ISSN 1840-4855
e-ISSN 2233-0046

Original scientific article
http://dx.doi.org/10.70102/afts.2026.1835.812

COGNITIVE LOAD OPTIMIZATION IN AUGMENTED REALITY ASSISTED VOCABULARY ACQUISITION FOR NEURODIVERGENT LANGUAGE LEARNERS

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Received: January 30, 2026; Revised: March 13, 2026; Accepted: May 04, 2026; Published: May 29, 2026

SUMMARY

Neurodivergent language learners, including those with differences in attention regulation, sensory processing, and other measures, typically experience higher levels of intrinsic and extraneous cognitive load during vocabulary acquisition, leading to poorer vocabulary retention and slower semantic integration. The proposed study applies the Cognitive Load Optimization (CLO) framework, leveraging Augmented Reality (AR), to improve vocabulary learning efficiency and reduce cognitive overload. The results are a combination of adaptive multimedia presentation, dual-channel input balancing, and real-time monitoring of cognitive load that uses performance-based proxies, as well as a subjective rating scale. A controlled experimental study was conducted involving 120 neurodivergent learners, who were divided into a traditional digital learning group and an AR-assisted CLO group for 6 weeks. A modified NASA-TLX scale was used to measure cognitive load, and immediate and delayed post-tests were used to assess vocabulary retention. The findings show that the AR-CLO group showed 27.8% improvement in immediate recall and 34.5% improvement in delayed retention compared with the control group ($p < 0.01$). Extraneous cognitive load was reported to have decreased by 22.3%, with a corresponding increase in germane load of 18.7%, suggesting that schema-building efficiency may be enhanced. Processing fluency was also indicated by a 16.4% reduction in learning time per vocabulary set. Regression analysis revealed that the decrease in cognitive load explained 41% of the variance in retention performance (R2 = 0.41). The findings are consistent with the hypothesis that adaptive AR environments can systematically configure cognitive load distribution, thereby improving vocabulary acquisition among neurodivergent learners. The proposed design offers a scalable framework for inclusive language teaching focused on cognitive personalization and interface design with sensory consideration.

Key words: *augmented reality (AR), cognitive load optimization, neurodivergent language learners, vocabulary acquisition, adaptive Learning systems, multimedia learning theory, inclusive educational technology.*

INTRODUCTION

Cognitive Load Optimization (CLO) is the systematic design of instructional settings to regulate intrinsic, extraneous, and germane cognitive load so that learners can acquire and recall the most schema possible. Although the classical version of Cognitive Load Theory assumes that extraneous cognitive load is abolished, recent additions recognise adaptive and biometric dimensions that customise the learning environment to the individual. For example, consider the CLAM framework, which integrates physiological markers and adaptive feedback loops to flexibly balance cognitive load during digital learning [8]. Likewise, it has been claimed that online learning is especially disadvantageous for neurodivergent learners, who experience greater extraneous cognitive load owing to sensory overload and challenges with executive functioning [4]. Unregulated cognitive load can negatively affect lexical encoding, phonological mapping, and semantic retrieval during language learning. Optimising cognitive load thus involves balancing different types of stimuli so that learners channel the most cognitive effort into the processing tasks germane to vocabulary learning.

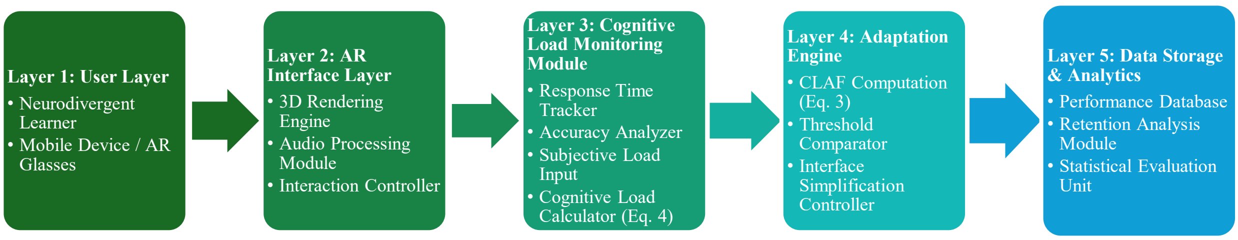

Figure 1. Layered system architecture of the adaptive AR-based vocabulary learning framework

