



Systematic Review

Assessing Cognitive Load Using EEG and Eye-Tracking in 3-D Learning Environments: A Systematic Review

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Abstract

The increasing use of immersive 3-D technologies in education raises critical questions about their cognitive impact on learners. This systematic review evaluates how electroencephalography (EEG) and eye-tracking have been used to objectively measure cognitive load in 3-D learning environments. We conducted a comprehensive literature search (2009–2025) across PubMed, Scopus, Web of Science, PsycInfo, and ERIC, identifying 51 studies that used EEG or eye-tracking in experimental contexts involving stereoscopic or head-mounted 3-D technologies. Our findings suggest that 3-D environments may enhance learning and engagement, particularly in spatial tasks, while affecting cognitive load in complex, task-dependent ways. Studies reported mixed patterns across psychophysiological measures, including spectral features (e.g., frontal theta, parietal alpha), workload indices (e.g., theta/alpha ratio), and gaze-based metrics (e.g., fixation duration, pupil dilation): some studies observed increased load, while others reported reductions or no difference. These discrepancies reflect methodological heterogeneity and underscore the value of time-sensitive assessments. While a moderate cognitive load supports learning, an excessive load may impair performance, and overload thresholds can vary across individuals. EEG and eye-tracking offer scalable methods for monitoring cognitive effort dynamically. Overall, 3-D and XR technologies hold promise but must be aligned with task demands and learner profiles and guided by real-time indicators of cognitive load in immersive environments.

Keywords: 3-D learning environments; cognitive load; EEG; eye-tracking; psychophysiology; immersive technologies; multimodal measurement; XR in education; spatial learning



Academic Editor: Arun
K. Kulshreshth

Received: 31 July 2025

Revised: 10 September 2025

Accepted: 16 September 2025

Published: 22 September 2025

Citation: Khan, R.; Vernooij, J.; Salvatori, D.; Hierck, B.P. Assessing Cognitive Load Using EEG and Eye-Tracking in 3-D Learning Environments: A Systematic Review. *Multimodal Technol. Interact.* **2025**, *9*, 99. <https://doi.org/10.3390/mti9090099>

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1. Introduction

1.1. Overview

Humans engage their cognitive abilities in many ways, spanning from daily decision-making to complex learning processes. Cognitive research, particularly in learning and memory, is applicable across disciplines such as STEM, psychology, neuroscience, and education. The findings from this research are crucial for developing educational tools, programs, and curricula aimed at enhancing learning and knowledge retention and transfer. The integration of technological advancements into daily life and educational frameworks has opened a new realm of possibilities for the use of three-dimensional (3-D) technologies

in the cognitive and educational landscape. While some view 3-D learning environments as transformative, others argue that they may distract from core learning objectives or impose heightened mental demands on learners [1,2]. Such concerns underscore the need for objective, time-sensitive methods to assess individuals' cognitive load and mental effort during engagement with these technologies. This systematic review aims to identify and synthesize empirical studies that have employed electroencephalography (EEG) and/or eye-tracking methodologies to investigate the cognitive implications of 3-D learning technologies.

To ground the use of such technologies in theory, one influential framework is Mayer's cognitive theory of multimedia learning (CTML) [3,4]. This theory posits that learning is enhanced when information is presented through multiple modalities—such as visual and verbal channels—because this approach leverages the brain's dual processing systems. It suggests that well-designed multimedia instructional materials can improve comprehension and retention by facilitating a more effective use of cognitive resources.

1.2. Learning & 3-D Technologies

In 3-D learning environments, it is the spatial depth, interactivity, and multisensory fidelity of the experience that create a heightened sense of immersion—an experiential state strongly associated with improved engagement, deeper comprehension, and better retention of information [5–8]. Building on this foundation, the integration of new 3-D technologies like extended reality (XR), which represents a technology spectrum that includes augmented reality (AR), virtual reality (VR), and mixed reality (MR), into learning environments introduces a new dimension to learning, performance enhancement, and retention of skills [9]. Among these, stereoscopic 3-D technologies deliver depth perception by presenting offset images to each eye, typically through 3-D glasses or specialized screens, while 3-D headsets, such as VR head-mounted displays (HMDs), integrate stereoscopic imagery with motion tracking to create immersive environments [10,11]. Research has shown that 3-D technologies such as AR and VR significantly enhance learners' sense of immersion—the feeling of being enveloped in and engaged by the learning environment—and presence, the psychological state of “being there” within the virtual space [6,7]. These experiential factors are associated with increased motivation, attentional focus, and, in some cases, improved knowledge retention and skill transfer, particularly in domains that require spatial reasoning or hands-on practice [2,9].

Transferring two-dimensional (2-D) knowledge into the three-dimensional (3-D) domain is very important in disciplines pertaining to, e.g., medicine or veterinary science, where learners interpret information from textbooks into the context of their patients. It is also crucial when interpreting medical images (e.g., CT, MRI), which are often 2-D in nature. Domain specificity of knowledge, i.e., being two-dimensional or three-dimensional, requires “interdimensional travel” [12], which can be supported by 3-D visualization technologies. To assess the beneficial and practical qualities of 3-D technologies in learning environments, some studies have used experimental paradigms to assess how 3-D technologies, on their own or compared to other more traditional 2-D learning settings, impact learning, retention of knowledge, and transfer of knowledge. For instance, various studies propose that 3-D environments have the potential to lessen the cognitive load in scenarios that necessitate the transfer of knowledge across dimensions. This reduction is attributed to improved engagement and interaction, as well as the strategic use of specialized visualization technologies [13–15].

