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Adaptive Repetition: A Control Strategy for Active Exploration and Long-Term Memory Retention

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Abstract:

In this paper an adaptive repetition model is used as a tool for active exploration in 3D Virtual Learning Environment (3D VLE) and keeping information in long term memory. While using cognitive aids, e.g. textual, auditory and visual cues, can reduce the cognitive load of the learner, excessive use of these aids may make exploration behavior difficult and may have a negative impact on performance under uncontrolled conditions in real-world settings. To overcome this, the proposed model quantifies the learner's performance from the time taken for task completion, number of errors, and assessment scores. It then classifies learners as weak, average and proficient. The system automatically decreases the amount of cognitive support delivered to average and proficient learners after repeated trials, thus helping to promote learner interaction with, and exploration of, the environment. By gradually removing these external cues, learners are prompted to actively recall procedural steps and complex concepts rather than passively relying on the system. This dynamic retrieval in the virtual lab improves cognitive connections, collateral that the newly acquired skills are deeply encoded and associated into long-term memory. An experimental study design was used with 80 learners in a Multimodal Virtual Laboratory (MMVL) in the assessment of the model. The findings show that the adaptive repetition strategy was significantly more effective than the conventional methods in a real laboratory with respect to fewer errors and less time to complete the task. Furthermore, long-term memory retentions specifically evaluated using the recognition method demonstrated significant improvement in learners after learning with the adaptive repetition model. In general, the proposed structure has a positive impact on the effectiveness of learning, in terms of being able to carry out active exploration and reducing the negative effects of relying too much on cognitive aids in 3D VLEs.

Keywords*:* 3D-Virtual Learning Environments, Virtual Reality, Adaptive 3D-Virtual Learning Environments, Cognitive Aids, Long Term Memory Retention, Adaptive Repetition, Recognition Test, Active Exploration.

1. Introduction

Virtual Reality (VR) is a new paradigm in Information Technology (IT) that has revolutionized the world of simulation by producing results that are both very immersive, interactive and realistic, while also having very

little operational risk [1]. But VR technologies are more and more being applied in many practical fields such as sports, like in basketball skills training, haptic manipulation devices [2] and in the field of driving simulation and behavior analysis [3,4] in surgery training and palpatory diagnosis [5,6] in aviation and aeronautics simulation framework [7] in motor and neurological rehabilitation [8] in emergency nursing education [9] in power system training [10] in social physical fitness [11] etc. VR offers a virtual environment that mimics or emulates real-world scenarios in educational settings, allowing learners to experience them as if they were happening to them, while avoiding physical risks or resource costs virtual platforms that can be reproduced, expanded, and reused for effective, experiential learning [12,13]. The value of virtual reality is not limited only to novelty. It can increase the appeal of education because it can substitute verbal instructions by means of visual and tactile sensation.

3D Virtual Learning Environments (3D-VLE) are “advanced digital worlds enabling teaching/learning processes where human participants can interact with objects in real time and move around them, thus enabling a more authentic examination of information and transforming raw data into something tangible.” With 3D-VLE, the learner can immerse himself in the virtual environment, giving him a feeling of "being there" in the virtual world, which generates a high level of psychological presence and consequently increases the intrinsic motivation, spatial sense and task engagement [14-16]. Nevertheless, the traditional static 3D-VLEs provide a fixed instruction content that does not take into consideration individual differences with respect to their previous learning, spatial competence, and learning rates. Adaptive 3D VLEs go beyond this, by adaptively adjusting the instructional sequences, task level and guidance at the fly based on live information about what learners are doing and their results. An adaptive system mimics an expert human tutor in continually evaluating learners' interactions, including the time spent on tasks, the number of errors made, and the results of the assessments, to adapt the learning experience [17,18]. Adaptive 3D-VLEs can be designed specifically for the individual learner, making users' cognitive workload more sustainable and avoiding boredom for high-level learners, which creates an environment that is balanced and customized to maximize competent learning [18-20].

The 3D VLEs cognitive aids are a good thing for trainers and trainees as adaptive 3D-VLEs are typically equipped with multimodal cognitive support which helps a learner to complete complex virtual tasks such as multimodal text instructions, visual arrows and audio instructions. The in-the-moment cues in terms of instructional support are beneficial as they reduce the immediate cognitive load and guide learners during a complex procedure while maintaining their focus in space [21,22]. It would be pedagogically detrimental, however, if it is continually used. Learners begin to expect that these helpful reminders will be there for them and do not read the prompts or understand the content but follow them with time. Learners will then likely produce the desired virtual performance without having a sense of how the different parts connect to one another or how to function and navigate through space on their own. [23,24] This passive habit would make learners struggling to solve problems independently and it is difficult to transfer knowledge to physical environments with no guidance or instruction when using digital tools [22,25,26]. To tackle this challenge, an effective control strategy for adaptive repetition cognitive aids use in the 3D-VLEs is needed to preserve the positive effects of these cognitive aids in teaching and learning process while mitigating the negative effects of these cognitive aids on the learners [27].

We can make sense of this over-reliance problem through cognitive information-processing theory and how human memory works. As we come across new information, we pass it through our brain creating a sequence of stages that take it from sensory into STM (short-term memory) and then into WM (working memory) before it gets

organized into LTM (long-term memory) [28,29]. The problem is that the capacity for working memory is limited and can be easily overwhelmed when the demands for it are high. Static cognitive support is very effective in reducing working memory overload during the learner's initial learning, but they also remove the "desirable difficulties" required for deep learning. When scaffolding is not being de-escalated or modified, the learner is not required to actively bring about information and/or to mentally rehearse the steps [30,31]. Thus, critical task knowledge remains in temporary working memory long enough to complete the task at hand but not long enough to form permanent schemas in long term memory [29,31]. If there is no slow fade for the learner to remember the spatial steps and logic on each run, the pathways to create lasting memory are never established, and the skills rapidly decay as soon as they are no longer assisted.