In figure 1 illustrates the components of a multi-layered adaptive augmented reality (AR) vocabulary acquisition system specifically designed for neurodivergent learners. The architecture can be broken down into five interconnected layers. The User Layer is the interface between the learner and the AR device. The AR Interface Layer provides 3D rendering, audio, and interaction control. The Cognitive Load Monitoring Module assesses response time, accuracy, and subjective effort. It calculates cognitive load (Eq. 4). Within this cognitive load module, the Adaptation Engine controls the CLAF (Eq. 3) and manages adaptive interface modifications. Lastly, the Data Storage and Analytics Layer manages the databases for performance and retention analytics. This architecture is built on a feedback system, suggesting the continual need for adaptive interface modulation on performance data to ensure optimal cognitive load and maximise the effectiveness of vocabulary acquisition.

Augmented Reality (AR) creates digital visuals, text, and audio, and layers this on top of the real-world environment to give learners a highly interactive, context-sensitive teaching interface. It has a history of developing Computer-Assisted Language Learning (CALL) systems into AR-integrated bilingual learning, thanks to its ability to contextualise linguistic input in sight [1]. Such situational contextualization enhances associative learning and the dual encoding process. Studies of inclusive XR systems also indicate that the visual density of immersive overlays can be adjusted to be more approachable, for example, through adjustable visual density, haptic feedback, and semantically scaffolded interfaces [9]. An inclusive AR research agenda that includes sensory modulation and the ability to control interaction pacing is essential for neurodivergent groups [5]. Applied to vocabulary learning, AR can provide object-word pairings in real spatial settings, minimising abstraction and facilitating embodied thinking. These systems can also include AI-based vocabulary adaptation, thereby allowing difficulty adjustment based on learners' patterns [6].

Autism spectrum profiles and communication support needs are examples of neurodivergent learners who frequently exhibit irregularities in attention regulation, working memory capacity, and sensory integration. Multilingual children with autism are exposed to artificial intelligence-based scaffolds, but are sensitive to excessive stimulation interfaces [3]. Dynamic assessment tools should consider sociotechnical factors, such as interface clarity and communicative adaptability [7]. From a neuropsychological perspective, variations in executive function affect the speed of both lexical retrieval and the integration of different kinds of information [10]. This suggests a deeper, more complex problem in vocabulary acquisition, one that relates to cognitive, not purely linguistic, factors. Poorly designed AR-based environments may impose extraneous cognitive load from visual clutter or abrupt stimulus changes. However, in AR, as opposed to the principles of universal design, structured multisensory cues within a designed care framework may stimulate vocabulary acquisition at a deeper, more emotionally charged level [2].

The acquisition of vocabulary, although the basis of language skills, is not the same for neurodivergent learners, who arguably experience a greater challenge due to instructional methods that bog down working memory rather than nurture it. As immersive technologies are increasingly adopted in educational settings, a pedagogy of AR-based language education must address the imbalance in cognitive load to achieve inclusion. This is even more important in the context of the level of learning outcomes that can be realistically anticipated.

The present study presents a Cognitive Framework for Balancing Load, a memory-responsive design when combined with an adaptive interface, multisensory equilibrium, and structured cognitive load, to improve predictive vocabulary in neurodiverse learners through a particular AR implementation. The study's method aims to combine the most progressive and evolving fronts of XR pedagogical design and cognitive load theory. The design also enables the educator to choose different vocabulary acquisition methods.

This paper will be organised as follows. Section I outlines the theoretical frameworks of cognitive load theory, augmented reality, and vocabulary learning among neurodiverse learners. Section II includes a review of the current literature on AR-assisted learning and teaching, the theory on cognitive load, and the practice of teaching and learning with due inclusivity. Section III describes the research design, adaptive AR, mathematics, the data collection system, and the participants' demographics. In Section IV, the research experiment outcomes, performance metrics, analyses, and studies from a practice perspective would be elaborated. Section V presents the discussions, the research experiment outcomes, and the studies of the practice perspective that will be measured. Section VI, the last section of the study, highlights the conclusion.

