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A Nuanced Perspective on VR Learning: Exploring the Effects of Immersion Levels on Knowledge Acquisition Using Electrodermal and Eye Tracking Sensors

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ABSTRACT

Background: This study investigates the effect of immersion levels in virtual reality (VR) learning environments on the acquisition of declarative and procedural knowledge. Prior research indicates that immersion affects cognitive load, but its impact on declarative and procedural knowledge outcomes remains unclear. This study utilises a multimodal approach, combining self-reports with data from psychophysiological sensors.

Objectives: The study aims to evaluate how different levels of immersion in VR—high-immersive VR (head-mounted display, HMD-VR) and low-immersive VR (Desktop-VR)—affect cognitive load and learning outcomes, focusing on procedural and declarative knowledge.

Methods: A prospective experimental study was conducted with 74 sophomore nursing students, assigned to either the HMD-VR group or Desktop-VR. Eye-tracking and electrodermal activity (EDA) were used to assess cognitive load during learning. A pre-test/post-test design measured declarative and procedural knowledge using a Medication Administration Test (MAT), whilst a presence questionnaire evaluated user experience.

Results and Conclusions: Both study groups demonstrated significant improvements in declarative and procedural knowledge. However, the low-immersive Desktop-VR group exhibited significantly greater pre- to post-test gains in procedural knowledge compared to the high-immersive HMD-VR group. The HMD-VR group exhibited higher cognitive load during procedural tasks, indicated by lower blink rates and a higher rate of EDA peaks. No significant differences were found in the sense of presence between the two groups. This study contributes to understanding learning with immersive VR, showing that high-immersive VR may require careful instructional design to mitigate cognitive overload, especially for procedural tasks. Low-immersive VR presents a cost-effective alternative for immediate knowledge gains.

1 | Introduction

Virtual reality (VR) provides an immersive and authentic learning experience by simulating reality in computer-generated environments, making it a powerful platform for education and training (Yu 2021). Within these environments, participants interact as avatars, moving, sensing, touching, and acting upon computer-generated objects, thus fostering a sense of real-world interaction. These immersive characteristics of VR align well with several learning theories, including constructivist

Summary

- What is currently known about this topic?
  - High-immersive VR can enhance learning but may induce cognitive load.
  - VR learning effectiveness varies by type of knowledge and immersion level.
  - Eye-tracking and EDA are useful for measuring cognitive load and attention.
  - Low-immersive VR is a cost-effective alternative for knowledge acquisition.
- What does this paper add?
  - High-immersive VR increased cognitive load during procedural tasks.
  - Low-immersive VR led to higher gains in procedural knowledge acquisition.
  - Both VR formats showed similar improvements in declarative knowledge.
  - The study provides nuanced insights into the impact of VR immersion on learning.
- Implications for practise/or policy
  - Low-immersive VR offers an effective and economical approach to teaching procedural tasks.
  - High-immersive VR requires careful instructional design to manage cognitive load.
  - VR educators should tailor immersion levels based on learning objectives.
  - Policy should support diverse VR tools in educational and training programmes.

perspectives, situated and embodied learning, and experiential learning approaches (Fromm et al. 2021; Tusher et al. 2024). The potential of VR in education, particularly in fields such as STEM and medical training, is reflected in the rapid growth of its market value—from $4.4 billion in 2023; projections suggest it could reach $28.7 billion by 2030 (Mordor Intelligence 2024; Shubham 2024).

Despite its growing popularity, research on the effectiveness of VR in education provides no strong evidence supporting its superiority, showing only small effect sizes compared to other educational practises (Yu 2021). Coban et al. (2022) and Luo et al. (2021), who reviewed two decades of VR research, argued that the small effect size may be attributed to variability in approaches, as a one-size-fits-all model may not apply. Conrad et al. (2024) and Makransky and Mayer (2022) suggest that more nuanced research is needed to account for different knowledge types and levels of VR immersion, which may affect the effectiveness of VR on educational processes. Indeed, Mayer et al. (2023), in their review, call for further studies on how different types of knowledge interact with varying levels of VR immersion.

In response to this call and to contribute to a more nuanced understanding of learning with VR, the present study investigates the effects of different levels of VR immersion on the acquisition of declarative knowledge, which indicates static knowledge about facts, concepts, and principles that apply within a certain domain, and of procedural knowledge, which indicates actions or manipulations that are valid within a domain (De Jong and Ferguson-Hessler 1996). Although studies have examined the effect of learning with VR on declarative and procedural knowledge (Mayer et al. 2023; Radianti et al. 2020), there is a lack of research examining interactions between levels of VR immersion and types of knowledge. Based on the adaptive control of thought (ACT) learning theory (Anderson 1982), which differentiates between declarative and procedural knowledge and the cognitive demands associated with each type of knowledge, and on the cognitive load theory (Sweller et al. 1998), which suggests that learning is facilitated when conditions match the human cognitive architecture and therefore associates higher cognitive loads with lower learning gains, this study examines the relationship between levels of immersion and knowledge type acquisition. Specifically, in the current study, we compare learning processes and outcomes in high-immersive VR, using a head-mounted display (HMD-VR), versus low-immersive VR, using a desktop display (Desktop-VR). To piece together a bigger picture of students' learning processes, we employ a multimodal methodology that combines subjective self-reports with objective measures, including eye-tracking and electrodermal activity (EDA). By doing so, this study expands current insights into the learning experiences that influence VR-based learning processes and outcomes.

1.1 | Characteristics of Virtual Reality

Virtual reality (VR) is a computer-generated environment designed to emulate real-world experiences (Slater and Wilbur 1997; Steuer 1992). It mirrors the real world by providing the brain with sensations of movement, touch, and sight. VR environments allow users to feel a sense of presence, creating the perception of being immersed within and interacting with a simulated world rather than remaining aware of their actual physical surroundings (Witmer and Singer 1998). It has been suggested that the core characteristics of VR affecting one's subjective sense of presence are the objective design variables of interactivity and immersion. The level of interactivity in VR refers to the extent to which users can engage with and influence the virtual environment and its elements (Steuer 1992). For example, watching 360° videos, where users can only observe but not manipulate objects or alter the environment, is considered low interactivity. In contrast, fully simulated VR environments, where users can navigate, use tools, or interact with multiple elements or other avatars, are classified as highly interactive.