This role of cognitive aids has been widely discussed. They can facilitate the learner's understanding of the concept and the completion of learning tasks, but if the learner continues to make use of them during the learning process, it can also limit active exploration. Learners, therefore, may experience problems when they are asked to do the same in a real-life context where such instructions are not present [32-35]. Even though cognitive support has been shown to have short-term benefits in virtual learning environments, it is still scarce research that focuses on the management and adaptation of cognitive scaffolding for repeated interaction in an immersive learning environment [36]. In the majority existing 3D Virtual Learning Environments (3D-VLEs), cognitive support stays on fixed, either being accessible throughout the entire session or removed completely, without considering the learner's performance during repeated practice [37].

To overcome this challenge, the current study presents an Adaptive Repetition Framework designed to create complexity through scaffolding and allow students to explore independently. The model was implemented and evaluated in a Multimodal Virtual Laboratory (MMVL), where the level of multimodal support was gradually adjusted across repeated virtual trials according to each learner's performance, including task completion time, number of errors, and mini-test scores. Based on this frame, the research evaluates the following hypotheses:

H_1: Adaptive repetition increases active exploration in 3D-VLEs.

H_2: Adaptive repetition enhances long-term memory retention (LTM) in 3D-VLEs.

The overall objective of this methodology is to assist learners move from directed training in the virtual environment to individual functioning in the physical laboratory. By gradually dropping instructional support as learners develop competency, the model encourages active learning, improves skill transfer, and promotes long-term procedural skill retention.

2. Literature Review

Cognitive aids such as visual (arrows), written (instructions), and auditory (voice guidance) support have a significant impact on the learner's cognitive burden in 3D Virtual Learning Environments (VLEs). As a result, these can be widely used in building immersive training systems to aid in job execution, hence increasing learning efficiency [21,22]. However, they are not always effective if not integrated into the learning process. Several research have looked into different forms of guides for virtual environments. As an example, Nguyen et al. [38] examined navigational aids, including compasses, lighting cues, and directional arrows, and found that arrow-based guidance and compasses are better than lighting cues for spatial navigation. Likewise, Gavish et al. [21]

discussed multimodal guidance, which used verbal instructions and pointing devices. Their results show that such devices can help to alleviate cognitive stress but can also decrease performance if the learner becomes less engaged. Gavish et al. [39] developed another system called Immersive Maintenance and Assembly Virtual Reality (IMA-VR) that also included both haptic and visual feedback. Their findings highlight the need for having detailed procedural instructions for improving cognitive modelling. Similarly, Jorge et al. [40] created a 3D haptic virtual environment to support assembly tasks both with direct assistance (e.g. object highlighting) and indirect assistance (e.g. providing textual instructions). They propose that guided assistance enhances the performance of their tasks in virtual contexts and facilitates the transfer of knowledge in physical contexts [41].

The Guided Virtual Reality Training System (GVRTS) has been introduced by Rehman et al [12] that combines both semantic (audio-visual) and direct (visual cues) aids. Their study shows how to balance the use of multimodal guidance to improve learning outcomes and to encourage active exploration. Likewise, Ali et al. [5,7] created a Multimodal Virtual Laboratory (MMVL) to give real-time interaction and audio-visual support during chemistry experiments. Their experimental outcomes show enhanced learners' confidence and improvement in actual laboratory environments [42]. Ryoo et al. [43] explored interactive molecular visualizations with inquiry support methods. The high school students were facilitated with the help of text, symbols, molecular animations and graphs to comprehend chemical phenomena' molecular mechanisms.

Khalid et al. [44-46] have investigated several navigation techniques: 3D map-liners (3DML), arrow casting, textual guidance and audio support. Three different design variants of the 3DML were investigated for user navigation performance: 3DML–audio, 3DML–textual, and 3DML–arrow casting; in addition, two variants in which the arrow casting or the textual navigation aid was provided in pairs with the audio navigation aid were investigated. Their results have always shown that hybrid methods, especially visual (arrows) and spatial (mapping) methods, work best than spatial methods only. The 3D virtual learning environment can also enable cognitive support to facilitate easier learning by eliminating mental workload and giving learners step-by-step instructions on how to accomplish assignments [21,22]. Concurrently, such assistance may occasionally be similar to shortcuts, which, in turn, may inhibit active exploration which is a vital aspect of learning to work in unsupervised environments [22,23,47]. Due to this, there is a necessity of a middle way that can be employed by using cognitive aid and at the same time reducing their tendency to deter active activity and exploration in 3D-VLEs [48,49]. There have been some researchers that have recognized the need for controlled use of cognitive aids. Jorge et al. [40] propose, for instance, that guidance that is regulated can help to reduce the negative impact of overly helpful guidance. In the same way, Rehman et al. [12] point out that the use of direct and semantic assistance can be effective when they are balanced. However, such strategies are mostly fixed or pre-established settings of aids and fail to change dynamically with the learner's performance.

Research Gap and Contribution: Cognitive aids play an important role in improving learning in 3D Virtual Learning Environments (3D-VLEs). However, most existing systems provide these aids in a fixed manner throughout the learning process. Earlier research studies have focused primarily on the identification of effective combinations of verbal, auditory, and visual cues, leaving aside the issue of instructional support reduction as the learner becomes more experienced. As a result, several learners become overly reliant on instruction, which reduces their freedom of exploration and initiative. Moreover, little effort has been made to examine the

mechanisms that allow for the downscaling of guidance during successive learning events and the effects of such processes on long-term memory.

The current study presents an Adaptive Repetition Framework that adjusts instructional support based on the learner's ongoing performance in order to close this gap. As competency increases over several trials, the model progressively eases these scaffolds using a combination of text-based reminders, auditory cues, and arrow-based graphical aids. This method gradually shifts responsibility from outside aids to the learner's own abilities rather than offering constant support throughout the learning process. In addition to promoting active inquiry, this intentional fading of cognitive support improves long-term retention and facilitates a more effective transfer of skill from the virtual environment to the real laboratory.

3. Adaptive Repetition Model: Proposed Methodology

This study introduces the concept of adaptive repetition, in which the level of instructional support is dynamically adjusted based on learners' performance across repeated trials. At the start, the learner is given an opportunity to use multiple aids to perform experiments in VE. However, whenever the trials are repeated, the proposed adaptive system automatically reduces the number of aids for weak, average and good learners in subsequent repetitions, which compels them to be active learners. As a result, the VE is explored, and learners perform well in the physical environment.

