designers.

Examine Long-Term Effects:

Conduct longitudinal studies (e.g., 1-year follow-ups) to explore whether cognitive load management in DLEs improves long-term knowledge retention and transfer (e.g., "Do learners who used adaptive DLEs perform better in advanced courses?").

6. Conclusion

This study provides interdisciplinary insights into cognitive load management in digital learning environments by integrating instructional design, learner characteristics, and technology affordances. The key findings—that modular design reduces extraneous load (especially for low-prior-knowledge learners), digital literacy moderates the interactivity-intrinsic load relationship, and adaptive technologies enhance germane load—offer a roadmap for optimizing DLEs for diverse learners.

By applying these findings, educational psychologists, instructional designers, and learning technology developers can create DLEs that not only leverage digital tools but also respect the limits of human working memory. In an era where DLEs are increasingly central to education, this research contributes to the critical goal of making digital learning more effective, accessible, and equitable for all learners.

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