Another key characteristic of VR is its degree of immersion. According to Slater and Wilbur (1997), immersion refers to the capacity of VR technology to engage users' senses through visuals, auditory inputs, and other sensory channels whilst providing feedback on bodily movements (Mayer et al. 2023). VR systems can be categorised into high- or low-immersion based on their technological features. High-immersion VR typically includes advanced interaction capabilities and utilises specialised peripheral equipment. For instance, a head-mounted display (HMD) with high-resolution screens positioned close to the eyes, combined with separate lenses for each eye and integrated earphones, enhances the immersive experience. This setup reduces distractions from the physical environment and synchronises sensory inputs with the virtual environment, enabling users to engage more deeply with the virtual space. Interaction in this mode is governed by head-motion tracking integrated with a computer system, so that when users move their heads, their field of view within the 360° virtual environment adjusts accordingly. Additionally, high-immersive VR allows interaction through bodily motions and teleporting via controllers, further enhancing one's sense of presence.

In contrast, desktop VR, which is a form of low-immersive VR, provides a window into a virtual environment displayed on a computer monitor. Users interact with the environment using devices such as a mouse, keyboard, or joystick (Choi et al. 2016). Since the virtual environment is presented on a standard monitor and audio is delivered through speakers, participants stay fully conscious of their real-world surroundings during the desktop VR learning experience.

1.2 | Learning With VR

Recent studies clearly demonstrate that VR design characteristics, such as levels of interactivity and immersion, significantly affect learning processes, particularly regarding cognitive load. Cognitive Load Theory, introduced by Sweller et al. (1998), models the functioning of learners' working memory. This theory posits that cognitive architecture is fundamental to learning in multimedia-based environments such as VR (Makransky 2022). According to this theory, learning from words and images engages three key cognitive processes (Mayer and Fiorella 2021): (i) Essential processing, triggered by the inherent complexity of the material; (ii) Extraneous processing, caused by inefficient instructional methods, irrelevant or distracting content, and excessive task demands that do not contribute to learning goals; and (iii) Generative processing, also known as germane cognitive load, which results from the mental effort dedicated to deeply understanding information. Generative processing involves actively organising and integrating new knowledge with existing cognitive structures. This type of processing is crucial for fostering meaningful learning, as it encourages learners to make connections, engage in critical thinking and apply the information in new contexts. Whilst generative processing complements essential processing by helping learners deeply organise and integrate the core material, it competes with extraneous processing for cognitive resources. Since learners' cognitive processing capacity is limited, it is important to determine how, within the context of VR, it is possible to minimise extraneous processing whilst encouraging generative processing.

Interestingly, several studies indicate that a higher level of interactivity, which enables substantial user control and produces responsive outputs, is associated with lower extraneous cognitive load from the environment. Petersen et al. (2022) manipulated the degree of interactivity levels in their VR study, demonstrating that when learners had less control over their interactions (e.g., passive viewing), they found the learning experience more mentally taxing, ultimately impacting their acquisition of factual knowledge. Lehikko et al. (2024) demonstrated that higher interactivity in VR increases the germane cognitive load, which benefits learning, without increasing the extraneous cognitive load that could hinder the learning process. Building on interactivity as a key VR pedagogical feature (Won et al. 2023), Dubovi (2023) demonstrated that interactivity in VR can be fostered not only through design elements that enable direct hands-on interaction within the environment but also through instructional activities that promote 'minds-on' engagement. This includes strategies such as dialogue and reflective learning experiences, as highlighted by Chi et al. (2018) and Chi and Wylie (2014).

Whilst there is a consensus regarding the impact of VR interactivity on learning, the effect of VR immersion yields contradictory findings. On the one hand, (Makransky et al. 2019b) demonstrated through EEG that high-immersive VR is associated with higher cognitive load, which might inhibit knowledge acquisition compared to low-immersive Desktop-VR. On the other hand, a meta-analysis by Wu et al. (2020) found that high-immersive VR using HMDs is more effective than low-immersive Desktop-VR approaches. Furthermore, a study by Petersen et al. (2022) showed that higher levels of immersion, such as using HMDs, reduced extraneous cognitive load associated with the VR environment. Morélot et al. (2021) suggested that high-immersive VR may be more effective for promoting procedural learning, especially when it involves gesture-based interaction, but may not offer similar benefits for declarative knowledge learning. This possible interaction between immersion levels and the type of knowledge provided by VR highlights the need to define the conditions under which VR design is most suited to support learning. To achieve this, we examine the impact of immersive levels on procedural vs. declarative knowledge acquisition using eye-tracking and electrodermal activity measures.

1.3 | Declarative and Procedural Knowledge

Declarative and procedural knowledge play a pivotal role in the ability to solve problems, and therefore their acquisition is regarded as a major goal of educational processes (Conrad et al. 2024). Whilst declarative knowledge encompasses facts, concepts, and principles relevant to a domain, procedural knowledge involves actions or processes required to perform tasks effectively (De Jong and Ferguson-Hessler 1996). Procedural knowledge is often acquired implicitly through experience and practise, though explicit instruction can enhance its development (Anderson and Krathwohl 2001; Krathwohl 2002). Learning cognitive skills typically follows a progression: first, acquiring the relevant declarative knowledge, then applying it to procedural execution (Anderson 1982). Therefore, learning declarative knowledge might require less cognitive effort than learning procedural knowledge, which involves the coordination of multiple cognitive and motor processes and real-time decision making (Anderson 2015).

