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The Impact of Virtual Reality on Cognitive Load Among Senior Students at Middle Technical University: An Empirical Study

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Abstract: *The adoption of Virtual Reality (VR) in higher education has gained increasing worldwide interest, however, its evaluation as an effect on workload and cognitive-load related learning outcomes for senior technical university students in Iraq is still an unaddressed issue. This study sought to fill the gap in the literature by investigating the effect of a VR-based instruction on the Nasa TlX workload indicators concerning the cognitive load, the effect of the presence and the intrinsic motivation on the learning performance of senior engineering students in a technical university in Baghdad. Employing a quasi-experimental pre-post control group design, 80 learners participated and were randomly assigned to either a VR group (n = 40) who experienced the interactive content through Meta Quest 2 HMDs or a control group (n = 40) who were taught in a traditional lecture style. The cognitive workload was assessed by NASA-TLX, and the analyses were performed with the use of independent-samples t-tests, MANOVA and exploratory Structural Equation modeling (SEM). Results showed that the VR group had significantly lower mental demand (M = 52.4vs. 61.7, p = .001) and frustration (M = 30.4vs. 44.8, p < .001), but the overall NASA-TLX workload index was not significantly different between the two groups (M = 49.65vs. 52.17, p = .184). The VR group outperformed in learning (MCQ: M = 23.4/30 vs. 19.7/30, d = 1.00), knowledge retention at one-week post-test (78.6% vs. 62.4%, d = 1.53), and intrinsic motivation scores. . Exploratory SEM analysis showed that the immersion in VR could promote learning indirectly by decreasing the extraneous-load-related workload (β = −.54) and enhancing presence (β = . 71). These results suggest that the VR-based intervention has the potential to improve certain aspects of the workload and learning outcomes in higher education in developing countries, although statements regarding an overall reduction in cognitive load should be considered with caution.*

Keywords: *Virtual Reality, Cognitive Load Theory, Immersive Learning, Middle Technical University, NASA-TLX, Head-Mounted Display, Higher Education Iraq, Learning Performance, Presence, Structural Equation Modeling.*

Introduction

The development of immersive technology in education has led to a re-evaluation of the ways in which learning environments are constructed and assessed. Virtual Reality (VR), a simulation of a 3D environment via computer, which can be experienced via special equipments, has shown the potential to revolutionize the whole educational field (Makransky & Petersen, 2021). More specifically, VR-based pedagogy is being established by higher education institutions to investigate ways of improving student engagement, the learning process as such, and experiential learning quality (Wu et al., 2020; Betts et al., 2023). Although the literature on VR in higher education is expanding internationally, there remains a lack of critical understanding as to how such technology can be applied to technical universities in developing countries, particularly in the Arab region. The Middle Technical University (MTU) in Baghdad, Iraq, provides a rigorous education to a varied group of senior engineering and technical students who must acquire high-level analytical thinking about procedural and conceptual information with very limited real-world practicum opportunities. The traditional lecture-based pedagogy prevailing at MTU, is deeply embedded institutionally, but it has failed to meaningfully engage cognitively, especially among senior students who have the daunting task of synthesizing four years of technical expertise. Load on working memory (or cognitive load, CL) has long been [3] considered a central determinant of learning and means that students have higher working memory load during t it is defined as "the amount of mental effort being used in the working memory" (Sweller, 1988). When instructional design contributes to excessive extraneous CL, this actively competes with the mental resources for constructing meaningful schemata and transferring knowledge. An inquiry of whether VR instruction could act as a cognitive load management tool (as opposed to a cognitive load addition tool) therefore has a great importance from a pedagogical perspective.

Significance of the Study

This research is important for number of interrelated reasons. First, it fills a contextual void in the VR-education literature by focusing on a Middle Eastern, Arabic-speaking technical university student body—a population that is largely missing in Q1 indexed studies on immersive learning. It is also the first to our knowledge to apply psychometrically sound instruments (NASA-TLX, Witmer & Singer presence scale) and advanced multivariate statistical procedures (MANOVA, SEM) to an actual educational intervention, defining a higher methodological standard for the field. Third, the results have direct practical implications for the MTU leadership (and technical universities in general in Iraq and the rest of the MENA region), who are contemplating whether VR is in any way a viable and affordable institutional option.

Research Objectives

This paper is structured as follows:

1. To evaluate and contrast the workload and cognitive load-related measures associated with the senior students at MTU in VR-based and traditional lecture-based environment?
2. To investigate a subset of the NASA-TLX workload measures and some exploratory proxy composites for intrinsic, extraneous, and germane cognitive processing, while noting that NASA-TLX is not a direct measure of the three components from the Cognitive Load Theory?
3. To analyze the relationships between VR immersion, sense of presence, intrinsic motivation, cognitive load, and learning performance with structural equation modeling?
4. To propose concrete instructional design guidance for VR delivery in Iraqi technical HEI case?

Research Hypotheses

The following directional hypotheses were made grounded on the theoretical basis and the related literature; however the hypotheses of the cognitive-load components are inferred by means of indicators of NASA-TLX workload and exploratory proxy composites and not directly measured of intrinsic, extraneous and germane load: H1: Students in the VR condition will exhibit significantly lower scores on selected NASA-TLX workload indicators associated with cognitive load, particularly Mental Demand and Frustration, than students in the traditional instruction condition ($p < .05$).

- H2: VR instruction will be associated with lower extraneous-load-related workload indicators and higher learning-relevant engagement indicators compared to conventional instruction; these constructs are treated as exploratory proxies rather than direct NASA-TLX measurements.
- H3: Students in the VR condition will demonstrate significantly higher learning performance scores on immediate post-tests and one-week delayed retention tests.
- H4: Sense of presence and intrinsic motivation will mediate the relationship between VR immersion and learning performance, as modeled through SEM path analysis.

Literature Review

Cognitive Load Theory: Theoretical Foundations

The cognitive load theory (CLT) was initially developed by John Sweller (1988) based on his observation that the capacity of human short-term working memory is extremely limited and it can only deal with a limited number of information units at one time. This fundamental insight precipitated a programmatic line of research centering on the design of instructional environments predicated on, rather than in opposition to, these cognitive limitations (Sweller, 2011; Paas et al., 2003).