3.1 Adaptive Repetition Strategy: A Controlled Approach for Dynamic Exploration

The core contribution of this study lies in the adaptive repetition mechanism, which dynamically adjusts cognitive assistance based on learner performance.

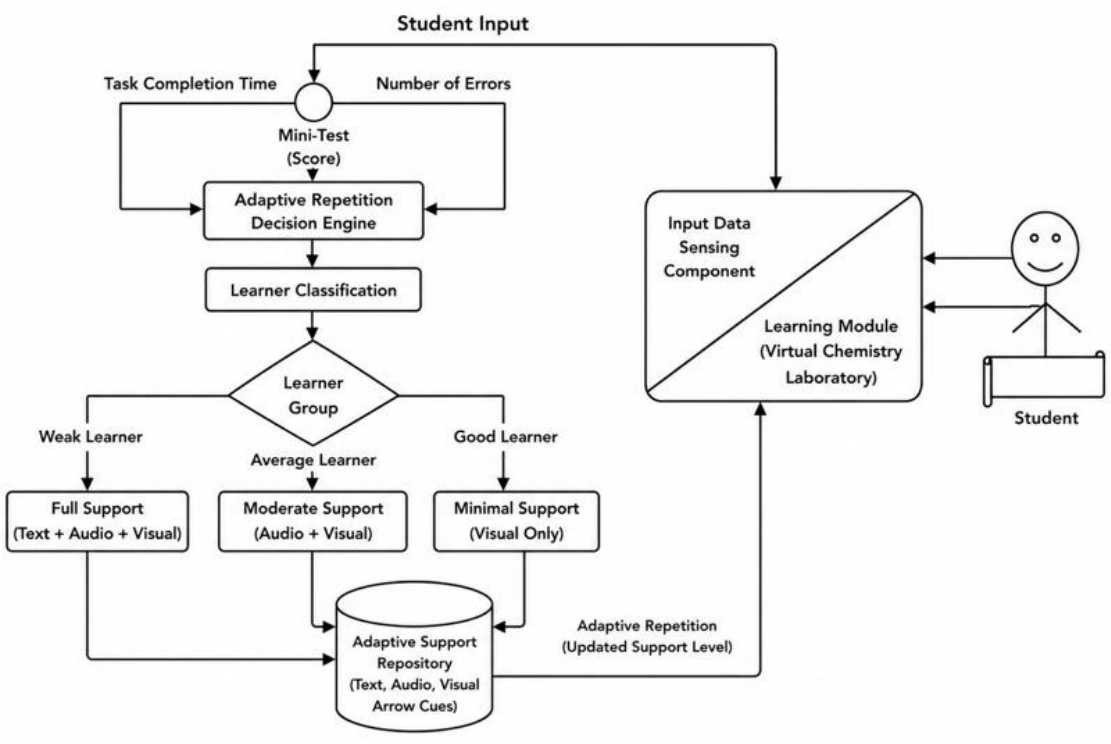


Figure 1: Architecture of the recommended adaptive system

3.1.1 Initial Phase

At the beginning of a learning module:

- All learners receive full cognitive support, including:
    - Visual aids
    - Audio instructions
    - Textual guidance

This ensures reduced cognitive load and facilitates initial understanding. When the learner begins to module M in 3D-VLEs, providing full aid reduces the mental load on the learner, which increases learners' learning capability in 3D-VLEs.

3.1.2 Adaptive Phase (Repetitions)

After each iteration:

Learner performance is evaluated within each module by integrating task completion time, error counts, and assessment scores, which together determine the appropriate level of cognitive assistance. Based on this evaluation, learners repeat the learning module through distinct adaptive paths X, Y, and Path Z each tailored with customized scaffolding designed specifically for weak, average, or good learners as illustrated in Figure 1.

- **Path X (Weak Learners):**
  Full support (visual + audio + textual)
  → Focus on guided learning: Uses visual, audio, and written support to minimize mental effort, making it well-suited for weak learners.

- **Path Y (Average Learners):**
  Partial support (visual + audio)
  → Balanced guidance and exploration: Includes audio and visual aids that assist the average learner.

- **Path Z (Good Learners):**
  Minimal support (visual only)
  → Encourages independent exploration: This approach incorporates visual guidance alone, which adequately meets the needs of good-performing learners.

3.2 Proposed Adaptive System Implementation

The given adaptive system was designed in the form of Multimodal Virtual Laboratory (MMVL) with the Microsoft Visual Studio Code and OpenGL. It was tested on a laptop with a Core i7 processor, an Intel HD graphics card, with a speed of 2.7 GHz, a 256 GB SSD and 16 GB RAM. MMVL is a 3D virtual space illustrated in figure 2, in which the learners can carry out experiments of chemistry at the school level in an interactive environment.

In the virtual lab, there is a central table at the center of the room with the commonly used equipment in the form of a burette, spirit lamp, and digital balance that will be available at any time. Other chemicals and glassware are stored on nearby shelves. Learners are allowed to choose the necessary materials, carry them to the center table

and go through the given procedure to perform their experiments. The environment provides interaction with the help of Simple Virtual Hand (SVH) where learners can pick up and manipulate objects easily.

