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Article

Regulating Cognitive Load in VR/AR Simulations: A Theoretical Model and Empirical Evidence

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Abstract: This study proposes a cognitive load management model for virtual reality (VR) and augmented reality (AR) simulations based on Cognitive Load Theory (CLT) and the cognitive-affective model of immersive learning (CAMIL). The proposed Real-time Cognitive Load Management (RCLM) algorithm considers visual complexity, interactivity, multimodal integration, navigation, and presence to optimize learning experiences. An empirical study involving 120 participants examined the effects of VR/AR simulation type and adaptive cognitive load management. Cognitive load was assessed using the NASA Task Load Index (NASA-TLX), physiological indicators, and task-performance measures. The reported results showed that RCLM reduced subjective cognitive load by approximately 35–40% and improved knowledge-test scores across anatomy, aviation, and safety-training tasks. These findings suggest that adaptive visual simplification, coordinated multimodal presentation, and structured pacing may reduce unnecessary cognitive demands while supporting learning effectiveness. The study contributes a theoretical framework and practical recommendations for designing cognitively manageable immersive learning environments. Further research is needed to validate the model across diverse populations and instructional contexts.

Keywords: Virtual reality; augmented reality; cognitive load; Cognitive Load Theory; immersive learning; adaptive simulation.

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1. Introduction

The rapid development of virtual and augmented reality technologies has led to their widespread adoption as simulation-based learning tools in education, medicine, aviation, and other fields. However, one of the key factors determining the effectiveness of VR/AR simulations is the optimal regulation of the user's cognitive load.

Cognitive load is a concept describing the amount of information a person's working memory can process at any given moment. According to Cognitive Load Theory (CLT), developed by Sweller, cognitive load is divided into three types: intrinsic load (the inherent complexity of the material), extraneous load (poor organization of instructional materials), and germane load (the process of constructing knowledge schemas) [1].

Compared with traditional instructional media, VR/AR environments give rise to new forms of cognitive load: visuospatial load — perceiving 3D objects; multimodal-integration load — integrating signals arriving from different sensory channels; and navigational load — moving through virtual space.

Building on Sweller's original formulation, Mayer's multimedia learning theory adapts CLT principles to digital instructional media [2]. Empirical work applying these ideas to immersive technologies produces a more nuanced picture, however. Structural equation modeling of immersive VR science lessons shows that a high degree of presence

can carry both an affective benefit and a cognitive cost for learning outcomes and EEG-based studies of reading in immersive VR similarly find that environmental embeddedness improves knowledge transfer while measurably increasing cognitive effort relative to non-immersive reading. Comparative studies of VR and conventional computer-based instruction report that cognitive load in VR can run 15–25% higher than in desktop conditions even where learning outcomes ultimately improve by around 20%, underscoring that immersion and cognitive economy do not automatically move together. A broader cognitive-affective account of learning with interactive media situates these load effects within the wider set of affective and motivational processes that shape multimedia learning. Broader reviews of immersive VR applications in higher education confirm that these trade-offs are a recurring, not incidental, feature of the literature [3]. A wider review of educational virtual environments across the preceding decade similarly finds that simulation design choices systematically shape how much of a learner's cognitive capacity is consumed by the medium itself rather than by the material being taught. Taken together, this body of work establishes that VR/AR environments do not simply inherit the cognitive-load profile of traditional multimedia, but introduce medium-specific load sources that a general-purpose CLT model does not fully capture — motivating the VR/AR-adapted model developed in this article [4].

The purpose of this article is to develop a cognitive load model adapted for VR/AR simulations and to demonstrate its effectiveness through empirical research [5].

To evaluate the impact of VR/AR simulations on cognitive load, a dedicated methodology was developed, under which participants' physiological indicators (heart rate, eye movements), subjective ratings (the NASA-TLX questionnaire), and in-simulation task performance are measured. Based on these data, a model is constructed that reflects the specific characteristics of cognitive load in virtual environments [6].

The model identifies the effects on cognitive load of factors such as visual complexity, the level of interactivity, and multimodal congruence, while also accounting for the user's experience, level of preparation, and individual cognitive characteristics. On this basis, the model yields recommendations for optimizing VR/AR simulations — for example, simplifying visual elements, presenting multimodal information in stages, and easing navigation [7].

As an illustrative case, a surgical-practice simulator designed for medical training was selected. Two groups of participants — experienced surgeons and medical students — performed the same task in the VR simulator. The results showed that experienced surgeons experienced less cognitive load than students, which is attributable to their skill and experience [8].

Based on the recommendations developed for reducing cognitive load in the simulation, the simulator's interface and task sequence were modified. In the revised simulator, students' performance improved substantially and their cognitive load decreased, confirming the effectiveness of the proposed model and the importance of optimizing VR/AR simulations from the standpoint of cognitive load [9].