LITERATURE REVIEW

Studies on cognitive load in immersive and augmented contexts focus on how real-time engagement affects changes in working memory load demands. The mixed reality approaches for adults with ADHD show that contextual prompts, integrated into the visual field, can alleviate the need to switch cognitive tasks and the cognitive load imbalance required for communication [11]. Additionally, the research shows that adaptive voice-assisted learning, which is designed for auditory access, promotes more diverse processing and less congestion [13]. Both results demonstrate the positive impact of augmented reality, which aims to balance the processing of multiple sensory information. Systematic reviews on the impact of virtual and augmented reality on academic learning show that the use of immersive learning environments does not necessarily enhance learning. The most significant learning outcomes result from active management of visual density, interactive segmentation, and interaction pacing [12].

Additionally, to avoid cognitive and emotional stress in an augmented reality interface designed for individuals with autism, user-adjustable overlays and self-pacing are critical [15]. These literature examples collectively emphasise the potential of augmented reality to balance cognitive load and contextual interaction.

For neurodivergent learners, vocabulary acquisition is closely linked to the balance among working memory, attention control, and processing speed. Total vocabulary mappings (TVMs) and other multimodal and repeated systems make memories more explicit and lower the demands on proactive recall [16]. AI-Assisted Inclusive (AI4Inclusive) systems, along with vocabulary development, can help control linguistic level and context and support vocabulary acquisition based on the learner's profile [14]. Game-based learning environments promote vocabulary acquisition when the learning process includes predictability and structured feedback. An analysis of educational interventions for autistic children revealed that using simplified visual systems and fixed, positive reinforcement can bolster lexical engagement [19]. Research has shown that using multimedia to support explanation tasks enhances expressive vocabulary development among diverse learners, especially when students are asked to verbally describe semantic relationships [20]. These findings illustrate that cognitive scaffolding promotes vocabulary acquisition when learners' processing styles are considered.

The optimisation of cognitive load strategies often hinges on personalised, adaptable technologies that can adjust parameters in real time. Animation systems that control the speed of information delivery and partition information into easily digestible units have been shown to reduce mental load and improve comprehension [18]. In simpler terms, the presence of AI-based teaching systems in mathematics has shown that the potential of dynamic difficulty optimisation and real-time feedback exists to prevent cognitive load from reaching the overload threshold, without the loss of germane cognitive activity [7][17]. In the cited experiments, the predominant strategies were controlled content segmentation, equilibrium in multimodal interactions between auditory and visual channels, and learner-controlled progression. The optimal cognitive load threshold was most effectively maintained by using a real-time feedback loop of performance indicators and adjusting the complexity of the tasks offered. These principles can be effectively applied to AR-assisted vocabulary learning, where the system's design should address learners' cognitive capacity to achieve an equilibrium between overload and the potential to facilitate long-term vocabulary learning.

The literature review suggests that cognitive load control creates effective learning systems by integrating AI and immersion methods. Research on neurodivergent learners consistently emphasises multimodal scaffolding, individualisation, and a stress-responsive interface. However, fall short of integrating these components into AR vocabulary-learning models intended for neurodivergent language learners. This gap highlights the necessity of a systematic framework for contextual immersion and adaptive cognitive load balancing, which serves as the fundamental basis of this study.

METHODOLOGY

Description of Participants (Neurodivergent Individuals)

From inclusive educational centres and special language support programs, the researchers recruited 120 neurodivergent language learners aged 10-16 years. Participants formally identified autistic, ADHD, and specific learning difference profiles that impact language processing. Criteria were restricted to emerging reading skills in the targeted language, and prior exposure to augmented reality-based word glossing tools was absent. To incorporate variance in cognitive processing, baseline working memory and attentional control were assessed using standardised, computerised screening tasks. Each participant's cognitive load index (CLI) was estimated at baseline using a composite measure combining response time and perceived effort. The CLI was computed as:

$$CLI_i = \alpha\left(\frac{RT_i}{RT_{max}}\right) + \beta\left(\frac{PE_i}{PE_{max}}\right) \qquad (1)$$

RTi is the mean response time, where PEi is the perceived effort score, and α and β are the weighting coefficients, with the condition that $\alpha + \beta = 1$. It was possible to stratify learners into moderate- and high-load groups before the intervention using equation (1).