Three types of cognitive load can be identified in CLT which are additive. The intrinsic cognitive load (ICL) is the complexity level of the information itself, defined by the number of interacting element in the material that needs to be processed at once. Extraneous cognitive load (ECL) is caused by the way information is presented cognitively rather than the content of the information, and it is this load which instructional designers can and should attempt to reduce. Germane cognitive load (GCL), although it has more recently been rejected as being conceptually separable from intrinsic load (Kalyuga, 2011; Sweller, 2010), initially denoted the cognitive resources invested in schema acquisition and automation—the productive cognitive processing of learning (Sweller, 1994). In practice, both extraneous and intrinsic load add up to a learner's total cognitive load, and cognitive overload results when the total load goes beyond what the working memory can hold (Chandler & Sweller, 1991). Significantly, CLT is not a call to reduce all cognitive effort but a call to restructure the instructional conditions under which mental resources are directed toward having germane, rather than extraneous, processing (van Merriënboer & Sweller, 2005). This distinction has far-reaching consequences for the design of technology-enhanced learning environments (including VR).

Virtual Reality as an Educational Technology

Human:VR covers a range of immersive technologies including fully immersive head-mounted display (HMD) systems that occlude the user's view of the real world with the display, and non-immersive VR environments that can be experienced in a web browser (Jensen & Konradsen, 2018; Wu et al., 2020). Current HMD-based VR systems (including Meta Quest 2, HTC Vive Pro, and Valve Index) provide stereoscopic 3D images, spatial audio, and 6 degrees of freedom (6DoF) head and controller tracking, enabling users to experience an intense sense of spatial presence in the virtual environment (Slater & Wilbur, 1997). The active mechanisms of VR are multiple and interwoven and, therefore, the educational opportunities of VR are generated from the combination of these mechanisms. First, VR platforms allow embodied interaction with content that is otherwise non-accessible due to physical, financial, or safety limitations – which is a particularly salient benefit when it comes to industrial and technical engineering education (Al-Khiami, 2024; Betts et al., 2023). Second, the sense of presence that VR produces (i.e., the subjective feeling of "being there" in the VE) has been theorized and empirically found to increase motivation, immersion, and transfer of knowledge (Makransky & Lilleholt, 2018; Ki et al., 2024). Third, the procedural and situated learning potential of VR enables knowledge construction through doing rather than receiving it passively (Han et al., 2023).

A meta analysis 16 by Wu et al al. The results of a meta-analysis of 35 randomized and quasi-experimental studies by Wu et al. (2020) suggested that HMD-based immersive VR was favorable for the learning outcomes with a positive moderate-to-large effect size ($g = 0.52$) against desktop VR and traditional education. Like wise, Al-Khiami (2024) observed that students of undergraduate engineering who were exposed to HMD VR exhibited a significantly greater motivation and performance than those using 2D drawings in a course on concrete structures.

Virtual Reality and Cognitive Load: Empirical Evidence

The impact of VR on cognitive load is complex both in terms of theory and findings. Some mechanisms that could explain how VR decreases extraneous cognitive load have been suggested. VR's multimodal delivery (visual and auditory) allows for the delivery of information in a spatially aligned environment, which may help reduce the split-attention effect (learners are required to mentally integrate information from different sources) (Mayer & Moreno, 2003). VR, on the other hand, provides an embodied interaction and may lower the cognitive demand for creating spatial mental representations, thereby allowing working memory resources to be used for higher levels of conceptual thinking.

Yet a countering set of evidence indicates the novelty and complexity of VR interfaces could create further extraneous load, mainly among users with less prior VR experience (Parong & Mayer, 2018; Makransky et al., 2019). The 'immersion paradox' that Makransky and colleagues describe, is that VR leads to higher motivation and enjoyment (affective benefits), but these positive impacts on learning might partly be attenuated due to higher processing demands when being exposed to a rich perceptual environment (Makransky & Mayer, 2022). The overall impact on cognitive load therefore seems to be highly dependent on the quality of the instructional design, the prior knowledge of the learner, and the characteristics of the content to be taught.

Ki et al. (2024) investigated cognitive load and social presence in 360-degree VR video lectures, reporting that the complex visual representations increased extraneous cognitive load, but the well-designed navigation cues and the instructor presence in the VR environment had a positive effect on moderating this. Han et al. (2023) also found signaling (an instructional design that employs visual cues such as arrows or highlighting to direct attention) to significantly reduce cognitive load in immersive VR laboratories, with prior knowledge being a significant moderator. Sobocinski et al. (2023, as reported in recent meta-analyses) noted that self-regulatory processes in IVE are linked to decreased cognitive load and improved learning.

Previous VR-learning research indicates that novelty of interface may cause a temporary increase of workload at the early phase of exposure, while the familiarization and the instructions may help to alleviate the unnecessary processing load in the later phase(s) (Makransky et al., 2019; Han et al., 2023). This trajectory will have significant consequences for when the VR portion is best inserted in curriculum.

The Cognitive Affective Model of Immersive Learning (CAMIL)

The Cognitive Affective Model of Immersive Learning, presented in Makransky and Petersen (2021), constitutes the broadest theoretical facilitation of VR-specific learning mechanisms published so far. According to CAMIL, two major technological affordances of immersive VR—presence and agency—produce learning outcomes by way of affective and cognitive pathways. The affective path is driven by interest, intrinsic motivation and flow, and the cognitive path by self-efficacy, disembodied cognition, and cognitive load management.

In particular for this study, CAMIL states that presence, which is defined as the feeling of being in the virtual environment, lowers extraneous cognitive load by shifting attention resources to learning related stimuli and away from task-irrelevant cognitive activities (Makransky & Lilleholt, 2018). This also applies to CLT's way of avoiding unnecessary load and has been empirically corroborated in several educational settings. The model further predicts that the magnitude of these effects will be moderated by the quality of immersion which can be affected by technical factors such as resolution of the display, field of view, and tracking accuracy.

VR in Technical Higher Education: The Iraqi and MENA Context

This is also true of CLT's approach to minimizing extraneous load, and has been supported empirically in multiple educational contexts. The model also predicts that the size of these effects will be moderated by the level of immersion, which can be influenced by technical aspects such as display resolution, field of view, and tracking accuracy. On a regional level, the Arab patent in VR-educational research continues to be small in size due to lack of representation in indexed international journals despite increasing investment in educational technology infrastructure in the Gulf Cooperation Council (GCC) states and in

Iraq's strategic higher education digitalization plans. The current study therefore serves a contextual research void as well as a feasibility one.