For instance, in surgical skills training, stereoscopic 3-D visualization systems significantly accelerated novices' proficiency in laparoscopic pattern-cutting tasks, reducing the time-to-proficiency by over 65 s compared to 2-D setups [16]. Other studies confirm that 3-D vision enhances learning curves more broadly in minimally invasive surgery [17].

Likewise, in architecture and 3-D scene design, interactive context-aware suggestions have been shown to reduce the overall modeling time by 32% and minimize re-orientation efforts by 27% [18].

A key area where 3-D technologies show significant promise is in the acquisition and application of spatial knowledge—a critical component in disciplines requiring precise manipulation, positioning, and rotation of objects in space [19]. The results of this research have posed interesting findings such as differential benefits for individuals with low spatial ability compared to those with higher spatial ability. Stereoscopic 3-D visualization improved the performance of those with low spatial ability compared to those with high spatial ability [19,20]. To better understand how 3-D visualizations affect learning and performance in spatial tasks, it is necessary to investigate how these technologies may impact the brain and behavior. Therefore, it is pertinent to explore how mental effort and the cognitive load are affected when using 3-D technologies. This systematic review aims to extract how 3-D technologies influence cognitive processes, with a keen focus on cognitive load. Since 3-D technologies allow additional possibilities for adapting the learning process to achieve optimal levels of mental effort, it is instrumental to be able to objectively measure cognitive load to assess how this occurs.

It is worth mentioning that the effectiveness of 3-D learning is not determined by technology alone. Factors such as the topic being taught, the curriculum design, the learning context, and the expertise of the teacher can all influence outcomes independent of the medium. Instructors play a pivotal role in selecting when and how to integrate 3-D tools, ensuring that they align with curriculum goals and avoiding introducing unnecessary complexity [21,22]. Evidence suggests that 3-D approaches are most beneficial for topics with a high spatial component—such as anatomy, engineering design, and complex molecular structures—where visualizing and manipulating objects in three dimensions supports schema construction and skill transfer [19,23,24]. Conversely, for highly abstract or low-spatial tasks, simpler formats may be equally or more effective, as they avoid the extraneous cognitive load sometimes associated with immersive environments [2].

1.3. Cognitive Load

Cognitive load refers to the amount of mental effort required to process information in working memory during learning or task performance. It reflects the strain placed on an individual's cognitive system by the complexity, novelty, or volume of incoming information. When this load exceeds the working memory's capacity, performance deteriorates, and learning can be impaired [25–27]. Therefore, it is important to achieve a balance between enhancing learning efficiency and avoiding cognitive overload.

Cognitive load theory (CLT) guides this exploration, categorizing cognitive loads into intrinsic, extraneous, and germane types, each of which plays a distinct role in learning and memory formation [25]. The intrinsic load increases when there is greater complexity in a task, and this adds strain to the working memory system [28]. Extraneous load is the load imposed by methods of instruction and delivery that can increase the cognitive load and cognitive processing as opposed to activating existing schemas [26]. Alternatively, germane load can be a positive aspect of cognitive load that enhances learning acquisition of new information by increasing engagement, motivation, and creation of new schemas [29,30].

In related research, mental effort is often treated as a key indicator of cognitive load, particularly in studies using subjective rating scales or performance-based metrics. While cognitive load refers to the demands imposed by a task, mental effort reflects the learner's voluntary investment of cognitive resources in response to those demands, which may vary between individuals or across time even under identical task conditions [26,31].

Recent conceptual work has emphasized that the cognitive load is not static over the course of a task. Instead, it fluctuates across task segments, which leads to constructs such as instantaneous load, peak load, and average load over time [32]. These distinctions have proven valuable for understanding how learners manage their cognitive resources dynamically during complex or interactive tasks.

To capture these different types of loads—especially as they fluctuate over time during complex or immersive tasks—researchers increasingly require methods that provide continuous, objective insight into learners' mental effort in real time.

1.4. Psychophysiological Measurements

Understanding how 3-D technologies affect cognitive load in real time requires methods that go beyond self-report and post hoc testing. Psychophysiological techniques provide this capability, enabling researchers to link observable neural and ocular responses directly to the cognitive demands imposed by a task. This review emphasizes how 3-D technologies can influence cognitive load. The underlying hypothesis is that when instructional design aligns with the technology's spatial fidelity, interactivity and the pacing of task demands, it can maintain cognitive load within an optimal range. This optimal range is high enough to foster engagement and schema construction (germane load) but low enough to avoid overload from unnecessary complexity (extraneous load). In measuring how 3-D technologies influence cognitive load, a distinction must be made between subjective and psychophysiological measurements. Although subjective methods, such as self-report questionnaires, provide valuable insights into participants' perceived experiences and effort, they inherently lack the continuity, precision, and time-sensitivity required to understand the role of fluctuating cognitive dynamics.

Physiological measurements of cognitive load are objective and have been employed by researchers to gain insight into mental processes underlying cognitive processing, load, and effort. These methods offer an alternative tool for measuring load, especially as it fluctuates over time and during a task. Researchers have utilized a broad range of physiological methods to investigate cognitive load, including but not limited to the following: heart rate variability (HRV), fMRI, EEG, galvanic skin response (GSR), eye-tracking, and pupillometry.