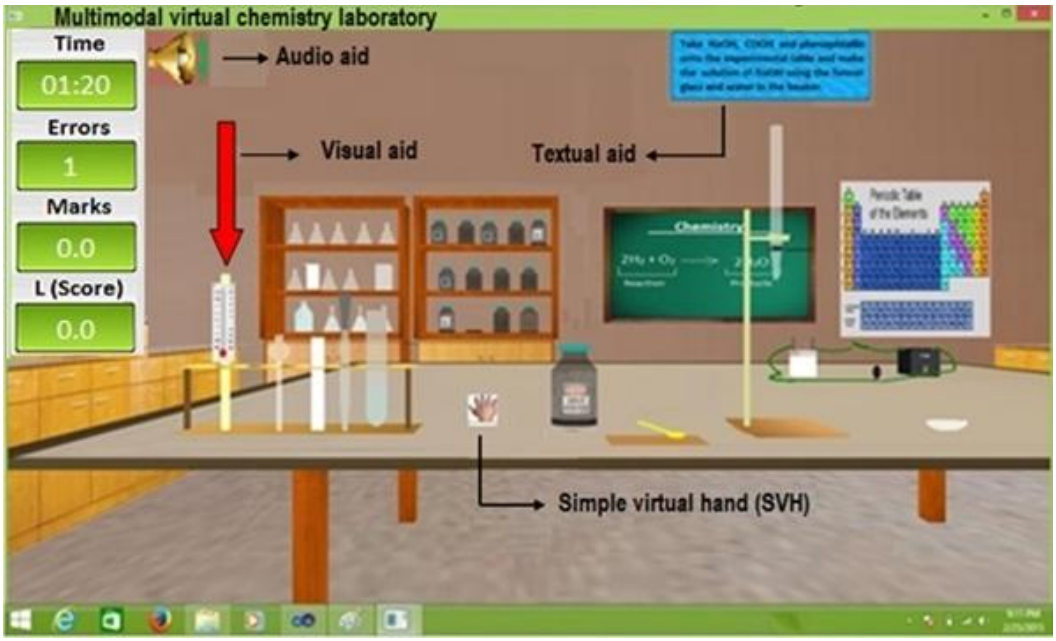


Figure 2: Multimodal virtual chemistry laboratory (MVCL)

The system assists the learning process by aiding cognitive effort in a controlled way by delivering a variety of modalities to enable learners to comprehend and carry out each step of the process with minimized mental effort. These aids include:

Visual resource: The arrows help learners to follow the right sequence of steps.

Audio support: Step-by-step instructions are presented audio-visually.

Textual assistance: There is a text box that shows the experimental procedure.

3.3 Experimental Protocol:

To carry out this study, we selected 80 tenth-grade learners (both boys and girls) from 12 different schools. They were split into two equal groups of 40: Group G1 and Group G2 as shown in figure 3. All learners had a brief tutorial before the actual experiment, on how to use the virtual lab environment, such as moving around, picking up and manipulating things. The chemistry topic selected for the experiment was sodium chloride. The post intervention cued recall test was used to determine the ability to remember information in long-term memory. This approach was exercised to assess structural procedural recall and active retrieval capability without depending on continuous visual or auditory prompts.

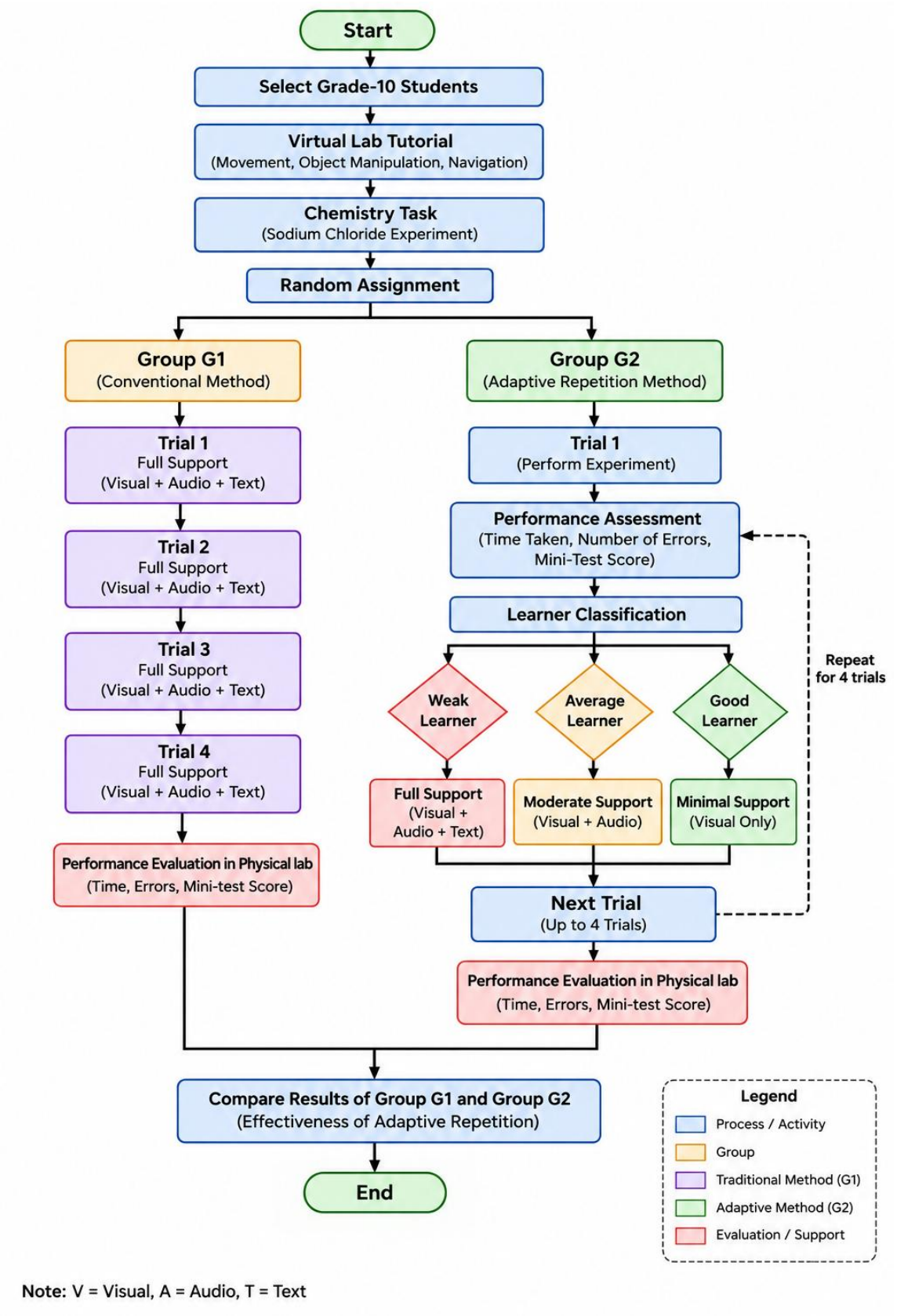


Figure 3: Flowchart illustrating the comparative experimental procedure for Group G1 (Conventional) and Group G2 (Adaptive Repetition).