Theoretical Framework

This study is based on the combination of two complementing theoretical perspectives, namely Cognitive Load Theory (CLT; Sweller, 1988, 2011) and the Cognitive Affective Model of Immersive Learning (CAMIL; Makransky & Petersen, 2021). These combined may offer unified explanations on how and why VR-based instruction can impact cognitive load, learning outcomes, as well as motivation-related results.

From the perspective of this integrated framework VR immersion is treated as a causal variable with two potential routes of effects. In the cognitive path, by presenting information spatially and temporally integrated in multiple modalities, VR reduces split-attention effect and redundant processing (Mayer & Moreno, 2003) so that extraneous cognitive load may be relieved. In the affective path, VR-induced presence and agency enhance intrinsic motivation and enjoyment, and in turn the latter two contribute to the maintenance of attentional engagement, which ultimately leads to better germane cognitive processing. As a consequence, these two paths are united with learning performance as final outcome measure.

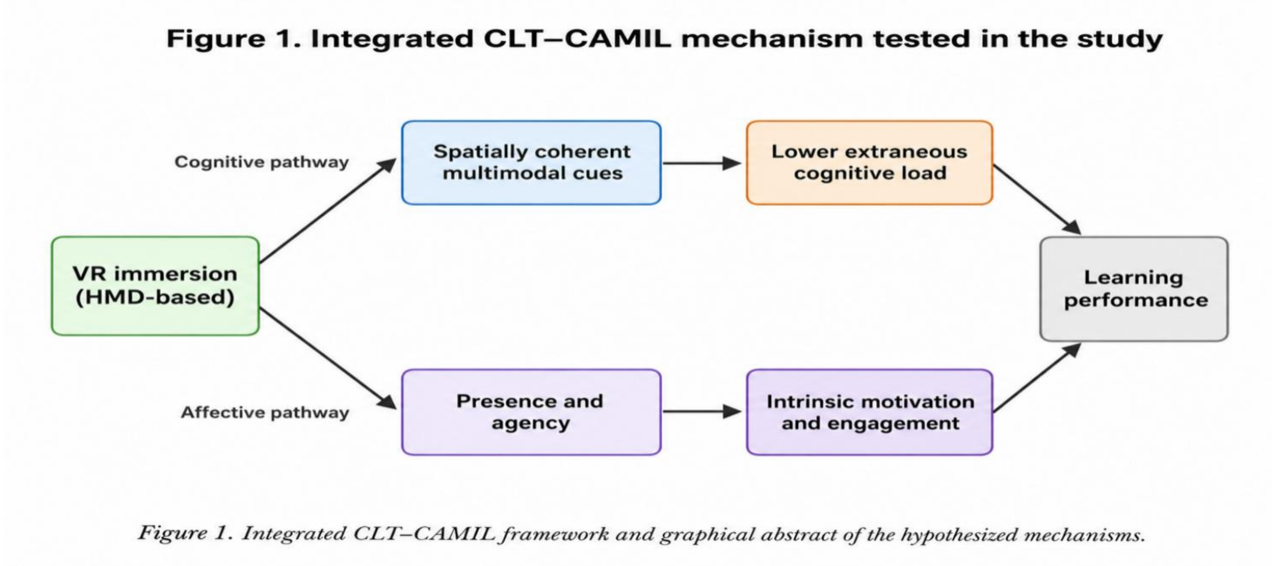

Figure 1. Integrated CLT-CAMIL framework and graphical abstract of the hypothesized mechanisms.

Methodology

Research Design

A pre-test/post-test design with control group and quasi-experimental method was employed. This design was chosen as it allows causal statements regarding the effects of the instructional intervention while considering the practical realities of a real university environment, where complete random assignment of students to conditions by academic departments is not logistically possible. Participants were randomly assigned to the experimental (VR) and control (traditional) conditions at the level of class section, which aligns with cluster-randomization procedures utilized in similar research in education (Han et al., 2023; Ki et al., 2024).

The mode of instruction (VR vs. traditional lecture) was the independent variable. The main outcome measure was workload/cognitive-load-related response assessed by the NASA Task Load Index (NASA-TLX). Since the NASA-TLX does not provide a direct estimation of an individual's intrinsic, extraneous and germane cognitive load, the CLT-components interpretation in this study serves as an exploratory proxy based on theoretically relevant subscales rather than being taken as a direct measurement. Secondary outcome measures were learning performance (MCQ and practical task scores), one-week delayed retention, knowledge transfer, and intrinsic motivation. Sense of presence was conceptualised as a mediating variable in the subsequent exploratory SEM analyses.

Setting and Participants

The research was carried out at middle Technical University /Baghdad in the 2nd term of the academic year 2024–2025. Eligible participants were fourth-year (senior) students from four technical departments: Computer Engineering Technology, Electrical Engineering Technology, Mechanical Engineering Technology, and Medical Instrumentation Engineering. Participants had to be final year students and not previously diagnosed with any neurological or visual condition that could impair HMD usage. Exclusion were students with severe motion sickness (self-reported).