However, some of these physiological measures, while informative, face practical and methodological limitations that reduce their applicability to authentic learning contexts. For instance, one measurement that has been employed in relation to cognitive load is HRV, which has been said to be insensitive to fluctuations in instantaneous load during a task [33] and not able to capture sensitive variations in load in educational scenarios [34]. Alternatively, neuroimaging techniques like fMRI are quite slow at capturing instantaneous and momentary processes and are also expensive to employ. Therefore, for the purpose of this review, we focused primarily on the psychophysiological methods of EEG and eye-tracking.

There exists a vast amount of literature in regard to these methods being used to measure cognitive load and mental effort. Their accessibility and feasibility in real-world settings make them ideal methodologies for measuring cognitive load in 3-D contexts. To provide an overview of how they are applied, Table 1 summarizes the main psychophysiological methods explored in this review alongside the metrics they use and their interpretations in relation to cognitive load.

Table 1. Summary of Methods & Cognitive Load interpretations.

Method	Metrics	Cognitive Load Interpretations
EEG (Spectral)	Theta (4–7 Hz), Alpha (8–12 Hz), Alpha/Theta Ratio	Theta increases reflect task difficulty, processing demands, and working memory load. Alpha decreases indicate heightened attentional engagement. Alpha/theta ratio provides greater sensitivity in distinguishing load levels across tasks and individuals.
ERPs	Time-locked components (N1, N2, P1, P2, P3/P3b)	Early sensory components (P1/N1) scale with perceptual load and selective attention; P2 reflects early stimulus evaluation. N2 typically increases with conflict/selection demands, indexing control. The P3/P3b is workload-sensitive: higher load generally reduces amplitude and prolongs latency, indicating constrained attentional/working-memory resources
Eye-tracking	Fixation duration, fixation counts, saccade patterns, pupil dilation, gaze distribution	Longer fixations and fewer saccades often indicate higher cognitive demand. Pupil dilation reflects increased effort but is sensitive to luminance, arousal, and fatigue. Gaze distribution and scanning patterns reveal attentional strategies and search costs in complex 3-D tasks.

1.4.1. EEG

Electroencephalography (EEG) is a non-invasive technique that continuously captures the electrical activity of the brain through electrodes placed on the scalp [35], offering high temporal resolution for studying dynamic neural processes [36,37]. EEG is particularly valuable in cognitive load research due to its sensitivity to rapid fluctuations in mental effort, attentional engagement, and memory [38,39].

The task difficulty and mental workload are commonly indexed by spectral changes in theta (4–7 Hz) and alpha (8–12 Hz) frequency bands. Increases in theta power have been shown to be sensitive to changes in task difficulty or processing [38–41], as well as heightened cognitive control and working memory demands, whereas decreases in alpha power often reflect reduced cortical inhibition and increased attentional resource allocation [40,42]. Emerging methods that use alpha–theta ratios have demonstrated improved sensitivity in differentiating levels of cognitive load across tasks and individuals [43]. These indices provide temporally precise insights into how learners process and manage information in cognitively demanding 3-D environments.

Complementing spectral analyses, event-related potentials (ERPs) offer time-locked measures of brain responses to task-relevant stimuli. Components of ERPs reflect sequential stages of information processing—from early perceptual attention to later cognitive operations like categorization, conflict monitoring, and memory updating [44,45]. While individual component interpretations must be made cautiously due to overlap and task confounds, ERP analyses nonetheless provide valuable markers of when—and how—cognitive effort unfolds in response to task complexity.

When applied with methodological rigor, EEG and ERP measures serve as complementary tools for assessing the mental workload during spatial and immersive 3-D tasks, illuminating how different populations allocate neural resources in response to varying cognitive demands.

1.4.2. Eye-Tracking

Eye-tracking is a non-invasive method that records eye movements and gaze patterns to capture where, when, and how long individuals visually attend to elements in their environment [46,47]. Through metrics such as fixation duration, saccade patterns, pupil dilation, and gaze distribution across predefined areas of interest, eye-tracking allows

researchers to infer individuals' cognitive load, mental effort, and engagement during task performance in an objective way and with enough time resolution to capture transient dynamics [46–49].

In studies involving 3-D technologies, eye-tracking offers insight into how users visually navigate and interact with complex stimuli. Fixation counts and durations are commonly interpreted as indicators of cognitive processing, while saccade patterns reflect search strategies and visual scanning behavior [48,49]. Increased fixation duration and reduced saccadic frequency may signal heightened cognitive load, demand, or difficulty in information integration [50,51].

Pupil dilation, another eye-based index, has been robustly linked to mental effort and task difficulty [52–54]. However, interpreting pupil-based metrics requires careful control, as pupil size is also highly sensitive to ambient luminance, screen brightness, emotional arousal, and fatigue—factors that can confound cognitive interpretations if not accounted for [55,56].

Despite these limitations, eye-tracking remains a powerful real-time tool for assessing how visual attention is distributed across learning environments. In the context of 3-D interfaces or virtual learning scenarios, it helps determine whether such technologies support cognitive efficiency or impose extraneous load by fragmenting individuals' attention or increasing search costs [57]. When used alongside EEG or ERP, eye-tracking provides complementary data about the visual and cognitive demands of technologically enhanced learning.