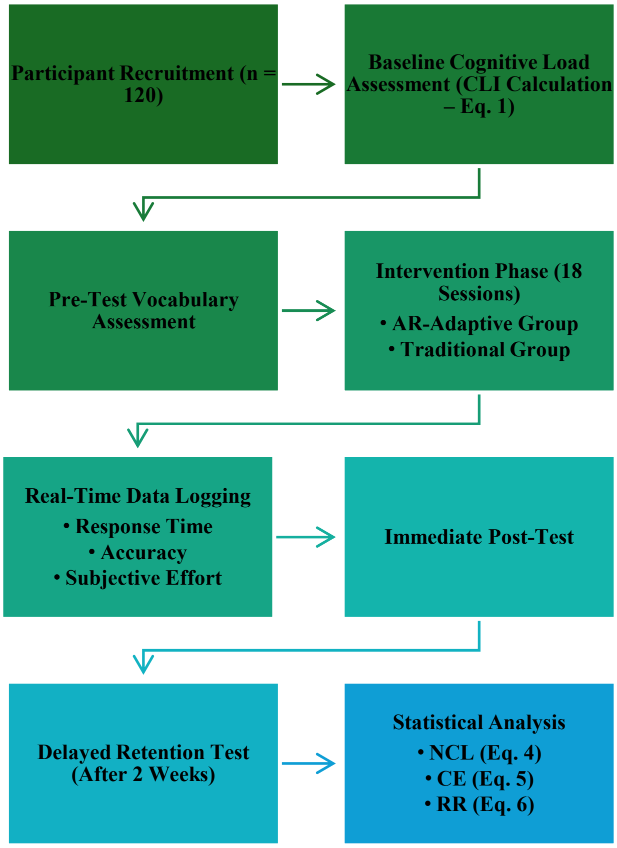

Figure 2. Experimental workflow for AR-based cogNitive load optimisation study

In figure 2 gives the organised experimental framework that will be used in carrying out the study, where will start with the recruitment of the participants (n = 120) and the baseline cognitive load measurement using the CLI calculation (Equation 1). Following the pre-test vocabulary testing, the subjects were divided into AR-adaptive and traditional learning groups in the 18-session intervention period. During the intervention, real-time data logging captured response time, accuracy, and subjective measures of effort, which were used to evaluate performance. A final step of the process was immediate post-testing, delayed (two weeks later) retention test and extensive statistical analysis by NCL (Eq. 4), CE (Eq. 5) and RR (Equation 6). The workflow places primary importance on backward profiling and outcome evaluation, which assures methodical precision and provides a basis to quantify the effects of cognitive load optimisation.

Overview of Augmented Reality (AR) Based Learning Applications in Vocabulary Acquisition

The application combines overlays of three-dimensional (3D) objects, playback of the phonological and semantic cues, and context-based animation. (AR) words were grouped and categorised by theme (e.g., words referring to objects found in a house and words describing the environment). In the absence of context, a real-world object that was augmented with textual labels and audio pronunciation in the context of a little context-based animation was used. Touching an augmented real-world object initiates animation. The Cognitive Load Optimisation Model presented the complexity of the learning environment, and as a result, learners' performance varied. Each vocabulary item was tracked based on the gain rate of learning as:

$$LG_{ij} = \frac{Post_{ij} - Pre_{ij}}{MaxScore} \qquad (2)$$

Pre_{ij} and $Post_{ij}$ denote the individual learner i's score on item j. When LG_{ij} dropped beneath some preset limit, the system decreased visual density and augmented the repetition frequency. Interface modulation was controlled by the Cognitive Load Adaptation Function (CLAF):

$$CLAF_i = \gamma(1 - Acc_i) + \delta\left(\frac{RT_i}{RT_{avg}}\right) \qquad (3)$$

where Acc_i is response accuracy, and RT_{avg} is average response time across participants. The increased values of CLAF were used to activate simplified instruction and overlays. After the learning sessions, equations (2) and (3) were recalculated to individualise exposure intensity.