VR has been employed to facilitate both forms of learning. For declarative knowledge, VR environments assist with memorisation and conceptual understanding, such as in science education (De Witte et al. 2024). For procedural knowledge, VR provides hands-on training for skill-based tasks, such as medical simulations (Radianti et al. 2020). However, research remains inconclusive regarding VR's effectiveness across these knowledge types. Some studies indicate comparable effectiveness between high- and low-immersion VR for declarative learning, whilst others suggest that immersion plays a more pronounced role in procedural knowledge acquisition (Mayer et al. 2023; Radianti et al. 2020). Given these mixed findings, this study seeks to clarify how different levels of VR immersion influence both declarative and procedural knowledge acquisition. By incorporating psychophysiological measures, we aim to provide deeper insights into the cognitive processes underlying VR-based learning.

1.4 | Psychophysiological Signals to Assess Cognitive Load

Psychophysiological metrics like eye-tracking and electrodermal activity (EDA) have been proposed as tools to continuously and objectively measure cognitive processes in real time within multimedia learning contexts (Alemdag and Cagiltay 2018; Dubovi 2022). Eye-tracking technology, in particular, allows for the observation of attentional patterns by capturing what learners focus on, the timing, sequence, and duration of their responses to specific stimuli during VR-based learning experiences (Rappa et al. 2022; Shadiev and Li 2023). Eye-tracking sensors can record various measures of visual attention; in this study, we focus on the most common ones in multimedia learning: fixations and blinks (Alemdag and Cagiltay 2018). Fixations, which represent the stable position of the eye at a single point, are closely related to the efficiency of information search. An increased number of fixations or longer fixation durations on a stimulus might indicate greater difficulty encountered by the viewer during information processing (Jacob and Karn 2003). This pattern suggests that as cognitive load or task complexity increases, individuals require more time and visual focus to process and understand information (Liu and Chuang 2011; Liu et al. 2022). Another key eye-tracking metric is the blink rate, which is considered an indicator of cognitive load (Holland and Tarlow 1972). Research has shown that blinking tends to decrease during cognitive and memory tasks, indicating an inverse relationship between task difficulty and blink rate; as task difficulty increases, the blink rate tends to decrease (Martins and Carvalho 2015; Stern and Skelly 1984; Vanneste et al. 2021).

An automated electrodermal activity (EDA) sensor is another method for measuring engagement (Andreassi 2010). This approach relies on the activation of the sympathetic nervous system, which stimulates sweat glands in the hands and feet in response to behavioural, cognitive, and emotional stimuli, preparing the body for action (Matsumoto et al. 1990). The resulting change in conductivity, caused by the presence of conductive sweat, has been interpreted as a sign of engagement (Dailly et al. 2015). Whilst EDA is often used as a measure of emotional engagement, recent research suggests it may not be sufficiently sensitive to detect changes in emotional states, making it more appropriate for assessing cognitive engagement (Harley et al. 2015; Larmuseau et al. 2019; Lee et al. 2019; Parong and Mayer 2021). EDA metrics have specifically been used as indicators of cognitive effort and increased cognitive load during demanding tasks such as complex arithmetic and reading (Armougum et al. 2019; Liberman and Dubovi 2023). Building on previous studies demonstrating that the integration of multiple sensors provides a more robust, time-sensitive assessment of cognitive states (Brishtel et al. 2020; Dubovi 2022; He et al. 2022), this study employs both eye-tracking and EDA psychophysiological measures to evaluate the cognitive processes involved in VR-based learning.

1.5 | Research Aim and Research Question

This study seeks to examine the effects of varying levels of immersion—specifically, low-immersive Desktop-VR compared to high-immersive HMD-VR—on the learning process and outcomes. Drawing on Cognitive Load Theory, which posits that immersive virtual environments can contribute to extraneous cognitive processing (Mayer and Fiorella 2021), this study focuses on cognitive effort. The key research questions addressed in this study are: (1) How do different levels of immersion, such as low-immersive Desktop-VR and high-immersive HMD-VR, influence students' learning processes? (2) How do different levels of immersion impact students' learning outcomes?

We hypothesized that both types of knowledge—declarative and procedural—would be positively improved by learning with VR. For declarative knowledge acquisition, which involves storing and retrieving information and therefore requires low cognitive effort, we hypothesized that there would be no difference in the effect of high vs. low immersive environments. However, for procedural knowledge, which involves the coordination of multiple cognitive and motor processes and real-time decision-making and therefore requires high cognitive effort, we hypothesized that better learning gains would be found in low immersive learning environments, which require less cognitive effort and place lower cognitive loads on the learner.

The learning process was assessed using psychophysiological measures, including EDA and eye-tracking metrics, along with a presence questionnaire, whilst learning outcomes were evaluated through a knowledge test. Analysing the relationship between VR, immersion, declarative and procedural learning, and cognitive load will support the development of instructional guidelines for learning with VR.

2 | Materials and Methods

2.1 | Research Design

This study employed a prospective experimental design with pre-test and post-test measures to compare two conditions: low-immersive Desktop-VR and high-immersive HMD-VR (Figure 1).

2.2 | Participants

Participants were sophomore nursing students enrolled in a four-year general programme for a Bachelor of Nursing Degree at an Israeli university. Students were assigned to either the Desktop-VR or HMD-VR group using a systematic random sampling method (interval sampling) (Elfil and Negida 2019).

Students' demographics and prior content knowledge were collected through a pre-test paper-and-pencil survey.

Of the 125 eligible sophomore nursing students invited to participate in the study, 83 agreed to participate, yielding an 80% response rate. Nine participants were excluded from the data analysis due to eye-tracking calibration or EDA signal errors. A preliminary statistical power analysis was conducted to estimate the required sample size using GPower software (version 3.1). With an alpha level of 0.05, a power ($1-\beta$) of 0.80, and aiming to detect a medium to large effect size (Cohen 2013), a sample size of approximately 68 participants was determined to be sufficient for conducting t-tests and Mann–Whitney U tests to compare the two groups. Consequently, the final sample size of 74 participants was considered adequate. The majority of participants were female ($n=64$), with a mean age of 24 ± 3.7 years; 54% of the students reported no prior experience with VR. There were no statistically significant differences in demographic characteristics or previous experience with VR between the study groups (see Table 1).