Table 1 summarizes the psychophysiological methods identified in this review, highlighting the metrics that are commonly used and how they are interpreted in relation to cognitive load. Spectral EEG indices (theta, alpha, and their ratios) are sensitive to task difficulty, attentional demands, and working memory load. Event-related potentials (ERPs) provide time-locked markers of perceptual and cognitive processes, with specific components (e.g., P1, N2, P3) reflecting stimulus evaluation, conflict monitoring, and working memory operations. Eye-tracking metrics (fixation, saccades, pupil dilation, gaze distribution) capture mental effort, attentional strategies, and visual search costs in complex environments.

1.5. Objectives and Research Questions (RQs)

Although both EEG and eye-tracking have been widely used to investigate cognitive load in educational settings, and several reviews have examined cognitive load in 3-D learning or simulation environments, there remains limited systematic analysis of how objective psychophysiological methods—such as EEG and eye-tracking—have been applied to assess mental effort in 3-D contexts.

Therefore, our reason for employing EEG and eye-tracking as our objective measures in this systematic review is twofold: they offer direct and indirect indices of cognitive load that are not accessible through subjective assessments, and they provide a continuous measurement of cognitive processes throughout a task. This approach enables a more precise and comprehensive exploration of the potential benefits and drawbacks of 3-D technologies in real-world learning settings. The outcomes from these objective measures could bear significant implications for educational design. If 3-D technologies can indeed combat cognitive overload for individuals, for example in contexts of spatial visualization, they could revolutionize educational paradigms, particularly in disciplines like medicine where the translation of 2-D knowledge to 3-D contexts is crucial.

To evaluate the advantages of immersive 3-D technologies for learning, this review synthesizes studies that vary across several key dimensions. These include the experimental design (e.g., within-subject or between-subject), the learning or cognitive task

employed (e.g., memory, navigation, reading, simulation), the types of 3-D technology used (e.g., VR headsets, stereoscopic displays, AR applications), the control condition (e.g., desktop monitor, 2-D video, physical materials), and the measured outcomes (e.g., task performance, EEG indicators, eye-tracking metrics). Other studies examined herein evaluate outcomes within immersive 3-D environments only, by comparing different task conditions or difficulty levels to infer the cognitive load or performance effects.

We categorize learning outcomes based on metrics such as accuracy, task efficiency, or knowledge transfer, and assess cognitive load using psychophysiological measures like frontal theta power, parietal alpha suppression, pupil dilation, or fixation behavior. Some studies rely on a single method (EEG or eye-tracking), while others combine both to triangulate mental effort.

From this review, we expect to find that 3-D technologies will be useful tools in improving learning and performance, especially in spatial tasks, compared to 2-D alternatives. However, in some instances, 3-D technology may contribute to cognitive overload as measured by fluctuations in EEG and eye-tracking measures.

We explore this in our review through two main research questions:

RQ1: What is the impact of 3-D technologies on learning and performance?

RQ2: What effects do 3-D technologies have on cognitive load as reflected by EEG and eye-tracking?

2. Materials and Methods

2.1. Registration of the Study

This study used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) as a guideline for reporting. The protocol was registered in Open Science Framework OSF: <https://doi.org/10.17605/OSF.IO/QXGZR> (accessed on 17 September 2025).

2.2. Search Strategy

Articles were selected from the following databases: PubMed, PsycInfo, Web of Science, SCOPUS, and Education Resources Information Center (ERIC). To select the search terms, we used our inclusion criteria as a framework and consulted with a librarian to identify the necessary keywords and medical subject heading (MeSH) terms. Our PubMed search string was as follows:

("cognitive load"[Title/Abstract] OR "mental effort"[Title/Abstract] OR "mental load"[Title/Abstract] OR "Working Memory"[Title/Abstract] OR "Memory Load"[Title/Abstract] OR "Memory Capacity"[Title/Abstract] OR "Working Memory Capacity"[Title/Abstract]) AND ("Virtual Reality"[Title/Abstract] OR "Augmented Reality"[Title/Abstract] OR "Mixed Reality"[Title/Abstract] OR "3D"[Title/Abstract] OR "3-D"[Title/Abstract]) AND ("electroencephalography"[Title/Abstract] OR "EEG"[Title/Abstract] OR "eye tracking technology"[MeSH Terms] OR "eye tracking"[Title/Abstract] OR "eyetracker"[Title/Abstract] OR "eyetracking"[Title/Abstract] OR "neuroimaging"[Title/Abstract] OR "psychophysio*"[Title/Abstract]) AND ("humans"[MeSH Terms]) AND ("english"[Language]) AND (2009/01/01[dp]: 2025/03/31[dp]).

Equivalent strategies were developed for SCOPUS, Web of Science, PsycInfo, and ERIC, with terms and syntax being adapted to each database's indexing system. These full strategies are reported in Appendix A for transparency and reproducibility. We utilized the search method strategy of using a truncation symbol such as an asterisk (*) to ensure that terms with differences in tenses and endings still appeared. Our search time window was from the year 2009 to March 2025. We further searched on Google Scholar to find any studies that were relevant to this review that may not have appeared in the databases.