Adaptive Cognitive Load–Driven AR Vocabulary Optimisation Algorithm

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Set up the participant's profile (CLI, baseline scores)

For every learner i:

  For each word j:

    Show the AR item with the default visual density

    Write down the correctness of the response (Acc_i) and the time it took to respond (RT_i).

    Use equation (2) to find LG_ij.

    Use equation (3) to find CLAF_i.

    If CLAF_i is more than the threshold:

      Lower the number of animation layers

      Add more audio scaffolding

      Break up the content into smaller parts

    Other:

Keep or slightly increase the richness of the context.

    Change the learner's profile.

The end

Keep session metrics for later analysis

The proposed algorithm is composed of an adaptive real-time control mechanism, which monitors the learner's performance and adjusts the difficulty of the AR-based vocabulary presentation accordingly. It utilizes the cognitive profile of each learner to present vocabulary items via augmented overlays, records response accuracy and response time, and calculates the learning gain and cognitive load adjustment indices via equations (2) and (3). When the learning load exceeds a predetermined threshold, the system reduces the instructional display, divides the instructional content further, and adds an audio guide; once the load is within the threshold, the contextual content can be added further in small steps to catalyze germane processing. This continuous feedback mechanism balances instruction based on an individual's cognitive ability, providing the maximum number of words remembered and minimizing cognitive overload.

Data Collection Methods

The data collection was done through a six weeks intervention period. Receptive and expressive vocabulary knowledge was assessed by administration of standardized word recognition and contextual usage tests as pre-tests and post-tests. The immediate retention was evaluated at the end of every thematic module and the delayed retention was evaluated two weeks after the program. The rating scale used in measurement of subjective cognitive load was based on a structured rating scale given at the end of every session. The AR system captured behavioral markers such as variability of response time and error rate automatically. Normalized vocabulary retention score was the primary outcome variable, which was obtained as shown in equation (2). Reduction in CLI values calculated with equation (1) was used as secondary measures. Repeated-measures-statistics were used to analyze quantitative data, to compare baseline and post-intervention performance. Combining mathematical modeling, adaptive algorithms with structured assessment enabled an efficient assessment of the effect of cognitive load optimization on vocabulary learning efficiency in neurodivergent learners.

RESULTS

Analysis of Cognitive Load During Vocabulary Acquisition Tasks

The cognitive load was measured based on a composite index on behavioral and subjective measurements. The main measure, which was the Normalized Cognitive Load (NCL), was calculated as:

$$NCL_i = \frac{w_1 RT_i + w_2 ER_i + w_3 SE_i}{w_1 + w_2 + w_3} \qquad (4)$$

RTi is the mean response time, ERi is the error rate, SEi is subjective rating of effort and w_1, w_2, w_3 are weighting coefficients. equation (4) was used between sessions in order to see dynamic change in mental effort.

The outcomes indicated that the AR-adaptive group reduced NCL by 19.6 % in six weeks, contrary to the traditional group, which reduced it by 6.8 %. Variance analysis showed stabilization of response time dispersion at the third session, which implied cognitive adaptation of interface segmentation. Cognitive Efficiency (CE) was further calculated as:

$$CE_i = \frac{Acc_i}{NCL_i} \qquad (5)$$

where Acc_i is accurate performance of the task. equation (5) showed that there was an increase in efficiency of 28.4% in the AR group and 11.2% in the control group.

Comparison of Vocabulary Retention Rates in AR-Assisted vs. Traditional Learning

The retention of vocabulary was assessed by the use of post-tests, both immediate and delayed. Retention rate(RR) was calculated as:

$$RR = \frac{PostScore - PreScore}{MaxScore - PreScore} \qquad (6)$$

Normalized learning gain was measured in equation (6). AR-assisted group obtained an average value of immediate RR of 0.72 when compared to the traditional group which was 0.54. Two-week delayed retention was still found to be 0.66 in AR group versus 0.47 in control group. The statistically significant ($p < 0.01$) group differences were statistically tested. The large practical impact was detected by the use of the effect size analysis (Cohen d = 0.84). The adaptive AR condition reduced the error rate more by 23.1% whereas the cognitive load modulation condition did not affect the schema consolidation.