2.3 | The VR-Based Simulation

The VR-based learning environment was designed using the Unity platform (https://unity.com) based on previous studies (Dubovi 2022; Dubovi et al. 2017). In the current research design, we adapted the existing Desktop-VR simulation to suit the highly immersive environment (HMD-VR). For example, we replaced keyboard navigation with teleportation and enabled users to grab objects with VR controllers instead of slicing or manipulating them through standard mouse interactions. In both the Desktop-VR and HMD-VR groups, students engaged in a three-dimensional (3D) simulated environment where they were represented as nurse avatars. The learning process within the simulation was structured in multiple phases. It began with familiarisation with the VR-based learning environment, followed by a focus on both declarative and procedural knowledge related to medication administration. The VR simulation modelled a hospital setting, including tutorials to provide a clear understanding of the medical administration process and detailed explanations of the virtual patient's health conditions. Additionally, the simulation allowed students to develop procedural skills by practising the medication administration process step by step. Importantly, both the Desktop-VR and HMD-VR groups experienced the same content and activities throughout the learning process.

2.4 | Data Collection Instruments

2.4.1 | Learning Process

2.4.1.1 | Cybersickness. The Simulator Sickness Questionnaire (SSQ) developed by Kennedy et al. (1993) was used to measure cybersickness levels. The SSQ was administered only

(a) (b)

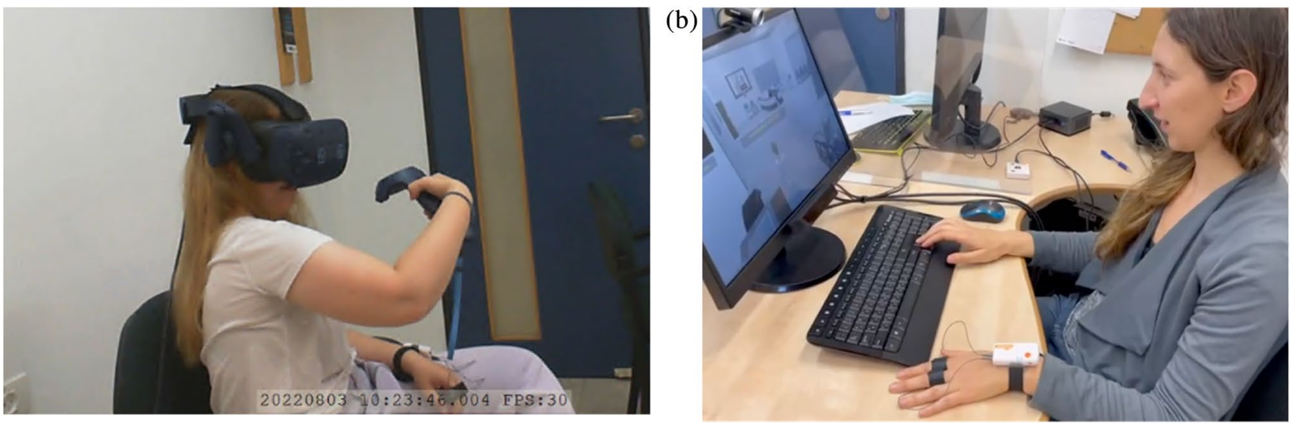

FIGURE 1 | Study groups: (a) A student learning with the high-immersive HMD-VR; (b) A student learning with low-immersive Desktop-VR.

TABLE 1 | Demographic characteristics by study groups.

	Desktop-VR ($n=35$)	HMD-VR ($n=39$)	Statistical tests
Age (years)	25.6 ± 4.4	23.3 ± 2.6	$t(73)=2.724$, $p<0.01$
Gender			
Male	5 (14.3%)	5 (12.8%)	$\chi^2(1)=0.034$, $p=0.854$
Female	30 (85.7%)	34 (87.2%)	
Economic status			
Above average	9 (29%)	14 (40%)	$\chi^2(1)=2.74$, $p=0.25$
Average	8 (25.8%)	12 (34.3%)	
Below average	14 (45.2%)	9 (25.7%)	

Note: Numbers represent N (%) or Mean ± SD.