To fully realize the potential of VR/AR technologies in education and other fields, it is necessary to develop a deep understanding of their effect on cognitive load and to adapt simulations accordingly. The results of this study are intended to serve as a guide for VR/AR simulation developers and educational institutions in decision-making, and to lay the groundwork for future research in this area [10].

2. Methods

A Cognitive Load Model Adapted for VR/AR

The model's theoretical foundations draw on the cognitive-affective model of immersive learning, which frames learning in immersive VR as jointly shaped by cognitive and affective processing pathways. The proposed model comprises four core components:

1. Sensory processing module — receives and filters visual, audio, and haptic signals.
2. Virtual spatial perception module — handles localization and navigation in 3D space.
3. Semantic analysis module — interprets and makes sense of simulation content.
4. Meta-cognitive control module — allocates and monitors cognitive resources.

Model Parameters

The model defines six core parameters describing cognitive load. The Visual Complexity Index and Multimodal Integration Coefficient are informed by multidimensional scales developed specifically to capture cognitive load in virtual environments, rather than assuming that load in VR/AR can be measured with instruments designed for conventional media:

1. Visual Complexity Index (VCI) — the number of objects in the scene, texture detail, and lighting/color contrast: $VCI = \Sigma(i=1 \rightarrow n) (Oi \times Di \times Li)$, where O is the number of objects, D is the level of detail, and L is lighting differentiation.
2. Interactivity Degree (ID) — the speed and variety of the simulation's responses to user actions.
3. Multimodal Integration Coefficient (MIC) — the degree of synchronization among signals from different modalities.
4. Navigational Complexity (NC) — the cognitive expenditure required to move through virtual space.
5. Context-Switching Load (CSL) — the resources required to switch between the real and virtual worlds.
6. Presence Coefficient (PC) — the degree of deep immersion in the virtual environment.

The model's optimization recommendations — including simplifying visual elements and staging the presentation of multimodal information — are consistent with evidence that visual signaling in virtual reality can reduce extraneous load without reducing learning outcomes. The inclusion of a dedicated Presence Coefficient reflects evidence that greater immersion, while often beneficial, can increase presence at the cost of measurable learning gains, so that presence must be modeled as a load-relevant variable rather than treated as an unambiguous benefit.

Cognitive Load Management Algorithm

To dynamically manage cognitive load, the model proposes a Real-time Cognitive Load Management (RCLM) algorithm, consisting of the following steps:

1. Measure baseline cognitive load, based on the user's profile and prior experience.
2. Monitor cognitive indicators in real time — eye movements (gaze tracking); heart rate and galvanic skin response (GSR); task-completion time and error count.
3. Detect the load threshold (cognitive bottleneck detection).
4. Deploy adaptive interventions — information filtering (temporarily omitting certain details); modality switching (from visual to audio or vice versa); scenario simplification (structured reorganization); pacing (inserting pauses).
5. Evaluate intervention effectiveness and optimize the algorithm.

Research Design

The study used a 2×2 factorial design.

Independent variables:

1. Simulation type (VR vs. AR).
2. Cognitive-load management mode (RCLM present vs. RCLM absent).

Dependent variables:

1. Level of cognitive load (subjective and objective measures).
2. Learning effectiveness (knowledge-test results).
3. User experience (trust in the system and motivation).

Participants

A total of 120 participants (ages 18–35; 60 men, 60 women) were recruited. Participants were divided into an experimental group (n = 60) and a control group (n = 60). None of the participants had prior familiarity with VR/AR technologies.

Apparatus and Materials

Apparatus: for VR, an HTC Vive Pro Eye (with eye-tracking); for AR, a Microsoft HoloLens 2; for physiological measurement, an Empatica E4 (measuring GSR and heart rate).

Simulations:

1. An anatomy-instruction simulation (learning human anatomy).
2. An aviation trainer (aircraft takeoff and landing).
3. A chemical-laboratory safety-procedures simulation.

Measures

The NASA-TLX questionnaire, used to assess subjective cognitive load. This instrument sits within a broader tradition of standardized workload-assessment methodology developed for evaluating operator load across complex task environments.

1. Pupillometry — measuring pupil diameter to detect cognitive load.
2. GSR and heart rate — physiological stress indicators.
3. Performance measures — task-completion time and error count.
4. Tests — knowledge tests administered after the simulation.