The group of learners in G1 repeated the experiment 4 times as described in the conventional method; they did not receive any changes in any of the four attempts but remained in the same condition: seeing the same amount of help (visual, audio and text). In G2, however, the pupils used our method of adaptive repetition. The system assessed their performance after each attempt, including the time they took, number of errors they made, and their performance on a mini test. From there on the system worked out support for the next trial. When learners were having difficulties (weak learners), they were provided with full support visuals, audio, and text to minimize frustration and move them step-by-step. Moderate support was provided to learners who were doing okay (an average learner), that is, only visuals and audio were provided to provide some freedom and still provide support. If a learner was doing well (a good learner), they got minimal support just visuals-encouraging them to explore and solve problems on their own. So, unlike the traditional group, learners in G2 got personalized help that changed as they improved. Figure 4 shows one of the learners working inside the virtual lab environment.

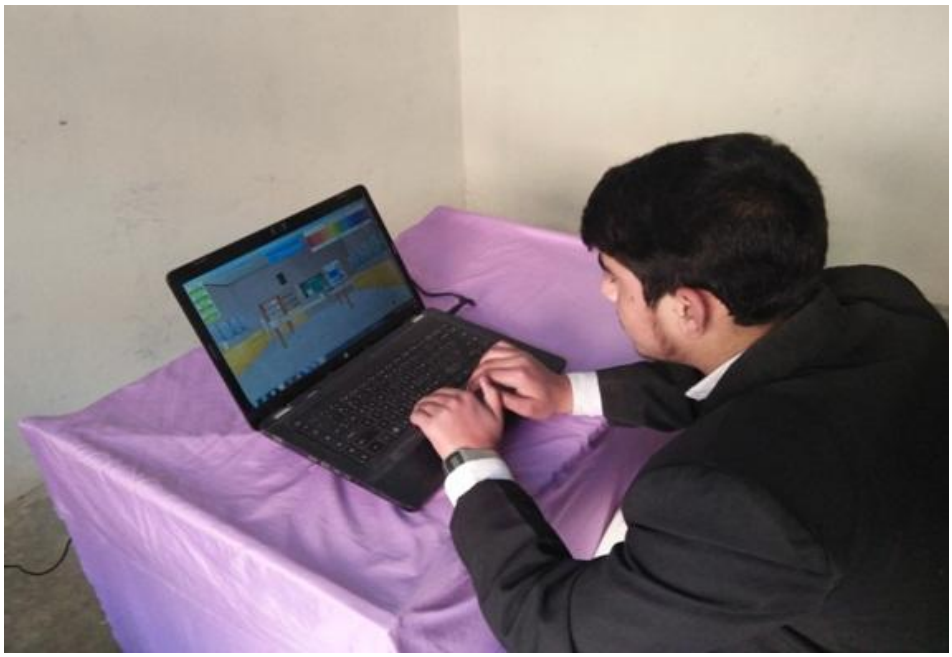


Figure 4: A learner performing experiment (Adaptive Repetitions)

4. Experimental Results

After completing the four repetitions in MMVL, learners from both groups were asked to perform a similar experiment in a real chemistry laboratory. Their performance was evaluated by recording the time taken to complete the task and the number of errors made by each learner.

4.1 No. of Errors in Real Lab Experiment

In the lab, learners learned four major aspects of the laboratory work. These include laboratory equipment and their uses, classifying laboratory reagents, choosing the right reactants for the chemistry experiment, and following the laboratory instructions in the appropriate order. Any form of deviation from the above steps was considered an error.

Results obtained from the comparison of the two groups' performance demonstrate that Group G2 (Adaptive Repetition) performed considerably better and improved their knowledge retention ability as compared to Group

G1 (Conventional Method). An independent-samples t-test conducted on N = 80 grade-10 learners ($n_1 = 40$, $n_2 = 40$) revealed a statistically significant reduction in physical laboratory errors for Group G2 (M = 5.00, SD = 1.85) compared to Group G1 (M = 8.00, SD = 2.35), $t(78) = 6.34$, $p < 0.001$, $d = 1.42$, as summarized in figure 5 and table 1. The lower standard deviation of G2 shows greater consistency and hence higher performance as scaffolding fading promoted systematic procedural skill acquisition.

The learners in G2 outperformed their peers in G1 in terms of cued recall scores. This outcome demonstrates the effectiveness of adaptive repetition as an instructional strategy that enhances memory consolidation and, as a result, improves long-term retention of the learned material. Adaptive repetition encourages active exploration while allowing for individualized adaptation of instruction based on performance. Therefore, the adaptive repetition strategy has the potential to improve both short- and long-term retention of the procedural skill under investigation compared to the conventional learning method.