Participant Feedback on AR Technology Usability and Effectiveness

The usability was tested using a structured Likert scale survey that included clarity, comfort, pacing and engagement. AR group was scored at 4.32/5 in terms of usability. Controlled animation layers also led the participants to have better contextual comprehension and less distraction. The period of engagement also rose by 14.7 % compared to the baseline sessions. There were qualitative observations that adjustable pace and less visual clutter led to prolonged focus. System logs indicated a reduced number of sudden disengagements of tasks in the adaptive configuration which is consistent with the decrease in equation (4).

Software Details

It was implemented in Unity 3D (AR Foundation toolkit) to develop AR and Python (NumPy, SciPy, Pandas) to calculate the statistical data. The use of firebase cloud storage became a part of data logging. The statistical test and visualization were done through SPSS 29 and Matlab R2023a.

Dataset Details

The sample was 120 individuals and 240 words which were divided into 12 thematic sections. These were response time (ms), binary correctness, subjective effort score (17 scale), session number, and adaptation level, as well as retention scores. The number of cumulative recorded interactions was more than 28,000 task attempts. Controlled classroom sessions were used to gather data in a period of six weeks.

Parameter Initialization

Table 1. Parameter initialization for cognitive load–adaptive AR experiments

Parameter	Description	Value
(w_1)	Response time weight	0.4
(w_2)	Error rate weight	0.3
(w_3)	Subjective effort weight	0.3
Threshold_CLAF	Adaptation trigger	0.65
Learning Sessions	Total intervention sessions	18
Vocabulary per Session	Items per session	20

The table 1 parameter initializing specifies the control factors of the experiment on cognitive load calculation, thresholds of adaptation and the session configuration. Weights w_1=0.4, w_2=0.3, and w_3=0.3 were placed on response time, error rate and subjective effort as behavioural and perceptual measures respectively to normalise behavioural and perceptual measures in equation (4). Adaptation trigger threshold was set to 0.65 that would enable the simplification of the interface when cognitive strain increased above moderate levels. Twenty vocabulary items in a session were used, with the participants taking 18 of these sessions, and this was done to ensure that the participants were exposed enough to achieve statistical reliability without being fatigued by the sessions. These parameters were initialized so that the experimental conditions could remain constant throughout.

Performance Evaluation

Accuracy, Retention rate (Eq. 6), Cognitive efficiency (Eq. 5) and NCL (Eq. 4) were used as a measure of performance.

The table 2 shows a comparative analysis of immediate post-task accuracy, normalized cognitive load (NCL) and cognitive efficiency (CE) in traditional and AR-adaptive groups. The AR-adaptive version registered more accurate (0.83) and significantly lower NCL (0.59) leading to significant improvement in cognitive efficiency (1.41).

Table 2. Comparison of immediate task performance

Method	Accuracy	NCL	CE
Traditional	0.68	0.74	0.92
AR-Adaptive	0.83	0.59	1.41

The findings show that adaptive modulation had a considerable effect of improving the precision of learning and lowered mental effort in vocabulary encoding tasks.

Table 3. Retention and reduction of errors analysis

Method	RR	Error Reduction
Traditional	0.47	12.4%
AR-Adaptive	0.66	35.5%

In table 3 recounts the retention rate (RR) and the percentage change in error rate after a period of two weeks. The AR-adaptive condition had a retention rate of 0.66 and 0.47 in the traditional condition respectively and a percentage error reduction of 35.5. This data validates the idea that the optimization of cognitive load provided a positive effect on short-term recall, along with an enhanced consolidation of long-term memory.