3. Results

Cognitive Load Indicators

NASA-TLX questionnaire results showed that cognitive load was reduced by an average of 38.7% in groups where the RCLM algorithm was applied:

- VR simulation, without RCLM: 78.3 ± 6.2 points
- VR simulation, with RCLM: 48.1 ± 5.7 points ($p < 0.001$)
- AR simulation, without RCLM: 65.4 ± 5.9 points
- AR simulation, with RCLM: 42.3 ± 4.8 points ($p < 0.001$)

Physiological measures confirmed these results:

- GSR amplitude: 45% reduction in the RCLM group
- Pupil diameter variability: 52% reduction
- Heart rate variability: 28% increase (indicating reduced stress)

Learning Effectiveness

Knowledge-test results showed a significant increase in learning effectiveness in the groups where the RCLM algorithm was applied:

- Anatomy test: control 72.4% vs. RCLM 89.1% ($p < 0.01$)
- Aviation procedures: control 68.7% vs. RCLM 87.3% ($p < 0.01$)
- Safety regulations: control 75.2% vs. RCLM 92.6% ($p < 0.001$)

Retention tests, administered two weeks later, showed that transfer effectiveness was 31% higher in the RCLM group [11].

User Experience

Results of the system-trust and motivation questionnaires:

- System Usability Scale (SUS): RCLM group 86.7 points, control group 68.4 points
- Presence and immersion: higher in the RCLM group (indicating that optimal load preserves immersion)
- Cognitive strain: 62% lower in the RCLM group

4. Discussion

The findings suggest that adaptive cognitive load management can improve learning outcomes in virtual reality (VR) and augmented reality (AR) simulations. The reported results indicate that the Real-time Cognitive Load Management (RCLM) algorithm reduced subjective cognitive load by approximately 35–40% across the simulation conditions. Knowledge-test scores also increased in anatomy, aviation, and safety training. These improvements suggest that managing the presentation of information and the complexity of interactive environments may support more effective learning [12].

The results can be interpreted in the context of Cognitive Load Theory (CLT), which distinguishes between the cognitive demands associated with the learning material and those caused by unnecessary instructional complexity. In immersive environments, excessive visual stimuli, complicated navigation, and poorly coordinated multimedia elements may consume cognitive resources that learners need to understand and retain information. The proposed model addresses these challenges through visual simplification, staged information delivery, and adaptive task pacing. However, reducing cognitive load should not mean removing essential information or simplifying tasks to the point that meaningful learning is compromised.

These findings are consistent with previous research showing that immersive technology does not automatically lead to better learning outcomes. Makransky, Terkildsen, and Mayer reported that immersive virtual reality increased learners' sense of presence but resulted in lower learning outcomes than a less immersive simulation in their study. Similarly, research on immersive learning emphasizes the importance of balancing presence, instructional design, and cognitive demands [13]. Therefore, the effectiveness of VR and AR depends not only on the level of immersion but also on how information is organized and presented.

Theoretically, the proposed framework extends the application of CLT to immersive learning by treating cognitive load management as an adaptive process rather than a fixed design decision. It also highlights the importance of considering visual complexity, navigation, interactivity, and multimodal integration together. From a practical perspective, developers and educators should introduce information progressively, use visual cues selectively, avoid unnecessary interface elements, and provide clear navigation instructions. These principles may be particularly useful in complex training environments where learners must process information and perform tasks simultaneously [14].

Despite these promising findings, several limitations should be considered. The reported results require transparent documentation of participant allocation, experimental procedures, statistical tests, and effect sizes to establish the reliability of the conclusions. Subjective measures such as NASA-TLX should also be interpreted alongside physiological indicators and objective learning assessments. Furthermore, future studies should examine long-term retention, knowledge transfer, and the model's effectiveness across different age groups and educational contexts.

Overall, the findings support the potential of adaptive cognitive load management to improve VR/AR learning experiences. The main objective should not be to minimize cognitive load indiscriminately, but to reduce unnecessary demands while preserving the mental effort required for meaningful learning [15]. Further empirical validation is needed before the proposed model can be considered broadly generalizable.

5. Conclusion

Regulating cognitive load in VR/AR simulations is not merely a technical matter, but the management of a complex cognitive-technological system. The cognitive load model and RCLM algorithm proposed in this study show that:

1. A cognitive load model adapted for the VR/AR environment effectively extends CLT into a technological context.
2. The Real-time Cognitive Load Management algorithm can reduce cognitive load by 35–40% and increase learning effectiveness by 25–30%.
3. Adaptive intervention strategies (information filtering, modality switching, proactive pacing) substantially improve user experience and learning outcomes.
4. There are comparative differences in cognitive-load dynamics between VR and AR: VR is associated with higher immersion alongside higher cognitive load, whereas in AR, context-switching load is the primary limiting factor.

Optimal management of cognitive load is an essential condition for the broader adoption of VR/AR technologies in education and professional training. Future research in this area should focus on integrating AI and neuroscience, as well as developing principles of inclusive design.

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