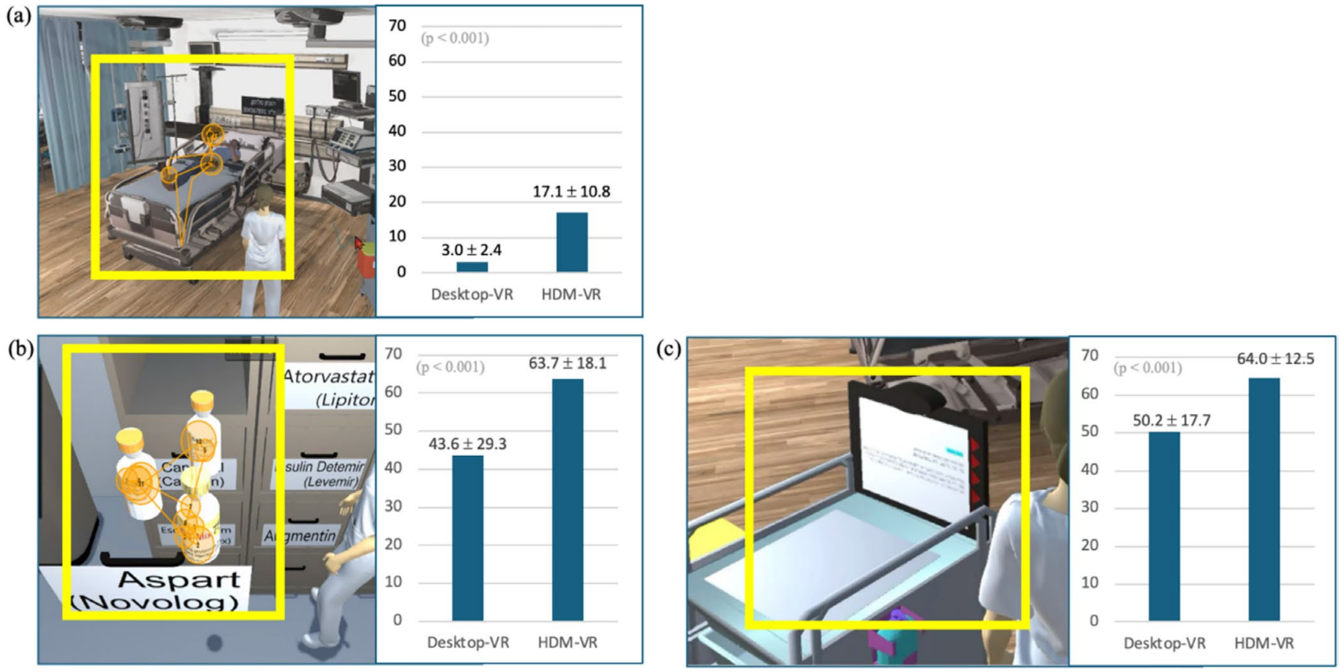

FIGURE 2 | Fixation dwell times (%) for Desktop-VR versus HMD-VR were assessed for eye-tracking metrics in the AOIs (highlighted in yellow in the screenshots: (a) A virtual patient; (b) The medication cabinet and medications; and (c) The patient's medical electronic record of medications.

to the HMD-VR group and not to the Desktop-VR group, as learning with a desktop display is considered to pose a very low risk of cybersickness (Martirosov et al. 2022; Yildirim 2020). The SSQ includes sixteen symptoms of cybersickness, rated on a 4-point scale. The total score demonstrated good reliability in the current sample (Cronbach's alpha = 0.82).

2.4.1.2 | Presence Questionnaire (PQ). The Presence Questionnaire, developed by Witmer and Singer (1998), assesses the extent to which interaction with a VR environment makes participants perceive the simulated experience as real. The instrument covers three subscales: (1) Involvement/Control (11 items), which evaluates how responsive the VR environment is to participants' actions; (2) Naturalness (3 items), which gauges the degree to which interactions within the environment feel intuitive; and (3) Interface Quality (3 items), which measures the level of distraction caused by the interface. Participants in both study groups completed the PQ immediately after engaging with the VR simulation. In this study, the overall internal consistency was $\alpha = 0.88$, closely matching previous reports (Witmer and Singer 1998).

2.4.1.3 | Cognitive Effort. Eye-tracking and EDA measurements were used as indicators of cognitive effort. We elaborate on this below:

2.4.1.3.1 | Eye-Tracking. The Smart Eye Aurora eye-tracking hardware was used to collect real-time gaze data at a frequency of 60 Hz. Designed for traditional screen-based research, the Smart Eye Aurora was utilised for the Desktop-VR group, whilst the HMD-VR group used the HTC Vive Pro Eye, which features an integrated eye-tracking system at a frequency of 60 Hz within the VR headset. Gaze metrics for three dynamic areas of interest (AOIs) were gathered and categorised using the duration dispersion filter (Holmqvist and Andersson 2017). These metrics were then post-processed using iMotions' moving tool to animate the AOIs based on the participant's perspective (Friedrich et al. 2017; Orquin et al. 2016). The three predefined AOIs were designed to capture students' visual attention (see Figure 2). The first AOI represented the virtual patient, who was animated and positioned on a bed; the second AOI encompassed the medication cabinet, where students needed to choose the appropriate medication for the virtual patient; and the third AOI covered the medical electronic record, which displayed clinical data and orders related to the patient's health. Extracted gaze metrics included indicators of cognitive load, such as the percentage of time spent looking at AOIs, the number of fixations, and the percentage of fixation dwell time. Additionally, blink rates during the VR learning session were recorded to assess the overall learning experience.

2.4.1.3.2 | EDA. The EDA signal was continuously recorded using the Shimmer 3 wristband to capture both skin conductance level (also known as tonic level) and the rapidly fluctuating component, referred to as the phasic response or skin conductance response (SCR). To isolate the faster changes in SCR from the underlying tonic signal, a smoothing filter was applied (Braithwaite et al. 2013). Following this, a peak detection algorithm, along with an artefact rejection filter, was used to calculate the number of EDA peaks per minute (Benedek and Kaernbach 2010). To minimise motion artefacts, a low-pass Butterworth filter (5 Hz cutoff) and a 500 ms moving median filter were applied to reduce noise and transient fluctuations. The EDA sensor was placed on the non-dominant hand to further mitigate movement-induced variations of the dominant hand.

TABLE 2 | Comparisons between the pre-test and post-test MAT scores of the two study groups.

Knowledge	Group	Pre-test	Post-test	Time X group interaction effect	η^2p
Declarative knowledge	Desktop-VR	57 ± 21	86 ± 20	$F(1, 73) = 0.496$, $p = 0.484$	0.007
	HMD-VR	57 ± 27	81 ± 22		
Procedural knowledge	Desktop-VR	87 ± 13	97 ± 8	$F(1, 73) = 2.496$, $p < 0.05$	0.300
	HMD-VR	89 ± 15	92 ± 18		

2.4.2 | Learning Outcomes

2.4.2.1 | Medication Administration Test (MAT). The MAT assessed the nursing students' declarative and procedural knowledge of medication administration guidelines. The test, validated in previous studies (Dubovi 2022; Dubovi et al. 2017), comprises 9 multiple-choice items across two dimensions: (1) Declarative Knowledge (four items) of procedures, such as what is the correct sequence of actions, or questions regarding guidelines on what to look for in a medicine label and how medications with expired dates should be handled. (2) Procedural Knowledge (five items) of the practical application of medication distribution. The procedural questions focused on ensuring the correct interpretation of several medication labels, for instance, identifying the correct medication by comparing generic and manufacturer names with the prescribed dosage.

Pre- and post-test MAT evaluations were identical, with questions shuffled, and were administered before and immediately after learning with VR in both study conditions.