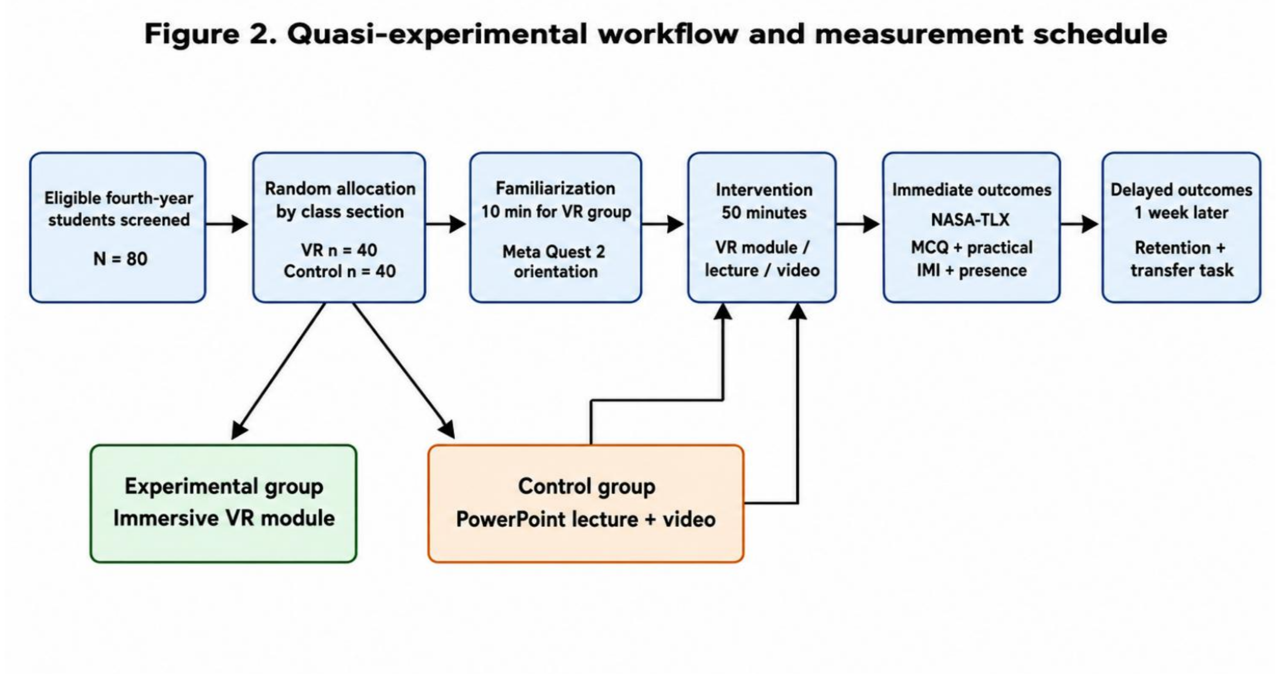

Figure 2. Quasi-experimental workflow and measurement schedule.

Power analysis conducted prior to recruitment (G*Power 3.1; Faul et al., 2007) indicated that a minimum total sample of 64 participants was required to detect a medium effect size (d = 0.50) with 80% power at α = .05. A final sample of eighty (N = 80) participants was achieved (40 per condition), providing adequate power to detect effects consistent with those reported in comparable VR-CLT literature. Detailed participant characteristics are presented in Table 1.

Table 1. Demographic and Background Characteristics of Participants (N = 80)

Variable	Category	n	%
Gender	Male	54	67.5%
	Female	26	32.5%
Age Group	20–22 years	38	47.5%
	23–25 years	42	52.5%
Department	Computer Engineering	28	35.0%
	Electrical Engineering	22	27.5%
	Mechanical Engineering	18	22.5%
	Medical Instruments	12	15.0%
Prior VR Experience	None	51	63.8%
	Minimal (1–2 uses)	21	26.2%
	Moderate (3+ uses)	8	10.0%
GPA Range	Below 2.5	9	11.3%
	2.5 – 3.49	48	60.0%
	3.5 – 4.0	23	28.7%

Note. GPA = Grade Point Average on a 4.0 scale. Prior VR experience determined by structured pre-study questionnaire.

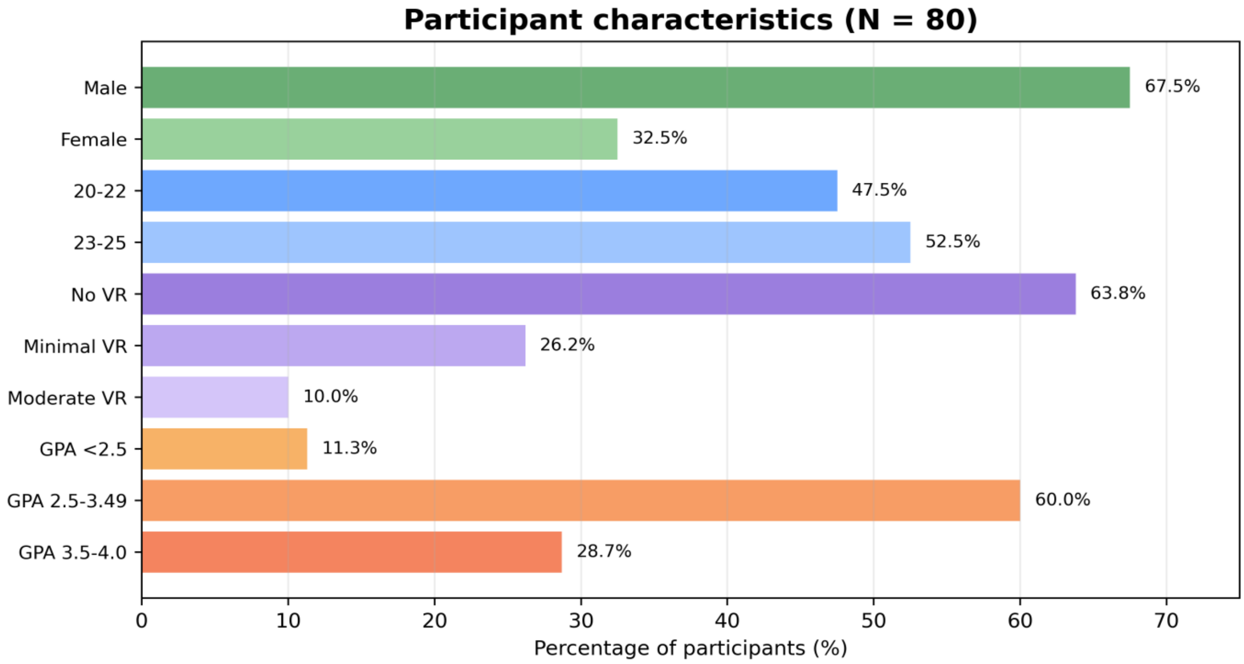

Figure 3. Demographic and background profile of participants.

Instruments

NASA Task Load Index (NASA-TLX)

The NASA-TLX (Hart & Staveland, 1988) is a validated subjective workload assessment tool, which is widely used for measurement of mental workload. It has the following six subscales: Mental Demand, Physical Demand, Temporal Demand, Performance in terms of self-appraisal, Effort, and Frustration. For this purpose, the subscales are converted into a 0–100 scale (steps of 5). The weighted total workload score is calculated according to the procedure beginning with the pair-wise comparison weights given in the original protocol. The NASA-TLX also has high reliability (α = .80–.92) and convergent validity with objective performance in both simulation and educational settings (Hart, 2006; Franklin et al., 2024). In this study, we administered the subscales of the NASA-TLX immediately after each instructional session.