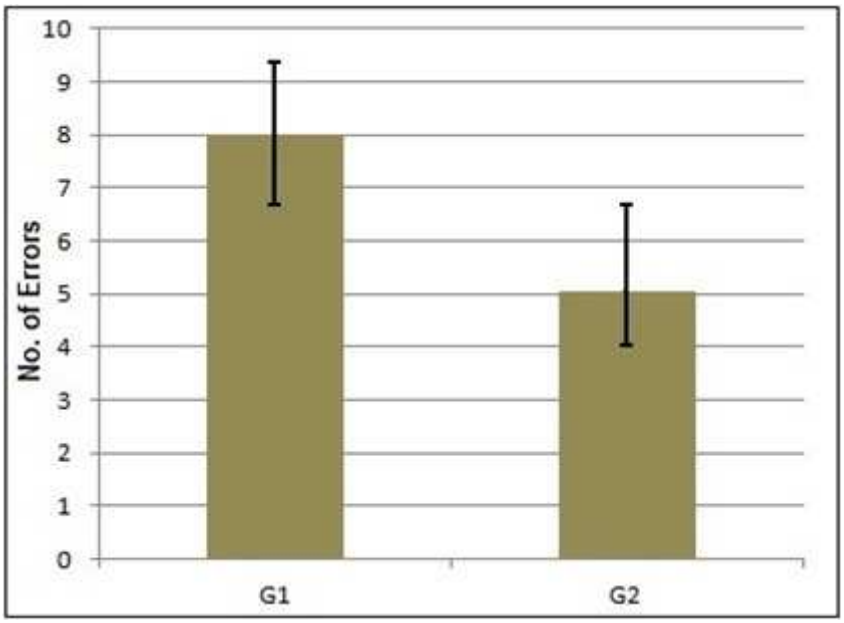


Figure 5: Average no. of Errors

Experimental Group	Methodology / Condition	Sample Size (n)	Mean Errors (M)	Standard Deviation (SD)	Standard Error (SE)
Group G1	Conventional Method (Constant Support)	40	8.00	2.35	0.372
Group G2	Adaptive Repetition Method (Faded Scaffolding)	40	5.00	1.85	0.293

Table 1: Performance outcomes in terms of Errors between Group G1 and Group G2 evaluated in the physical laboratory.

4.2 Task Completion Time in Real Lab

Task completion times were measured for both groups in the lab to assess their ability to perform procedures quickly and efficiently. The descriptive analysis revealed that the experimental group (G1: Conventional repetition) took significantly more time to complete the experiment than the control group (G2: Adaptive

repetition), which used an adaptive strategy to finish the task faster and more efficiently (M = 13 min, SD = 3.20; M = 8 min, SD = 5.10; Figure 6).

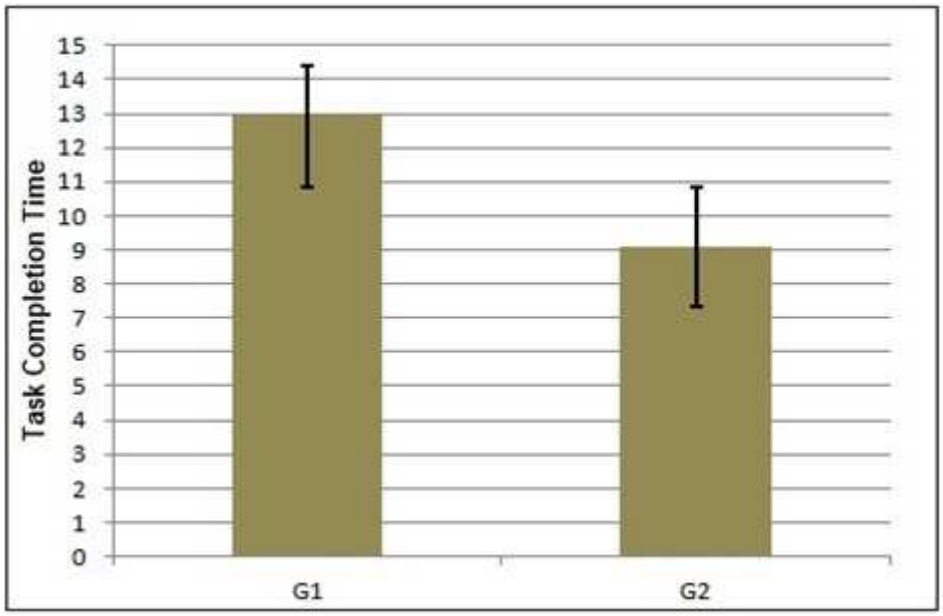


Figure 6: Average Task/Experiment Completion Time

The degrees of freedom (df) for the samples t-test was calculated by using Equation 1:

$$df = (n_1 - 1) + (n_2 - 1) = n_1 + n_2 - 2 \qquad \text{Equ. 1}$$

With equivalent sample sizes of n = 40 for both Groups G1 and G2 (*df* = 78), the statistical significance of observed differences across experimental conditions was evaluated using a t-distribution with $p < 0.05$. Analysis of task achievement times revealed a significant effect, $t(78) = 5.21$, $p < 0.05$. These results are summarized in Table 2

Group	N	Mean (min)	Standard Deviation (min)	t-value	Df	p-value
G1 (Conventional)	40	13	3.20			
G2 (Adaptive)	40	8	5.10	5.21	78	< 0.05

Table 2: Independent Samples t-Test Results for Task Completion Time

The statistical analysis demonstrates that students in Group G2 completed the real-world experimental tasks significantly faster and with greater speed consistency than those in Group G1. The higher the numbers of the completion count and slight errors, the more successful the learners were in automating key procedural steps beyond the simple perfection in speed. Progressive deceleration of automatic support during adaptive repetition resulted in greater memory consolidation and led to better long-term retention. Therefore, Group G2 successfully accomplished complex laboratory procedures with significantly lower cognitive load which demonstrated the effectiveness of adaptive repetition in optimizing immediate efficiency and in enhancing the long-term skill acquisition.

4.3 ANOVA Results and Statistical Analysis

For assessing the effectiveness of the proposed adaptive repetition strategy, a one-way Analysis of Variance (ANOVA) was performed. Two main performance metrics were analyzed across Group G1 (Conventional Method) and Group G2 (Adaptive Repetition Method): total physical laboratory errors and task completion time. Between-group variability (SS_B) and within-group variability (SS_W) were determined using Equations 2 and 3, respectively:

$$SS_{\text{between}} = \sum_{i=1}^{k} n_i \, (\bar{X}_{i\cdot} - \bar{X}_{\cdot\cdot})^2 \qquad \text{Equ.2}$$

$$SS_{\text{within}} = \sum_{i=1}^{k} \sum_{j=1}^{n_i} \left(X_{ij} - \bar{X}_{i\cdot}\right)^2 \qquad \text{Equ. 3}$$

Here, k=2 stands for the number of experimental groups, n_i=40 is the per-group sample size, $\bar{X}_i$ is the group mean score for each experimental group, $\bar{X}_{\cdot}$ is overall mean score ($N = 80$), and X_{ij} denotes individual participant scores. The ANOVA results (Table 3) demonstrated significant main effects between groups for error rates, $F(1,78) = 40.25, p < .001$, as well as task completion time, $F(1,78) = 27.14, p < .001$.