2.5 | Procedure

For the experiment, participants assigned to the Desktop-VR group were seated in front of a computer display, whilst those assigned to the HMD-VR group were asked to wear an HTC Vive headset (see Figure 1). For both groups, eye-tracking was calibrated and EDA signals recording was verified. This was followed by a highly interactive learning session using a similar VR-based simulation for all participants. Eye-tracking and EDA were recorded and analysed in real time during the entire learning experience with VR. Data collection was supported by the iMotions 9.2 Biometric Research Platform (https://imotions.com). After the learning session, participants completed a paper-and-pencil content knowledge post-test and the Presence questionnaire. In addition, participants in the HMD-VR group were asked to complete the cybersickness questionnaire at the beginning and end of the simulation. This was not required for participants in the low-immersive Desktop-VR group, since it is considered to pose a very low risk for cybersickness (Martirosov et al. 2022; Yildirim 2020).

The university's ethics committee approved the study (#0001776-5).

2.6 | Data Analysis

Descriptive statistics (means, standard deviations, and medians) were calculated for the eye-tracking metrics, EDA, PQ, and MAT tests. Paired t-tests were conducted to compare differences in SSQ scores. Additionally, two-way repeated measures ANOVA was used to assess differences in MAT pre-test and post-test scores between the Desktop-VR and HMD-VR groups. Unpaired t-tests were performed to compare EDA metrics and blink rates between the two groups. For non-parametric data (AOI metrics of time spent (%), fixation counts, and fixation dwell time), differences in eye-tracking metrics between the two groups were analysed using Mann–Whitney *U*-tests.

3 | Results

Participants who learned with HMD-VR were asked at the beginning and at the end of the VR simulation to complete the cybersickness self-report. Results showed no significant change in students' SSQ scores (38.5 ± 19.1 vs. 38.9 ± 24.4, respectively; paired $t = -0.123$, $p = 0.903$). More importantly, the mean SSQ scores were below the threshold score (40 or higher), indicating that the simulator did not trigger severe cybersickness (Caserman et al. 2021).

3.1 | Differences Between the Study Groups

3.1.1 | MAT Test

The normality of the relative MAT scores was assessed using the Shapiro–Wilk (SW) test, which indicated a significant deviation from normality ($p < 0.001$). Levene's test showed no significant difference in variances ($p > 0.05$), indicating homogeneity of variance. Since ANOVA is robust to violations of normality due to the Central Limit Theorem (Blanca et al. 2017), it is appropriate to use a two-way repeated measures ANOVA. As described below, we conducted a two-way repeated measures ANOVA with pre- and post-test as a within-subject factor and condition (Desktop-VR vs. HMD-VR) as a between-subject factor for each type of knowledge: declarative and procedural. For declarative knowledge, there was a significant main effect of measurement time point [$F(1, 73) = 58.409$, $p < 0.001$, $\eta^2p = 0.444$], indicating that students improved their declarative knowledge whilst learning with VR. However, the interaction between time point and study group was not statistically significant (Table 2), suggesting that knowledge gains did not differ between the two groups. For procedural knowledge, we also found a significant main effect of measurement time point [$F(1, 73) = 5.449$, $p < 0.05$, $\eta^2p = 0.069$]. Unlike declarative knowledge, there was a significant interaction between time point and study group (Table 2), indicating that the improvement in procedural knowledge varied by condition. Specifically, students in the HMD-VR condition demonstrated greater gains in procedural knowledge compared to those in the Desktop-VR condition. This suggests that higher levels of immersion in VR may enhance procedural learning more effectively than lower-immersion environments.

3.1.2 | Presence

Sense of presence within the VR environment is a crucial aspect of the learning experience. The SW test revealed that the relative accuracy of presence followed a normal distribution ($p > 0.05$). Levene's test showed no significant difference in variances ($p > 0.05$), indicating homogeneity of variance. The results showed no significant difference between the Desktop-VR and HMD-VR study groups across the three PQ subscales: Involved/Comparison (5.3 ± 0.6 vs. 5.2 ± 0.5, respectively; $t = 0.630$, $p = 0.531$), Natural (4.8 ± 1.2 vs. 4.6 ± 1.2; $t = 0.837$, $p = 0.405$), and Interface Quality (5.8 ± 0.8 vs. 5.7 ± 1.2; $t = 0.402$, $p = 0.689$).

3.1.3 | Cognitive Effort

To evaluate students' cognitive effort during the learning process, EDA and eye-tracking metrics peaks were assessed whilst learning with VR across two types of knowledge acquisition: declarative and procedural.

3.1.3.1 | EDA. The SW test revealed that the relative accuracy of EDA peaks followed a normal distribution ($p > 0.05$). Levene's test showed no significant difference in variances ($p > 0.05$), indicating homogeneity of variance. For the EDA peaks per minute, significant differences were detected between the Desktop-VR and HMD-VR study groups only during procedural learning. Specifically, students who learned with high-immersive VR using HMDs experienced significantly more EDA peaks per minute during procedural skills acquisition than those who learned with low-immersive Desktop-VR (6.49 ± 3.38 vs. 4.85 ± 3.00, respectively; $t = 2.107$, $p < 0.05$). There was no significant difference between the study groups during declarative knowledge acquisition (HMD VR: 4.85 ± 3.42 vs. Desktop-VR: 4.52 ± 3.13; $t = 0.415$, $p = 0.680$).

3.1.3.2 | Eye Tracking. The SW test revealed that the relative accuracy of blink rate peaks followed a normal distribution ($p > 0.05$). Levene's test showed no significant difference in variances ($p > 0.05$), indicating homogeneity of variance. A significant difference in blink rate was observed between the Desktop-VR and HMD-VR study groups, but only during procedural learning. Particularly, learning and training on procedural content resulted in a significantly lower blink rate amongst students who used high-immersive VR compared to those who used low-immersive VR (12.90 ± 7.40 vs. 16.32 ± 6.24, respectively; $t = 2.012$, $p < 0.05$). There were no significant differences between the two study groups in terms of blink rate for declarative knowledge acquisition (HMD-VR: 14.13 ± 9.22 vs. Desktop-VR: 16.47 ± 8.90; $t = 1.061$, $p = 0.292$).