2.3. Study Selection

The search identified a total of 1862 records from 5 databases and 5 additional records that were identified by handsearching the bibliographies of selected papers and with a search in Google Scholar (Figure 1). Out of the 5 databases and 1862 records, the results by database were as follows: Web of Science: 286, Scopus: 297, PubMed: 1024, PsycInfo: 226, and ERIC: 29. These studies were managed and collected in Rayyan [58], where 1251 records remained after duplicates were removed. These studies were further screened and tested for eligibility by screening their title and abstract. Further full-text screening occurred, in which 1002 studies were excluded due to either irrelevance or unsuitability to the topic, 117 were missing inclusion criteria, and 81 were remaining duplicates. Finally, 51 studies were included in the systematic review.

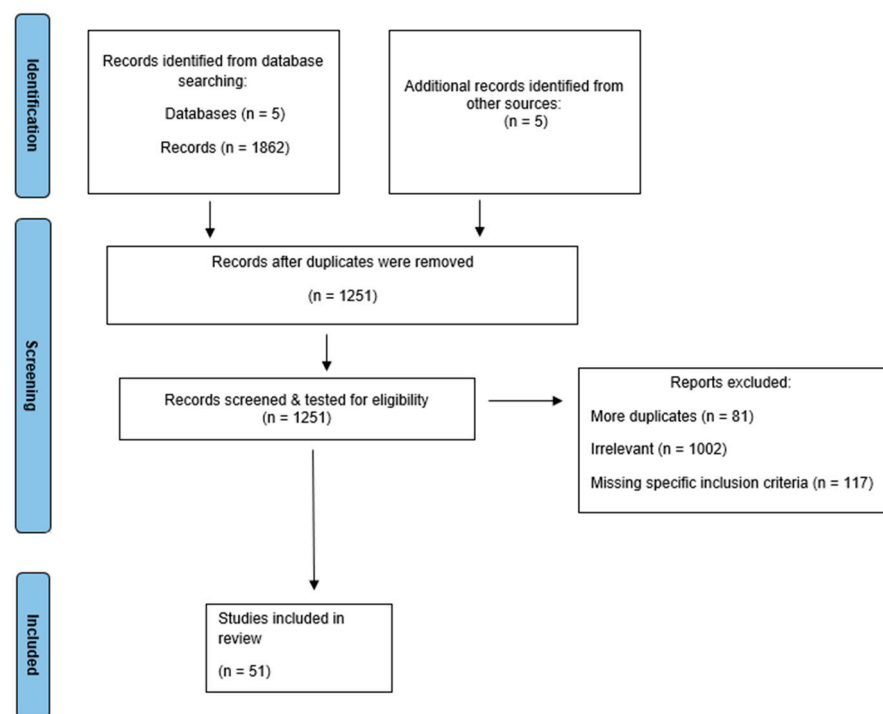


Figure 1. PRISMA chart. Flow diagram of manuscripts screened, included, and excluded from the systematic review.

2.4. Inclusion Criteria

The inclusion criteria of this systematic review were strict. Included studies had to consist of a study with a stereoscopic 3-D technology or 3-D headset (3-D on a 2-D screen with no headset or stereoscopy was not included), an experimental design with an intervention/task, the use of either EEG or eye-tracking, and changes in pre versus post measures of knowledge or skill following the use of a 3-D intervention. In terms of the 3-D interventions, we strictly adhered to the use of 3-D technologies that either used a headset or implemented stereoscopy. It was necessary for us that the participants had a total experience of 3-D visually rather than interacting with a 3-D model on a 2-D screen, which we did not count as a wholly 3-D experience or technology. The PICO framework was used to outline the specific types of search criteria (Table 2). The types of participants were healthy adults/young adults (no race/gender restrictions). For outcome measures, we selected studies that investigated the impact of 3-D technologies on knowledge acquisition, knowledge retention, skill training, and/or post performance after 3-D training in combination with psychophysiological measures of cognitive load. We did not restrict our search to a specific domain, i.e., education. Interventions using 3-D technologies included

but were not limited to head mounted displays (HMD), eye-trackers, and stereoscopic environments. The psychophysiological methods included were EEG and eye-tracking. Studies from 2009 until the search period's end in March 2025 were included.

Table 2. PICO framework.

Patient/Population	Intervention	Comparison	Outcome(s)
Young Adults/ Adults	VR/AR/MR/XR /3-D Technologies	2-D task versions, alternative control conditions (e.g., desktop, booklet, standard instruction), or no explicit comparison (3-D condition only)	Cognitive load (EEG indices: theta/alpha power, ERP components; eye-tracking: fixation duration, saccades, pupil dilation), mental effort, and behavioral outcomes (accuracy, retention, transfer, reaction time, task efficiency)

This table presents the PICO (Patient/Population, Intervention, Comparison, Outcome) framework used in the systematic review. The patient population includes young adults and adults. Interventions involve 3-D technologies such as extended reality (XR), which is sometimes referred to as virtual reality (VR), augmented reality (AR), or mixed reality (MR). Comparison/reference is made with 2-D interventions, control interventions, or no intervention. Outcomes measured include cognitive load, mental effort, task performance, retention, reaction time, and psychophysiological assessments.