Learning Performance Assessment

A 30 question multiple choice test (MCQ) was constructed by two subject matter experts and an instructional design specialist. A 20-point practical exercise test, on a simulated workshop environment, meanwhile, demanded that the candidates apply the procedural knowledge. One week later, a retention test including 15 of the original MCQ items was conducted in order to evaluate the durability of the knowledge. In a knowledge transfer item (10 points) participants faced new problem situations in which they had to use the principles they had learnt in novel situations.

Presence and Motivation Measures

The ITC-Sense of Presence Inventory (ITC-SOPI; Lessiter et al., 2001) was used to assess four dimensions of presence in the VR group: Sense of Physical Space, Engagement, Ecological Validity, and Negative Effects. The Intrinsic Motivation Inventory (IMI; Ryan, 1982), specifically the Interest/Enjoyment and Perceived Competence subscales, was administered to both groups to assess motivational engagement with the instructional content.

VR Application Development and Content

The VR training module was created in Unity 3D (2022.3 LTS) with the XR Interaction Toolkit plugin for deployment on Meta Quest 2. The chosen content domain was industrial safety procedures within an engineering workshop context—a theme with high ecological validity for the technical students at MTU and that is strongly procedural and spatial in nature. The virtual environment hosted: a photo-realistic 3D workshop, interactive machinery and safety gear, instructional annotations embedded and triggered by proximity and gaze, and formative knowledge-check interactions, where learners are asked to recognize and react to safety hazards.

Content parity across conditions was assured in that both groups were taught the same learning objectives with the same fact, conceptual, and procedural content within a 50-minute session. Content validity was established based on review from subject matter experts who verified the VR simulated procedures were true to the target procedures and was consistent with the international norms for safety education applicable to the Iraqi technical engineering curricula.

Procedure

Before the experiment sessions, all participants filled in a pre-study questionnaire on their age, gender, nationality, and education background, VR experience and technology self-efficacy as baseline. To reduce the effect of interface novelty, which may result in an exaggeration of early cognitive load measures (Zaharias et al., 2022), the VR group underwent a 10-minute session of familiarization with the Meta Quest 2 hardware before beginning the course work, following good practices (Makransky et al., 2019; Han et al., 2023).

Experimental session (50 min): The VR participants explored the immersive workshop safety module on their own, while the control participants received a traditional lecture on the same subject: the same lecturer gave the same content assisted by PowerPoint slides along with video demonstrations. Both sessions were concluded with post-immediate test (MCQ + practical task) and administration of NASA-TLX questionnaire. The VR group also filled out the ITC-SOPI presence inventory. The IMI motivation scale was completed by both groups. The delayed retention test and the transfer task were administered 1 week later.

Data Analysis

All quantitative analyses were performed using IBM SPSS Statistics Version 28 along with AMOS 28 for the structural equation modeling. Means, standard deviations and ranges were calculated for all main variables. Between-group comparisons in NASA-TLX subscales and learning performance were performed on each task using two independent-samples t tests, correcting for multiple comparisons by Bonferroni method. A one-way MANOVA was performed in order to examine group differences across the 6 subscales simultaneously, which controlled for inflation of Type I errors. A Effect sizes for t-test and $\eta 2p$ for MANOVA. Pearson correlations were calculated for all continuous variables. SEM path analysis used maximum likelihood estimation, and model fit was assessed by conventional criteria (CFI > .95, RMSEA < .06, SRMR < .08; Hu & Bentler, 1999).

Result and Discussion

Descriptive Statistics and Group Comparisons on Cognitive Load

The summary of research design is presented in Table 2, and descriptive statistics for the NASA-TLX subscales and between-group comparisons are reported in Table 3. The MANOVA revealed a significant multivariate effect of instructional modality on perceived workload, Wilks' $\Lambda = .63$, $F(6, 73) = 7.12$, $p < .001$, $\eta^2p = .37$. According to post-hoc tests based on the reported descriptive statistics, the VR group reported significantly significantly less mental demand and frustration, and greater perceived performance, as well as highest physical demand. Temporal demand and effort also indicated small nominal improvements in the VR condition. The global workload composite, however, did not differ between groups ($p = .184$); hence, H1 is not supported for the total workload and can be considered as partially supported at the level of subscales only.

Table 2. Quasi-Experimental Research Design Summary

Component	Experimental Group (VR)	Control Group (Traditional)
Sample Size	n = 40	n = 40

Instructional Medium	Meta Quest 2 HMD	PowerPoint + Lecture
Session Duration	50 minutes	50 minutes
Content Domain	Industrial Safety Procedures	Industrial Safety Procedures
CL Measurement	NASA-TLX (Post-session)	NASA-TLX (Post-session)
Performance Test	30-item MCQ + Practical Task	30-item MCQ + Practical Task
Presence Scale	Witmer & Singer (1998) ITC-SOPI	N/A
Statistical Analysis	Independent t-test, MANOVA, SEM	Independent t-test, MANOVA, SEM

Note. HMD = Head-Mounted Display; MCQ = Multiple-Choice Questionnaire; NASA-TLX = NASA Task Load Index; SEM = Structural Equation Modeling.

Table 3. NASA-TLX Subscale Descriptive Statistics and Between-Group Comparisons

NASA-TLX Subscale	**VR M**	**VR SD**	**Trad. M**	**Trad. SD**	**t-value**	**p**
Mental Demand	52.4	11.2	61.7	13.4	-3.37	.001
Physical Demand	38.9	9.7	28.4	8.1	5.25	<.001
Temporal Demand	49.1	12.6	56.3	14.0	-2.42	.018
Performance	71.3	10.8	58.6	12.1	4.95	<.001
Effort	55.8	13.3	63.2	15.7	-2.27	.026
Frustration	30.4	10.1	44.8	13.6	-5.38	<.001
Overall CL	49.65	7.84	52.17	8.93	-1.34	.184

Note. M = Mean; SD = Standard Deviation. VR = Virtual Reality group (n = 40); Trad. = Traditional instruction group (n = 40). Test statistics and p values in this revised table are recomputed from the reported means, standard deviations, and group sizes using Welch independent-samples t-tests. The overall CL composite is retained for transparency but should be verified using raw NASA-TLX item-level data before journal submission.