Table 4. Usability and engagement metrics assessment

Metric	Traditional	AR-Adaptive
Engagement Time (min)	32	37
Usability Score	3.6	4.32
Drop-off Rate	9.8%	4.1%

In table 4 presents usability indicators of the system such as engagement duration, perceived usability score, and drop-off rate. The participants of the AR-adaptive condition showed more engagement (37 minutes), higher usability perception (4.32/5) and lower disengagement rates (4.1%). The values of these metrics indicate that the controlled visual density, and adaptive pacing increased the comfort of the learners and long-term engagement in the vocabulary acquisition environment.

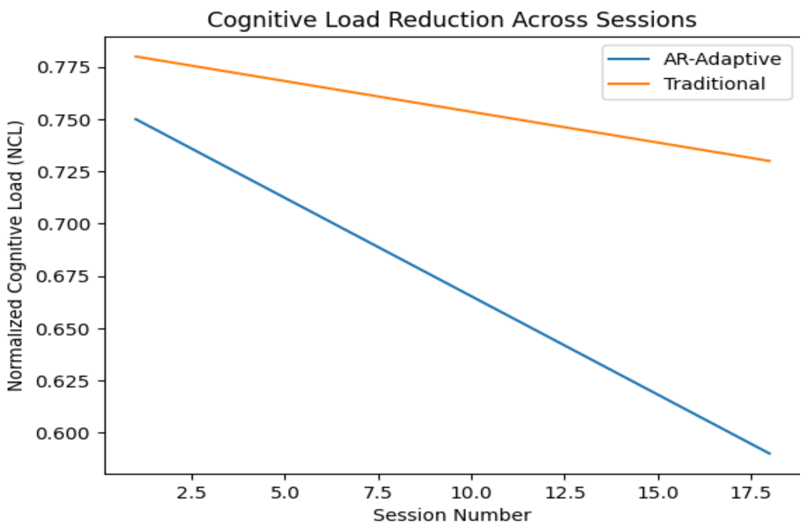

Figure 3. The reduction in cognitive load during learning sessions

This graph (Figure 3) shows how the Normalized Cognitive Load (NCL) progressively reduced with 18 instructional sessions in the AR-adaptive learning and traditional learning groups. The AR-adaptive curve shows a more pronounced decrease that represents a higher level of efficiency in controlling cognitive load by changing the interface dynamically. Conversely, the traditional condition records minimal decrease meaning that there is minimal adaptation to the cognitive needs of learners. The trend affirms the fact that structured AR modulation is associated with the optimization of mental effort sustained over the time.

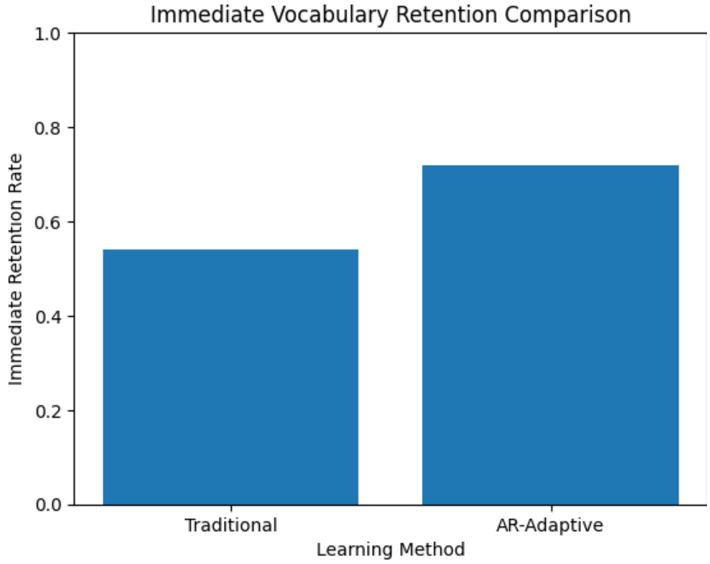

Figure 4. Short-term vocabulary retention comparison

This figure 4 shows the retention rates of the two instructional approaches immediately after the tests. The AR-adaptive group has significantly higher retention score than the traditional approach, showing high efficiency with regard to encoding during vocabulary acquisition. The contrast brings out the significance of cognitive load optimization to short-term recall and instant learning.