2.5. Exclusion Criteria

The exclusion criteria were developed alongside the inclusion criteria and to inform the search strategy. We excluded articles lacking full text, not written in English, using non-human subjects, investigating clinical populations, and lacking an experimental paradigm. As 3-D technologies have advanced considerably in recent years, studies older than 2009 were excluded. We excluded studies that did not use an appropriate 3-D visualization technology, for instance a lack of employment of a headset and/or a stereoscopic 3-D projection. We also excluded studies that did not have a combination of all of our search criteria: if the study met the 3-D requirement but did not involve measurement via EEG or eye-tracking parameters, we excluded the study and vice versa.

2.6. Screening

Two independent reviewers (R.K and B.P.H) assessed the eligibility of the studies by first examining the title and abstract of the studies that were exported to an AI-based reference manager (Rayyan) based on predetermined inclusion and exclusion criteria. Rayyan helped in keeping track of each of the decisions to exclude and include papers as well as detecting duplicate papers. This was followed by a full-text screening of the articles which had relevant titles and abstracts. Each of the reviewers was blind to the other reviewer's selections until they had independently screened all papers. Once all papers were screened independently in Rayyan, the authors were able to see each other's included papers and see whether conflicts existed in the selections. In instances when the two reviewers disagreed on whether a paper should be included, the two reviewers had a discussion regarding specific papers and were able to come to a conclusion.

2.7. Psychophysiological Methods

2.7.1. EEG

In studies that employed EEG methodology, we extracted data on signal components commonly associated with cognitive load and mental effort, including frontal midline theta (4–8 Hz) and task-dependent alpha activity (8–12 Hz) in parietal or central regions. Previous research has shown that the frontal theta tends to increase with rising working memory demands and task difficulty, while the alpha power is often modulated by attentional load and visual processing demands [38,59,60].

Building on these patterns, several researchers have developed load-sensitive indices that quantify the relationship between increases in frontal theta power and concurrent decreases in alpha activity. These composite measures, often referred to as cognitive load indices (CLIs), are designed to capture moment-to-moment variations in mental workload across task conditions, offering a continuous and scalable representation of processing demands [14,61,62]. Such indices are increasingly employed across applied neuroscience, multimodal human–technology interaction, and adaptive learning systems to distinguish between low-, moderate-, and high-cognitive load states.

In this systematic review, we included studies that employed event-related potentials (ERPs) including but not limited to P1, N1, P2, N2, and P3 and EEG indices/ratios to better understand the mental workload and/or cognitive load for a task or experimental manipulation [15,62,63]. We extracted any reported EEG-based indices or ratios—such as frontal theta to parietal alpha—that were used to operationalize cognitive load, mental effort, or workload state [15,61,62]. In addition, we noted studies that employed more complex multivariate workload indices, which combined multiple spectral and spatial EEG features into a single metric scaled from 0 to 1 that represented cognitive states such as low engagement, optimal effort, or cognitive overload [63–65]. These models often drew from machine learning or regression-based classification approaches and were validated against task difficulty or performance benchmarks.

While the present review focuses on classical psychophysiological signal interpretation, future EEG-based cognitive load studies may benefit from advances in signal acquisition, like electromagnetic interference (EMI) mitigation, developed in other biomedical domains. For example, carbon-fiber-reinforced polymer (CFRP) composites, used for EMI shielding, have demonstrated effectiveness in attenuating electrical noise, which suggests a possible role as low-profile shielding materials for EEG headset casings [66]. Likewise, soft computing approaches for eddy-current defect detection demonstrate how feature extraction and machine learning can robustly classify signals under noisy conditions—a paradigm that could translate into better artifact rejection in EEG data acquisition [67].

In parallel, recent work has highlighted the importance of monitoring the specific absorption rate (SAR) and thermal accumulation in smart electronic and headset-based devices, where prolonged use may increase local tissue heating [68]. Such thermal discomfort can itself act as a source of extraneous cognitive load, diverting attention away from task demands [25–28]. Addressing these issues by adopting such cross-domain strategies could enhance both the signal integrity and the safety profile of EEG and XR systems, though this was beyond the scope of the studies reviewed.

2.7.2. Eye-Tracking

Another technique of interest in this review was eye-tracking, which has been widely used to assess working memory, attentional strategies, mental effort, and cognitive load in a variety of learning and task environments [69,70]. Eye-tracking data offer temporally rich, non-invasive insight into where and how visual attention is allocated during task performance. We screened included studies for the use of eye-tracking metrics previously linked to cognitive load, including but not limited to fixation duration, saccade amplitude or frequency, blink rate, and pupil dilation. For example, longer fixation durations and increased pupil size have been associated with greater processing effort, while reduced saccade variability may indicate narrowed attentional focus under high-load conditions [71–73].

In our review, we extracted these metrics where reported, noting whether they were used to infer changes in task difficulty, processing demands, or mental workload. We also recorded whether studies interpreted these eye-tracking patterns as evidence of visual-cognitive overload or efficient attentional allocation. As with EEG, the focus was on

identifying how these metrics were used to characterize cognitive load specifically within 3-D environments, such as virtual or augmented reality learning tasks, spatial simulations, or interactive 3-D interfaces.