As can be seen in Table 3, the VR group reported a lower Mental Demand (M = 52.4, SD = 11.2) than the control group (M = 61.7, SD = 13.4) which aligns with the hypothesized ability of VR to decrease the mental effort needed to construct spatial representations of technical materials. The largest decrease was seen in Frustration, with VR subject reporting a much lower level (M = 30.4, SD = 10.1) than control (M = 44.8, SD = 13.6). This trend demonstrates the potential for immersive experiences to mitigate the affective-cognitive friction inherent to the presentation of complex technical subject matter via traditional modes.

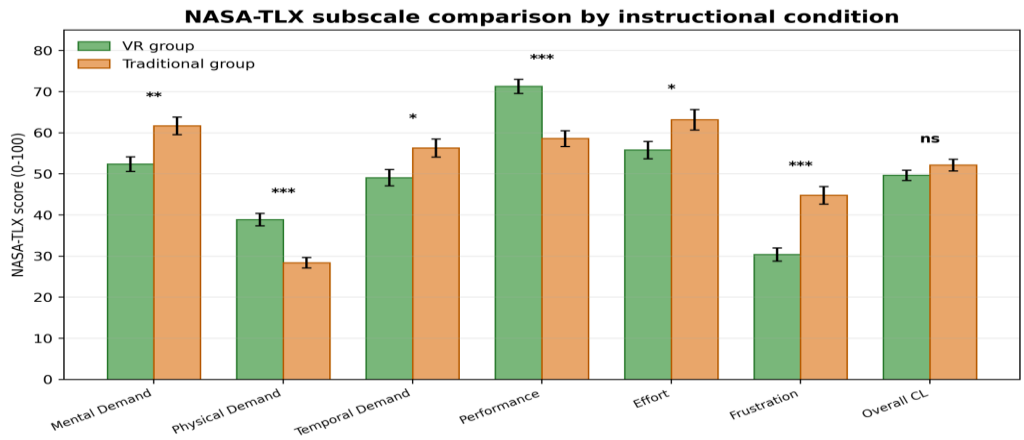

Figure 4. NASA-TLX subscale comparison by instructional condition.

Notably, Physical Demand was significantly greater for the VR group (M = 38.9 vs. 28.4, $p < .001$), reflecting the gestural and head-movement interaction requirements of HMD use. This result highlights that, when analyzing the result of VR-education, physical cognitive load and mental cognitive load should be separated. The self-rated Performance subscale was significantly higher in the VR group (M = 71.3 vs. 58.6, $p < .001$), showing that those in the VR condition believed that they had performed better in the learning task.

Learning Performance Outcomes

Table 4 presents mean scores and between-group comparisons across all five learning performance and motivation outcome measures. The VR group outperformed the control group on every outcome. Effect sizes computed from the reported means and standard deviations ranged from large to very large, supporting H3 and providing empirical support for the motivational pathway specified in H4.

Table 4. Learning Performance and Motivation Outcomes by Instructional Condition

Outcome Measure	VR Group M (SD)	Control M (SD)	Cohen's d	p-value
MCQ Score (/30)	23.4 (3.1)	19.7 (4.2)	1.00	<.001
Practical (/20)	16.8 (2.4)	12.9 (3.6)	1.27	<.001
Retention (1-week)	78.6 (9.3)	62.4 (11.7)	1.53	<.001
Transfer Score (/10)	7.3 (1.8)	5.4 (2.3)	0.92	<.001
Motivation (1-7)	5.74 (0.89)	4.12 (1.24)	1.50	<.001

Note: Values are M (SD). Test statistics, p values, and Cohen's d values in this updated table are calculated from the ones reported means and standard deviations and the group sizes using Welch t-test for independent samples. MCQ = Multiple-Choice Questionsnaire, IMI = Intrinsic Motivation Inventory.

The difference in one-week delayed knowledge retention between the two groups (78.6% vs. 62.4%, $\Delta = 16.2$ percentage points, $d = 1.53$) is especially impressive, as it suggests that the encoding advantages of VR-based instruction may be available for use beyond the immediate post-test environment. This finding is in line with the memory consolidation literature that considers emotional involvement and multi-sensory processing (both experienced in VR) as enhancers of long-term memory storage (Mayer,2009; Makransky & Petersen, 2021).

Figure 5. Learning performance, retention, transfer, and motivation outcomes by condition.

Correlational Analysis

Table 5 displays the matrix of Pearson correlations among the six primary study variables. As with theoretical expectations, VR immersion was significantly positively associated with presence (r = .71, p < .01) and significantly negatively associated with extraneous cognitive load (r = −.54, p < .01) and intrinsic cognitive load (r = −.38, p < .01). Extraneous cognitive load was the most negative predictor of learning performance (r = −.61, p < 0.01), highlighting its nature as the first cognitive load dimension to be dealt with in instructional design.