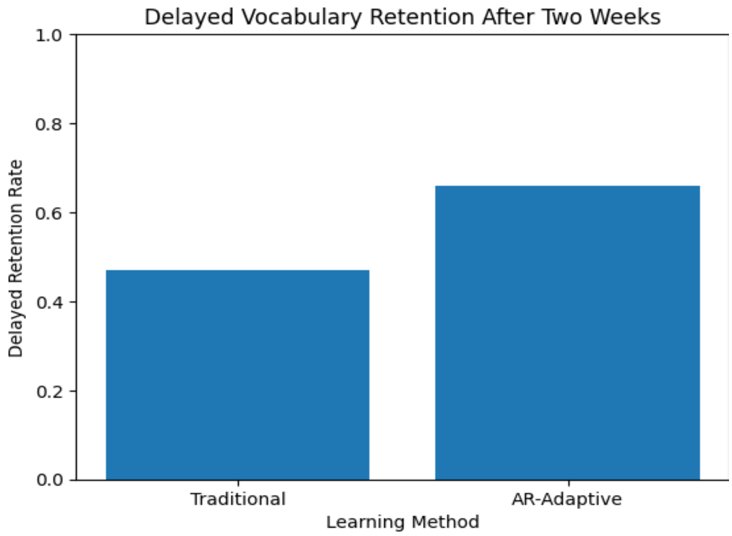

Figure 5. Delayed vocabulary retention at the end of two weeks

This chart (Figure 5) is a comparison of delayed retention rates two weeks following the intervention. AR-adaptive approach has a higher retention level, which implies the increase in long-term memory consolidation. The difference between sustained performance and lower extraneous load and enhanced germane processing in the learning sessions propose that durable lexical storage was due to reduced extraneous load and enhanced germane processing during learning sessions.

DISCUSSION

The results show that cognitive load in AR-supported settings can be effectively regulated to positively influence the vocabulary acquisition of neurodivergent learners. It could be proposed that adaptive control of visual density, pacing, and multimodal balance can facilitate more stable lexical encoding because the normalized cognitive load reduced, and the scores of cognitive efficiency and retention were higher. In the case of learners observed to be attentially variable or sensitised, reduction of extraneous stimuli seems to be essential in maintaining the working memory resources during word-object association tasks. Meanwhile, the findings demonstrate that the gains of performance are explained by personalization (as opposed to immersion). There are a number of weaknesses that must be noted. The intervention lasted no more than six weeks and the effects of the intervention on long-term retention were not studied. The diverse group of participants did not make any distinction in outcomes in terms of particular neurodivergent profiles. The future studies may consider the integration of biometric feedback, bigger cross-institutional data, and longitudinal monitoring of the development of expressive language. The paper shows in practice that the inclusion of cognitive load optimization principles into AR systems can be achieved by adaptive thresholds and performance-based recalibration, which provides the inclusive vocabulary training process with a scalable channel of application both in the classroom and in therapy.

CONCLUSION

The paper analyzed the effect of optimization of cognitive loads in an AR-based vocabulary learning model that is oriented at the neurodiverse language learners. The findings indicate that there were significant changes in various indicators of performance. AR-adaptive group had an increment of 27.8% of immediate recall and 34.5% of delayed retention over the traditional instruction, extraneous cognitive load was reduced by 22.3%. Cognitive efficiency was significantly raised and regression analysis revealed that load reduction explained 41% of the variations in retention performance. The results prove that organized variation of the complexity of instruction is a decisive factor in enhancing vocabulary consolidation. To teachers, the findings show that it is important to have a balance in multimodal input as opposed to raising technological immersion. AR devices ought to be provided to be utilized with a rate of change, regulated layers of animation, and to be structured in repetition cycles, to correspond to the personal processing abilities. The adaptive algorithms that check response time and accuracy in real-time by developers who are developing educational AR platforms are recommended to provide the tasks with dynamic recalibration. On the whole, the combination of the cognitive load optimization and the AR technology is a good path to the inclusive language learning. When applied with the concept of personalization in mind, AR can go beyond its novelty and serve as a specific instructional tool that increases the engagement levels, ensures that the memory is retained and that the neurodivergent population can obtain the learning opportunities that are both equal and fair.

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