2.8. Data Extraction

Following the screening process in Rayyan (Section 2.3), data from each included study were extracted manually into a structured Excel workbook (.xlsx format). The workbook was organized with one row per study and predefined columns for all extraction fields. Data regarding study characteristics and experimental set-up were extracted from the main text, figures and legends, and Appendices A–C, and recorded in an Excel worksheet. The extraction sheet included the following fields: (Table A1: Appendix B): (1) Title of paper, (2) Author name(s), (3) Journal, (4) Publication year, (5) Number of participants, (6) Gender of participants, (7) Design, (8) Task, (9) Task description, (10) Experimental group, (11) Comparison group, (12) 3-D technology, (13) Control Technology, (14) Psychophysiological Measure, (15) Research Question, (16) Cognitive Load/Mental Effort Measure, (17), Other Measures, (18) Conclusions.

To construct this extraction table, major features present in different papers were categorized, e.g., in instances of between-subject designs where experimental comparisons between 3-D technologies and a control condition were compared, we often referred to the alternate condition as ‘2-D’; comparison of cognitive load in a 3-D condition and control condition (2-D); analysis of psychophysiological outcome measures as indicators of cognitive load; other reported outcome measures.

2.9. Quality Appraisal

The quality of each paper was assessed using the ROB-2 tool for randomized controlled trials (RCTs) [74] and the ROBINS-1 tool for non-randomized studies [75]. A combination of these tools was chosen to comprehensively evaluate the diverse study designs included in our review. The ROB-2 tool assessed risks of bias from randomization, deviations from intended interventions, missing data, outcome measurement, and selective reporting in RCTs. Alternatively, the ROBINS-1 tool evaluated bias due to confounding, participant selection, intervention classification, deviations from intended interventions, missing data, outcome measurement, and selective reporting in non-randomized studies. These tools were adapted to fit the specific context and requirements of our systematic review. The core criteria and methodology were maintained to ensure consistent and reliable assessment of bias across studies (Appendix C: Tables A2 and A3).

3. Results

3.1. Overview

The search resulted in 51 eligible studies (Appendix B: Extraction Table). All studies included the use of 3-D technology, at least one psychophysiological measure, and an assessment of cognitive load/mental effort and/or working memory. In terms of cognitive load measures and analyses, 15 papers used a cognitive load index (CLI), mental workload, or a task-related EEG index; 27 papers used performance-based or learning-based outcomes as part of their measures; 39 papers used EEG as a methodological measure; 14 used eye-tracking. As several studies contributed to more than one measurement category, the summed counts are greater than the total of 51 studies.

The use of 3-D technologies on their own or in comparison with various 2-D technologies had an impact on learning outcomes: 15 studies revealed clear benefits of 3-D technologies on learning, performance, or feelings of presence and 4 studies found drawbacks of 3-D technologies in terms of increasing distraction and cognitive effort. A total of

14 studies found an increase in neural correlates of cognitive load in a 3-D condition and 12 found a decrease in psychophysiological measures of load in a 3-D condition.

Overall, a large variety of tasks were implemented in the included papers (further described in Appendix B): a folding test ($n = 2$), spatial navigation task ($n = 4$), photography task ($n = 1$), TV watching task ($n = 1$), face discrimination/processing task ($n = 3$), dual task paradigm ($n = 4$), stroop task ($n = 1$), motor/health training task ($n = 3$), robot control task ($n = 2$), knowledge and transfer tests ($n = 6$), reading task ($n = 3$), exercise/decision based game task ($n = 4$), arithmetic task ($n = 2$), n-back task ($n = 6$), assembly workstation task ($n = 3$), change detection task ($n = 2$), category learning task ($n = 1$), textual and visual cue response task ($n = 1$), observation task ($n = 4$), flight simulation task ($n = 3$), multiple object tracking ($n = 1$), auditory stimulus detection task ($n = 1$), language comprehension task ($n = 1$), delayed matching to sample task ($n = 1$), and skiing task ($n = 1$).

We used the data from our extraction table to analyze our two research questions, which had two major themes: (1) performance-based outcomes of cognitive load (Table 3) and (2) psychophysiological measures of cognitive load (Table 4).

Table 3. Learning and performance outcomes using 3-D interventions. A tabular representation of a subset of 27 papers from this review which illustrate how 3-D technologies impact performance and learning outcomes. These 27 studies were selected to answer RQ1 from the total dataset of 51 papers because of their focus on learning and performance outcomes using 3-D technology either in comparison to a control/2-D counterpart (between subject design) or to the study itself (within-subject design). The full data extraction of each of these 27 papers can be found in the data extraction table in Appendix B (data extraction table), which includes further details on the experimental designs of the papers.

Author	Design	Task	3-D Technology	Control	Learning Outcome/ Performance Outcome
Aksoy et al. [76]	Within Subjects	Visual N-Back Task	XR Headset (HTC Vive)	Desktop	No significant difference in 3-D and 2-D condition in N-back task
Alessa et al. [77]	Between & Within Subjects	Assembly maintenance task	XR Headset (Microsoft HoloLens)	Paper based instructions	AR instructions lead to a decrease in maintenance times and a decreased total task time (TTT)
Baceviciute et al. [78]	Between Subjects	Immersive reading: retention task and transfer Task	XR Headset (HTC Vive)	Physical booklet for reading	No Significant difference in knowledge retention but better knowledge transfer in 3-D condition
Barrett et al. [79]	Between Subjects	Category learning task	XR Headset (HTC Vive)	Desktop	No significant difference in learning outcomes between the two groups
Berger & Davelaar [80]	Between Subjects	Stroop Task	XR Headset (Oculus Rift)	2-D neurofeedback	Higher learning slopes in 3-D neurofeedback condition
Chang et al. [81]	Within Subjects	Desert Survival decision making game	XR Headset (HTC Vive Pro Eye)	None	No significant difference in performance between conditions
Chiossi et al. [82]	Within Subjects	Visual monitoring task & N-Back Task	XR Headset (HTC Vive Pro)	None	Positive adaptation improved 2-back accuracy. Negative adaptation reduced accuracy but sped reaction times. Visual monitoring largely unaffected

Table 3. Cont.