For the eye-tracking metrics, three dynamic AOIs were analysed: medications, the virtual patient, and the patient's medical electronic record (see Figure 2). Levene's test showed no significant difference in variances ($p > 0.05$), indicating homogeneity of variance. The normality of the relative scores of the three AOIs was assessed using the Shapiro–Wilk (SW) test, which indicated a significant deviation from normality ($p < 0.001$). Therefore, we conducted a Mann–Whitney *U* test for each of the AOIs. As shown in Table 3, students in the HMD-VR group devoted significantly more visual attention (time spent (%), fixation counts, fixation dwells) to the patient and medical records compared to the Desktop-VR group. Interestingly, for medications in the cabinet AOIs, there was no difference between study groups in time spent (%) and fixation counts. However, the significant difference in fixation dwells (%) suggests that visual attention was distributed differently within fixations rather than across the overall viewing behaviour. Specifically, students in the HMD-VR group held their gaze longer on medications, indicating higher cognitive processing demands (Liu et al. 2022).

4 | Discussion

Virtual reality is widely recognised as a promising educational tool, providing more than a mere replication of real-world learning environments. It possesses the potential to enhance cognitive learning processes by leveraging diverse visual–spatial representations, providing learners with more immersive and interactive experiences (Hamilton et al. 2021). The findings of this study reinforce this potential, demonstrating that students in both study groups significantly improved their post-test knowledge—both procedural and declarative—after learning with a VR-based simulation. The primary contribution of this study lies in offering a more nuanced perspective on learning with VR, examining the influence of immersion levels across different types of knowledge. Specifically, this study advances our understanding of the affordances of the VR medium for gaining procedural and declarative knowledge.

The first key finding of this study is that, in terms of immediate knowledge acquisition, learning with low-immersion Desktop-VR was comparable to high-immersion HMD-VR in declarative knowledge gain but not for procedural knowledge. Specifically, as hypothesized, we found that for procedural knowledge, the low-immersive Desktop-VR group showed significantly higher learning gains compared to the high-immersion HMD-VR group. For declarative knowledge, this result aligns with Klingenberg et al. (2024), who also observed no significant differences between the two VR formats. However, for procedural knowledge, whilst our findings align with those of Frederiksen et al. (2020), they contrast with the mixed results reported in previous studies. For example, Morélot et al. (2021) found that high-immersion VR enhanced procedural learning, whereas Klingenberg et al. (2024) reported comparable procedural performance between training with high-immersion VR and low-immersion VR.

This inconsistency in the impact of immersion levels on procedural learning could be explained by our second key finding of the higher cognitive effort observed in the HMD-VR group, as measured through eye-tracking and EDA metrics. Specifically, the results show that blinking rate, an indicator of cognitive load, was significantly lower for the HMD-VR group compared to the Desktop-VR group during procedural learning. As previous research has shown, blinking rate tends

TABLE 3 | Comparison of eye-tracking metrics in three distinct AOIs between HMD-VR and desktop-VR groups ($N = 74$).

Variable	Areas of interest (AOIs): Medications in the cabinet: Desktop-VR	Medications in the cabinet: HMD-VR	Medications in the cabinet: Statistical test (Mann–Whitney U)	Patient: Desktop-VR	Patient: HMD-VR	Patient: Statistical test (Mann–Whitney U)	Medical record: Desktop-VR	Medical record: HMD-VR	Medical record: Statistical test (Mann–Whitney U)
Time spent (%)	85 ± 19 Mdn = 85	84 ± 10 Mdn = 85	$U = 648$ $p = 0.851$	4 ± 3 Mdn = 3	17 ± 8 Mdn = 17	$U = 46$ $p < 0.001$	44 ± 30 Mdn = 41	64 ± 18 Mdn = 66	$U = 298$ $p = < 0.001$
Fixation counts	486 ± 342 Mdn = 417	650 ± 425 Mdn = 613	$U = 514$ $p = 0.097$	22 ± 20 Mdn = 15	59 ± 44 Mdn = 49	$U = 264$ $p < 0.001$	79 ± 61 Mdn = 61	161 ± 141 Mdn = 126	$U = 404$ $p < 0.01$
Fixation dwells (%)	50 ± 18 Mdn = 52	64 ± 12 Mdn = 64	$U = 360$ $p < 0.001$	3 ± 2 Mdn = 2	17 ± 11 Mdn = 15	$U = 36$ $p < 0.001$	29 ± 18 Mdn = 29	51 ± 16 Mdn = 51	$U = 214$ $p < 0.001$

Note: Data are Mean ± SD; Mdn = median. All comparisons via Mann–Whitney U test.

to decrease during cognitively demanding tasks, enhancing visual processing (Martins and Carvalho 2015; Stern and Skelly 1984). Therefore, we suggest that learning procedural information with highly immersive VR was associated with a higher cognitive load. Similarly, the findings indicated that students using HMD-VR devoted more visual attention—measured by longer fixation durations and increased time spent gazing at procedural information, such as details about medications and medical records—compared to those using Desktop-VR. Prior research suggests that a higher proportion of fixations within relevant areas is a marker of increased difficulty in information processing (Liu et al. 2022; Zu et al. 2018). Given the importance of medications and medical records for procedural decision-making, the longer fixation durations in these areas suggest that participants experienced a higher cognitive load during procedural learning.

A deeper consideration of the interaction between declarative and procedural knowledge provides additional insight into the cognitive demands observed in this study. In cognitive skill acquisition theory (Anderson 1982), declarative knowledge typically precedes and supports the development of procedural knowledge through a process of compilation. However, if learners are faced with excessive cognitive demands—such as those induced by high-immersive environments—the transition from declarative understanding to fluent procedural execution may be disrupted. The present findings suggest that whilst both VR conditions facilitated gains in declarative knowledge, only the lower-immersion Desktop-VR condition supported a more effective integration of declarative into procedural knowledge. This may be due to the reduced cognitive burden, allowing learners to retrieve, apply, and gradually automate their factual knowledge. In contrast, learners in the high-immersion condition may have been cognitively overloaded, inhibiting this integration process. Thus, the interplay between knowledge types is not only sequential but contingent on the learning environment's design and cognitive load management. This reinforces the need for instructional strategies in immersive VR that actively scaffold this knowledge transition, such as structured reflection or phased procedural practise.