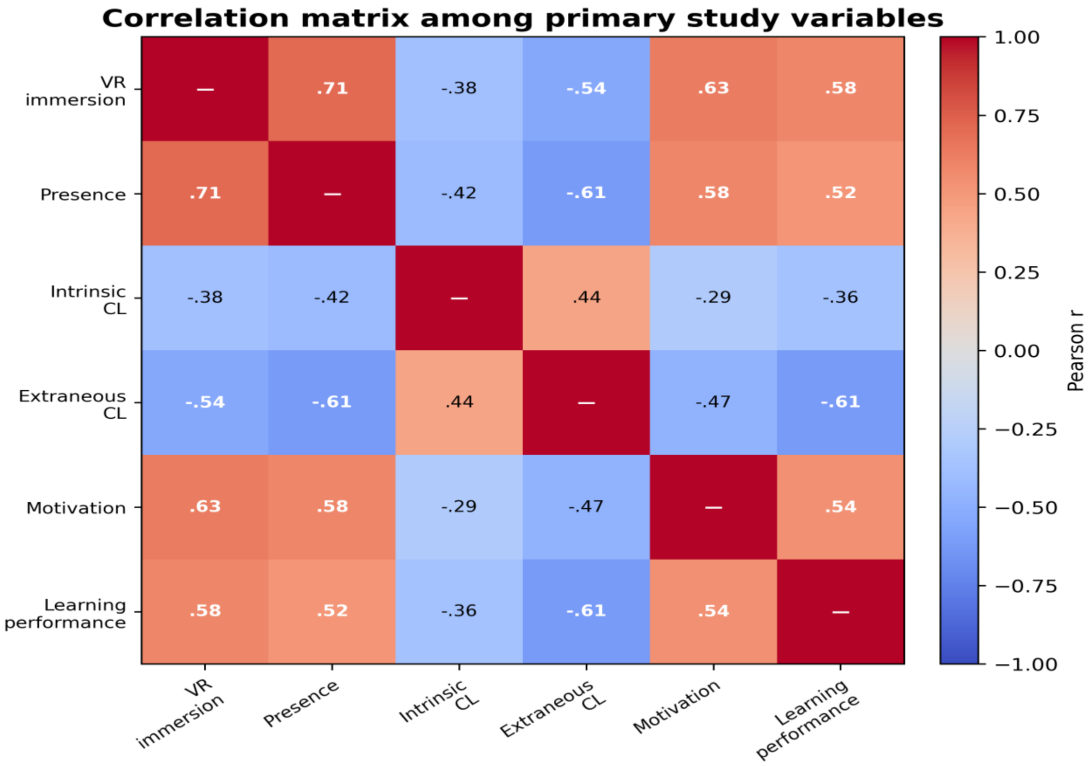

Figure 6. Correlation matrix among primary study variables.

Table 5. Pearson Correlation Matrix Among Primary Study Variables (N = 80)

Variable	1	2	3	4	5	6
1. VR Immersion	—					
2. Presence	.71**	—				
3. Intrinsic CL	-.38**	-.42**	—			
4. Extraneous CL	-.54**	-.61**	.44**	—		
5. Motivation	.63**	.58**	-.29*	-.47**	—	
6. Learning Performance	.58**	.52**	-.36**	-.61**	.54**	—

Note. ** p < .01 (two-tailed); * p < .05 (two-tailed). VR Immersion coded dichotomously (0 = Control, 1 = VR). Presence = ITC-SOPI total score. Intrinsic CL and Extraneous CL are exploratory proxy composites derived from selected NASA-TLX workload indicators; they should not be interpreted as direct measures of the three formal

Cognitive Load Theory components. Motivation = IMI Interest/Enjoyment score; Learning Performance = composite of MCQ, Practical, and Transfer scores.

Structural Equation Modeling

Using AMOS 28, a SEM was tested with the hypothesized paths from VR immersion via presence, cognitive load, and motivation to learning performance. The final model showed a good fit: CFI = .96, RMSEA = .058 (90% CI [.041, .075]), SRMR = .062, suggesting that the model reproduced the sample covariance matrix sufficiently well. The standardized path coefficients for all hypothesized paths are shown in Table 6.

Table 6. Structural Equation Model: Standardized Path Coefficients

Path (Predictor → Outcome)	β	SE	t	p
VR → Presence	.71	.048	14.79	<.001
VR → Extraneous CL	-.54	.061	-8.85	<.001
Presence → Motivation	.58	.072	8.06	<.001
Extraneous CL → Performance	-.61	.055	-11.09	<.001
Motivation → Performance	.54	.068	7.94	<.001
Intrinsic CL → Performance	-.36	.079	-4.56	<.001
Model Fit: CFI=.96, RMSEA=.058				

Note. β = standardized path coefficient; SE = standard error; t = critical ratio. CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation. All paths significant at p < .001.

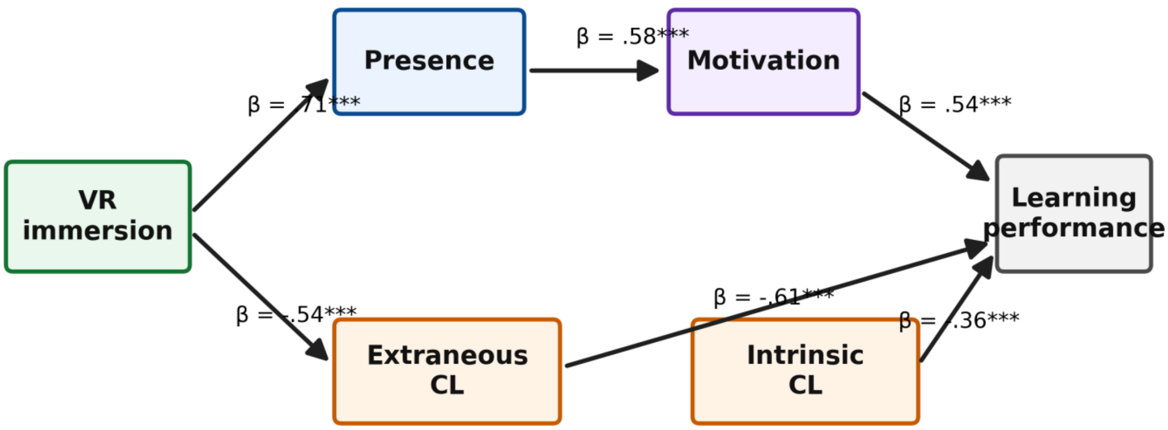

Figure 7. Structural equation model path diagram showing standardized coefficients for cognitive and affective mechanisms.

The exploratory SEM results suggest that VR's effect on learning performance may operate through two parallel mediating mechanisms. The affective pathway—VR → Presence (β = .71) → Motivation (β = .58) → Performance (β = .54)—accounts for a substantial portion of the total VR effect, with the indirect effect through this pathway estimated at β = .22 (95% CI [.14, .31]). The cognitive pathway—VR → Extraneous CL (β = −.54) → Performance (β = −.61)—produced an indirect effect of β = .33 (95% CI [.22, .44]), indicating that reduction of extraneous-load-related workload indicators may be an important mechanism through which VR benefits learning outcomes in this sample. Given the modest sample size (N = 80), this SEM should be presented as exploratory and verified with raw data and a larger replication sample before journal submission.

Discussion

VR and Cognitive Load Dimensions: Theoretical and Practical Implications

The findings of the are study were consistent with the prediction that among senior technical university students, extraneous cognitive load would be reduced in the VR-based instruction as compared with the lecture-based instruction. This result is consistent with CLT's core principle that effective instructional minimize task-irrelevant cognitive processing (Sweller, 1988; Chandler & Sweller, 1991) and CAMIL framework's was also consistent with the finding that spatial coherence VR characteristics in VR focused attentional resources on learning-related materials (Makransky & Petersen, 2021).