Table 3: ANOVA Results for Performance Measures

Performance Measure	**Source of Variation**	**Degrees of Freedom (df)**	**F-value**	**p-value**	**Significance**
Error Rates	Between Groups	1	40.25	< 0.001	Significant
	Within Groups	78			
Completion Time	Between Groups	1	27.14	< 0.001	Significant
	Within Groups	78			

The ANOVA results support the idea that using an adaptive repetition strategy can increase accuracy and efficiency. The participants in the Group G2 demonstrated fewer errors and faster performance than those in the control group ($p < .001$). Thus, the statistical significance of the results proves that performance changes were caused by the intervention. Group G2 received information about the reduction in the scaffolding, which they had to consider when performing the task. Those in the control group did not experience any changes in instruction support. The research results clearly show that the adaptive scaffolding strategy reduces the cognitive load and encourages learners to interact with the experimental setting actively.

4.4 Testing the Hypothesis H1: Active Exploration and Adaptive Scaffolding

To evaluate Hypothesis **H1** (*Adaptive repetition maximizes active exploration in 3D Virtual Learning Environments 3D-VLEs*), participants were divided into two experimental cohorts: Group G1 (Conventional Method) and Group G2 (Adaptive Repetition Method).

Learners in the G2 group outperformed significantly and were very consistent when tested under physical laboratory conditions. Specifically, the mean procedural error rate decreased from 8 errors in Group G1 ($M = 8.00, SD = 2.35$) to 5 errors in Group G2 ($M = 5.00, SD = 1.85$), indicating $t(78) = 6.34, p < 0.001$.

Operational efficiency also improved substantially: Group G1 required an average of 13 minutes ($M = 13.0, SD =$ 3.20 min) to complete the physical experiment, whereas Group G2 completed the task in only 8 minutes ($M =$ $8.0, SD = 5.10$ min), yielding $t(78) = 5.25, p < 0.001$. Participants in group G2 showed increased motivation and engagement in tasks completed in the virtual environment, in addition to quantitative increases in speed and decreases in errors. This directly translated into increased accuracy in the physical lab to complete the tasks and improved cued recall performance.

Repetition Trial	Weak Learner (Visual, Audio, & Textual Aids)	Average Learner (Visual & Audio Aids)	Good Learner (Visual Aid Only)
Trial 1	78%	10%	12%
Trial 2	35%	40%	25%
Trial 3	8%	12%	80%
Trial 4	2%	3%	95%

Table 4: Statistical Summary of Learner Classification Across Four Adaptive Repetition Trials

Table 4 illustrates the progression of the learners across four adaptive repetition trials on three tiers of cognitive support: weak (full assistance), average (visual and audio only), and good (limited visual aid). In Trial 1, initial performance indicated a very high level of support with 78% of students needing full multimodal support, compared to 10% in Average and 12% in Good. In Trial 2, this situation had changed, with the percentage of Weak learners falling to 35% and the percentages of Average and Good rising to 40% and 25%, respectively. In Trial 3, a major cognitive transition happened, with 80% of the subjects being in "excellent" status. At Trial 4, mastery was commonplace: 95% of students were in good condition, 2% were weak, and 3% were average.

This trajectory clearly shows the advantages of the gradual scaffolding fading. The adaptive model adapted the amount of text and audio cues presented, automatically decreasing them as competency increased, thereby gradually decreasing the need for external support by about 66% at the end of the experiment. Removing superfluous support lowered cognitive load and compelled students to engage in active retrieval practice. As a result of this technique, this cognitive encoding became deeper, schema processing became more automatic and long-term memory consolidation was enhanced. Therefore, our results indicate that the adaptive repetition led to a decrease in reliance on support and an increase in memory, supporting hypothesis **1** in a good empirical manner.

4.5 Testing Hypothesis H2: Long-Term Memory Retention via Cued Recall Evaluation

A cued recall test was administered to both groups during the designated interval following the virtual training in order to ascertain whether adaptive repetition enhances long-term memory retention (H2). The purpose of the test was to gauge how well participants remembered the proper protocols, safety guidelines, and chemical classifications. Table 5 shows that Group G2 (Adaptive VR) performed much better on the test than Group G1 (Traditional Practice) (t(78) = 5.71, p 0.001).

Table 5: Cued Recall Test Results for Long-Term Memory Retention ($N = 80$)

Assessment Metric	Group G1: Traditional	Group G2: Adaptive VR	t-value	df	p-value	Effect Size (Cohen's d)
Cued Recall Score (%)	58.20±12.10	72.50±10.20	5.71	78	< 0.001	1.28

The average score of the adaptive VR group (72.50%, SD=10.20%) was much higher than that of the standard group (58.20%, SD=12.10). The performance gain is statistically and practically substantial, as evidenced by the 14.30% difference and significant effect size (d=1.28).

When compared to conventional methods, the results demonstrate the effectiveness of adaptive repetition for long-term memory. A month after training, the cued recall scores for Group G2 showed that the participants had better retrieval of the procedural knowledge and core concepts. This edge stemmed from the process of progressive scaffolding fading; learners were required to make use of active recall as the support they received from others gradually faded. Overall, this strategy led to more in-depth processing and memory consolidation, with long-term retention of the knowledge and supporting **H2**.

4.6 Subjective Evaluation:

In addition to the objective measures, we gathered qualitative data from the learners of the Group G2 (n=40) at the end of the experiment. A post-intervention survey assessed learner perceptions of the following: helpfulness of initial cognitive aids, effect of scaffolding fading, active exploration, physical lab transfer, overall model utility, and long-term memory recall (Table 6). Furthermore, two statements were specifically explored that looked at the learner's perception of the retention of the procedural knowledge over time, as well as recalling experimental steps without the use of instructional supports.