In this context, students in the HMD-VR condition exhibited a significantly higher number of EDA peak responses whilst learning procedural content compared to those using Desktop-VR. EDA, which measures sympathetic nervous system activity, is commonly viewed as an indicator of attentional processing, with cognitively demanding tasks leading to increased EDA levels (Lee et al. 2019; Liberman and Dubovi 2023). These findings reinforce the conclusion that highly immersive VR imposes a greater cognitive load than less immersive desktop VR, especially when learning procedural tasks. Overall, these findings from psychophysiological measures of cognitive load suggest that procedural learning may demand more cognitive resources than declarative learning when using high-immersive VR compared to low-immersive VR, potentially impacting procedural knowledge outcomes. Whilst previous studies demonstrated that excessive extraneous cognitive processing is linked to learning with high-immersive VR (Frederiksen et al. 2020; Makransky et al. 2019a, 2019b; Parong and Mayer 2021), the current study provides a more nuanced perspective pointing toward specific knowledge acquisition, namely procedural learning. This finding suggests that immersion level should not be viewed as merely an entertaining add-on but as a factor that influences cognitive processing, requiring unique instructional design.

Challenging the instructional design of learning with VR, we suggest considering Chi and colleagues' cognitive theory (Chi and Wylie 2014), which classifies learning activities across four behavioural modes: interactive, constructive, active and passive (ICAP). Whilst Cognitive Load Theory (Sweller et al. 1998) models learners' working memory, ICAP provides an instructional framework that helps balance intrinsic, extraneous, and germane cognitive loads. According to the ICAP, deeper cognitive engagement with instructional experiences increases germane cognitive processes, leading to better learning outcomes (Chi et al. 2018). For instance, engaging learners in the constructive mode through self-explanation increases intrinsic and germane cognitive loads by enhancing understanding and schema construction, whilst reducing extraneous load by focusing on relevant information.

In the current study, our instructional design fostered similar levels of cognitive engagement. Based on the ICAP theory, both groups engaged in an active learning mode that required focused attention—such as rotating and moving medication bottles to select the correct one. The HMD-VR group used controllers for these actions, whilst the Desktop-VR group used a mouse and keyboard. To fully maximise the potential of high-immersive VR, which imposes a greater cognitive load during procedural learning, we recommend integrating higher ICAP instructional modes. Specifically, constructive and interactive strategies—such as self-explanation prompts (e.g., "What could go wrong if I skipped this step?"), guided reflection checkpoints, or collaborative role-switching in shared virtual environments—can support deeper processing whilst mitigating cognitive overload. For low-immersive VR, where cognitive demands are generally lower, learners may still benefit from constructive or interactive strategies, but in many cases, well-designed active learning tasks, such as making decisions based on presented clinical information, independently sequencing procedural steps or responding to patient scenarios, may be sufficient to support effective learning without overloading the learner. Aligning ICAP modes with immersion levels and task complexity ensures that cognitive resources are optimised across VR designs.

Lastly, the third key finding revealed that the perceived sense of presence was similar between both study groups. This result can be explained by Steuer (1992) assertion that the impact of VR interactions is influenced not only by the level of immersion but also by the degree of interactivity. Steuer (1992) describes interactivity as the extent to which users can alter the form or content of a mediated environment in real time, based on factors such as speed, range, and intuitive alignment between user actions and system responses. Since both study conditions offered high levels of interactivity, allowing participants to explore and modify the virtual hospital environment, it likely contributed to an equally strong sense of presence across both groups, regardless of immersion level.

4.1 | Limitations

This study has several limitations. First, although higher cognitive load was identified when learning with high-immersive VR, the post-tests evaluated only immediate learning outcomes. This highlights the need for further investigation, including assessments of long-term retention, transfer of learning, and the use of open-ended questions to measure students' deeper understanding and reasoning abilities. Additionally, this study was conducted in the nursing field, where women constitute 89% of the global workforce (WHO 2021). Given the significant female representation in this field, future research should aim to control for potential gender differences in VR-based learning by including disciplines with a more balanced gender distribution. Expanding the study to other healthcare professionals could further enhance the generalisability of the findings.

5 | Conclusions

This study contributes to the growing body of evidence supporting VR as an effective learning tool by providing empirical findings that highlight its impact on knowledge retention. Both low-immersive and high-immersive VR were found to facilitate immediate retention of knowledge, with low-immersive VR yielding greater gains in procedural knowledge. Through the integration of psychophysiological sensors, this study offers an in-depth explanation of the higher cognitive load experienced when learning procedural tasks in high-immersive VR compared to low-immersive VR. These findings underscore the importance of thoughtful instructional design in VR-based simulations to effectively manage and mitigate the external cognitive load imposed by high levels of immersion during procedural learning. Understanding how different immersion levels influence cognitive processes is crucial for optimising educational outcomes in VR settings.

Future research should delve deeper into pedagogical approaches that can address and balance the cognitive demands of immersive VR, enhancing its potential as an educational tool whilst maximising the learning experience. Future studies should apply machine learning algorithms to analyse the continuous nature of multimodal data, such as eye-tracking and EDA. These approaches can uncover real-time patterns in learners' cognitive and emotional states, enabling personalised, ICAP-based instruction. For example, adaptive systems could adjust task complexity or prompt constructive engagement based on physiological indicators, supporting more effective learning in immersive VR environments.

Author Contributions

Idit Adler: conceptualization, methodology, validation, supervision, investigation. **Liat Liberman:** investigation, data curation, formal analysis, conceptualization, validation. **Ilana Dubovi:** conceptualization, investigation, funding acquisition, writing – original draft, methodology, validation, visualization, writing – review and editing, formal analysis, project administration, data curation, supervision, resources.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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