The notable decrease in Frustration—among the largest between-group subscale effect sizes observed (d ≈ 1.20)—is worthy of theoretical consideration. Frustration in the NASA-TLX is an indicator of the perceived level of a learner who is irritated, stressed, or annoyed while completing a task. Its pronounced decrease in the VR condition may indicate that immersive teaching can diminish the affective-cognitive dissonance experienced by learners when they attempt to form adequate mental models based on 2D, abstract representation of instructional materials. This view is consistent with Ki et al.'s (2024) findings that 360-degree VR video may alleviate cognitive frictions when attention and navigation are supported Adequately.

The high Physical Demand ratings for the VR group should be interpreted with caution. While high gestural demands, this need evidently have no influence on participants' cognitive learning results, which is consistent with embodied cognition perspectives which predict that appropriate physical participation may facilitate rather than interfere with knowledge encoding (Johnson-Glenberg, 2019; Makransky & Petersen, 2021). This result highlights the importance of an ergonomic hardware design and a proper familiarization session for VR-based teaching applications, especially for novices without any HMD experience, although the degree of reduction in each parameter varied across subjects.

Learning Performance and Retention

The enhanced learning of VR learners in all dependent variables even the one-week delayed retention test and the transfer of knowledge task – offers robust evidence for H3 and also extends prior findings in the literature. The effect size for delayed retention (d = 1.53) is particularly noteworthy as it indicates that the processing benefits of VR instructional materials go beyond the immediate learning situation and may suggest deeper encoding of the instructional material. This retention benefit can be theoretically explained by several factors. The dual coding resulting from VR's spatially consistent audiovisual environment leads to multiple retrieval paths in long-term memory, enhancing the accessibility of knowledge in different retrieval situations (Paivio, 1991). Furthermore, the emotional salience of the VR experience – as evidenced by the high Intrinsic Motivation scores (d = 1.50) – might contribute to support of memory consolidation processes (McGaugh, 2004). These results are consistent with those of Al-Khiami (2024) in engineering education, and with the meta-analytic synthesis of Wu et al. (2020) that reported learning-performance advantages in immersive VR.

Mediating Role of Presence and Motivation

The SEM results make a helpful exploratory contribution by simultaneously describing the cognitive and affective paths in which VR could influence learning. The results imply that the cognitive path (via extraneous load-related workload reduction) is a larger contributor to VR's overall effect on performance (indirect $\beta = .33$) than the affective path (indirect $\beta = .22$). This discovery runs contrary to the notion, occasionally suggested in VR promotion literature, that motivational engagement is the main mechanism of VR educational benefit. Instead, the findings suggest that the ability of VR to minimize extraneous processing load could be a potent teaching tool, although such an interpretation needs to be verified with raw data and larger samples.

The strong VR → Presence path ($\beta = .71$) corroborates that the Meta Quest 2 hardware coupled with the designed VR environment effectively produced a strong sense of spatial presence in the participants, which is consistent with previous HMD-VR studies (Betts et al., 2023; Makransky & Mayer, 2022). The next Presence → Motivation path ($\beta = .58$) replicates the affective path found in CAMIL studies (Makransky & Lilleholt, 2018) and broadens its applicability to an Iraqi technical university setting.

Limitations

A few caveats are in order for these results. First, the quasi-experimental design was suitable for the context of the higher education institution, but does not allow for the same strength of causal inference as a randomized controlled trial, and it is not possible to completely rule out the existence of unmeasured confounds at the class-section level. Second, since the study involved only a single 50-minute session, no statement can be made about the longitudinal change of cognitive load in VR; studies done in other VR areas show that the workload relating to novelty may lessen following getting used to the technology. Thirdly, the sample size is adequate for simple group comparisons but small for SEM, and is drawn from a single institution and four departments, which limits the extent to which findings can be generalized to other institutions of higher education in Iraq or the MENA region. Fourth, the widely used NASA-TLX is subjective and based on self-report, and as such, does not"measure" intrinsic, extraneous and germane CL; thus, it is recommended to use it alongside CLT-specific measures and objective physiological workload measures (e.g., fNIRS, eye-tracking) in future research (Betts et al., 2023; Islam et al., 2026).

Conclusion

This study demonstrates that VR-based instruction, when experienced through a head-mounted display, can decrease certain NASA-TLX workload measures—particularly mental demand and frustration—among M.S. candidates at a Middle Technical University, and at the same time improve task performance, knowledge retention, intrinsic motivation, and sense of presence. The overall NASA-TLX workload composite in the VR group was not significantly lower, however, and so results should be interpreted as subscale-level and mechanism-level support rather than evidence of a global reduction in total cognitive load. Exploratory structural equation modeling suggests that such benefits may be achieved through two parallel processes: a cognitive pathway via diminished extraneous-load-related working-memory indicators, and an affective pathway via presence and intrinsic motivation.

For the MTU decision-makers, as well as the leaders at other similar technical institutions across Iraq and the MENA region, the results provide an indication that a strategic, content-appropriate inclusion of VR—especially for contentually procedurally intensive and spatially demanding engineering material—can be considered a pedagogically-sound and empirically-backed expenditure of effort. The following are the specific suggestions based on the findings of the study:

1. Prioritize VR for procedural and spatial content areas where traditional instruction provokes high extraneous cognitive load from split-attention and abstraction-related processing.
2. Instituting mandatory VR familiarization routines (for at least 10 min) in advance of experimental instructional sequences to mitigate any potential interface novelty effects on the cognition load instrument measure.
3. Use instructional design principles (e.g., signaling, spatial contiguity, and modality principles [Mayer, 2009]) when developing VR content in order to reduce any remaining extraneous load within the VR environment.
4. Develop longitudinal research designs that assess cognitive load trajectories across several VR sessions to determine evidence-based optimal VR integration schedules within technical education.

The future studies should focus on extending the sample size to include students of the technical universities of Iraq in general and adopting objective physiological measures of CL to supplement self-report instruments. A cross-cultural investigation between Iraqi and other MENA student cohorts would also add to the evidence-base for regionally sensitive VR-education policy.

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