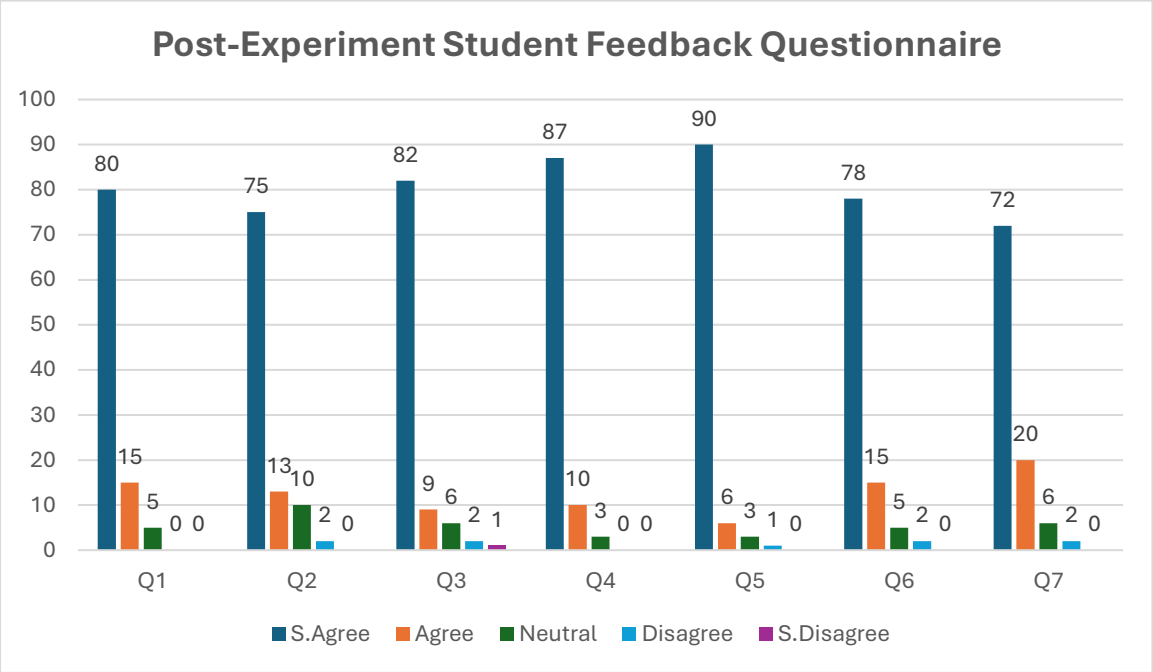
Table 6: Questionnaire regarding system attributes.

Q. No	Questions
1.	Cognitive aids provided at the beginning of the learning module were helpful.
2.	In subsequent adaptive repetitions, minimizing the number of aids did not negatively affect performance.
3.	In subsequent adaptive repetitions, you were compelled to learn and explore the learning module actively.
4.	After using the proposed system, it becomes easy to perform the same experiment in a physical lab.
5.	Adaptive repetition helps learners to explore 3D Virtual Learning Environments (3D-VLEs) more effectively.
6.	The adaptive repetition strategy helped you retain procedural steps and concepts over an extended period.
7.	You were able to recall key experimental steps during post-testing without needing to refer back to instructional aids.

The results of the learners' responses in the survey were overwhelmingly positive in all the items (Table 7). The majority of the participants tended to either agree or strongly agree that the adaptive repetition model helped their learning process without causing undesirable friction.

Table 7: Learners' Feedback

Q. NO	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
1.	80%	15%	5%	0%	0%
2.	75%	13%	10%	2%	0%
3.	82%	9%	6%	2%	1%
4.	87%	10%	3%	0%	0%
5.	90%	6%	3%	1%	0%
6.	78%	15%	5%	2%	0%
7.	72%	20%	6%	2%	0%



For initial support and fading (Items 1-3), 95% of the learners said that providing cognitive prompts early on helped with their performance and 88% said that fading the prompts during later trials did not interfere with their performance. In addition, 91% said the fading of prompts is an active process that encourages learners to think step by step and explore, instead of following prompts unconsciously. For skill transfer (Items 4 and 5), 97% agreed that 3D-VLE training reduced significantly the effort required in the physical lab work, and 96% agreed that the adaptive repetitions improved their engagement in the virtual lab work. Items 6 and 7 match the empirical retention findings: 93% believed that adaptive repetition has helped them retain procedural knowledge over time and 92% believed that they could remember important steps in the procedure without external cues when tested at the post-test.

In general, the qualitative results obtained from the learners are very valid regarding the quantitative results obtained in the study. The adaptive repetition method was seen by participants as a very good method to enhance engagement, confidence in laboratory tasks and recall of experimental procedures. Gradually reducing instructional support has been shown to have a positive effect on immediate laboratory performance and retention

of procedural knowledge in the long-term, as evidenced by their favorable experiences. These subjective observations corroborate the experimental findings and provide further evidence to support the assumptions and findings of the study, and the effectiveness of adaptive repetition in enhancing learning in 3D Virtual Learning Environments (3D-VLEs).

5. Conclusion

Although cognitive support in 3D Virtual Learning Environments (3D-VLEs) lean towards reducing cognitive load for novice learners, the intention was to promote their independence in the environment. The outcomes of our experimental study are consistent with the initial two research hypotheses:

Hypothesis 1 ("Lab Performance & Exploration") Compared to the traditional learning group, participants in the adaptive repetition group completed the experiments more quickly, made fewer procedural errors, and performed more consistently. Instead, than depending on outside cues, instructional prompts were dynamically fading, leading to more active participation.

Hypothesis 2 ("Long-Term Memory Retention"): Adaptive VR users outperformed other groups on the delayed cued recall test, demonstrating improved procedural knowledge retention and retrieval. These quantitative findings were supported by subjective questionnaire responses, which suggested that prompt fading assisted individuals in remembering key stages on their own.

Overall, these results suggest that adaptive repetition provides benefits that extend far beyond speedy task completion. It also fosters long-term procedural comprehension by fostering active exploration, methodical retrieval practice, and increasing autonomy, leaving students well-equipped to do difficult laboratory tasks on their own.

Future Direction: Future research should examine whether the number of repetitions/trials may be adjusted to accommodate learners with different abilities and earlier knowledge levels. Developing adaptive repetition models that adjust practice levels based on each learner's progress may improve learning outcomes and increase the efficiency of virtual laboratory settings.

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