Author	Design	Task	3-D Technology	Control	Learning Outcome/ Performance Outcome
Dan & Reiner [14]	Within Subjects	Origami Folding Test	Origami folding demo in 3-D stereoscopic environment	Origami folding demo in 2-D video	Improvement in folding test after 3-D viewing
Dan & Reiner [15]	Between Subjects	Origami Folding Test	Instructor presented in 3-D stereoscopic glasses (NVIDIA)	Instructor presented in 2-D glasses	Higher score in origami folding test in 3-D condition
Drouot et al. [83]	Within Subjects	Dual task paradigm	XR Headset (Microsoft HoloLens 2)	Desktop	The 3-D condition led to longer assembly times and higher mental workload
Jeong et al. [84]	Between Subjects	Neurocognitive Tests	3-D stereoscopic TV (polarized glasses)	Regular TV	No differences in cognitive outcomes between 3-D and regular TV
Liu et al. [49]	Within Subjects	Sample to match face identification task	XR Headset (HTC Vive)	Monoscopic images of faces	Face identification accuracy higher in 3-D stereoscopic condition for both frontal and intermediate face views
Liu et al. [57]	Between Subjects	Textual and visual cue response task to a 360 immersion video	XR Headset (HTC Vive)	None	Textual cues located in the field of vision (FOV) improved learning outcomes
Luque et al. [85]	Within Subjects	Dual Task Paradigm (Pedestrian crossing + Oddball)	XR Headset (Oculus Quest 2)	None	Dual-task VR crossing reduced accuracy of time-to-arrival judgments.
15. Makransky et al. [2]	Within Subjects	Virtual laboratory simulation: retention task and transfer task	XR Headset (Samsung Gear VR)	Desktop	Increase of feelings of enjoyment and presence but no improvement in learning outcomes
Mondellini et al. [86]	Within Subjects	N-Back task	XR Headset (HTC Vive Pro)	Desktop	No difference between 3-D and 2-D condition in performance
Nenna et al. [87]	Within Subjects	Arithmetic task, pick & place task, dual task, and physical actions	XR Headset (HTC Vive Pro)	None	Action-based XR controls had better performance outcomes
Parong & Mayer [88]	Between Subjects	Biology Lesson: retention task, transfer task	XR Headset (HTC Vive)	Physical Booklet for Reading	No significant difference in knowledge retention between groups but better transfer of knowledge in 3-D group

Table 3. Cont.

Author	Design	Task	3-D Technology	Control	Learning Outcome/ Performance Outcome
Parsons et al. [89]	Between Subjects	Multiple Object Tracking (MOT), Cognitive tests	Neurotracker (glasses)	None	Improvement in cognitive function using 3-D MOT compared to non-active control group
Redlinger et al. [90]	Within Subjects	Simple N-back task	XR Headset (HTC Vive Focus)	None	No significant effects of visual, game-like elements on task accuracy or speed
Sagehorn et al. [91]	Within Subjects	Stimulus discrimination task	XR Headset (HTC Vive Pro 2)	Desktop	Response times faster in the 3-D condition
Sloubonov et al. [92]	Within Subjects	Spatial navigation task in a virtual 2-D or 3-D corridor	3-D television (CrystalEyes stereo glasses)	None	Better navigation in 3-D virtual corridor
Suarez et al. [93]	Within Subjects	XR motor task training: Coordination, peg transfer, grasping	XR simulator (LapSim)	None	Improvement in performance post 3-D training in all tasks
Sun et al. [23]	Between Subjects	Studying of an astronomy module	XR Headset (Google Cardboard) in virtual environment	2-D Presentation slides	No significant difference in learning outcomes for low-spatial-ability participants but significantly better performance in 2-D condition for high-spatial-ability participants
Volmer et al. [94]	Between Subjects	N-back task & button pressing procedural task	Spatial Augmented Reality (SAR) projected onto a dome shape	Desktop	SAR predictive cues improved speed and accuracy compared to desktop baseline
Yang & Wang [24]	Between Subjects	Studying molecular shapes task	AR implemented on android tablets	None	Significant learning gain; high achievers used better integration strategies between 3-D models and explanatory text
Zhao et al. [95]	Between Subjects	Photography Task	Augmented reality photography application	2-D photography application	Most learning gain and improvement of scores for participants in AR App condition

Table 4. Impact of 3-D technology on cognitive load and mental effort as measured by EEG and eye-tracking. These 45 studies were selected for RQ2 from the total dataset of 51 papers because of their specific focus on EEG- and eye-tracking-based markers and use of 3-D technology either in comparison to a control/2-D counterpart or to the study itself (within-subject design). The full data extraction of each of these 45 papers can be found in the data extraction Table A1 in Appendix B (data extraction table), which includes further details on the experimental design of the papers.

Author	Design	Task	3-D Technology	Control	Psychophysiological Measure	Learning Outcome/Performance Outcome
Abdurrahman et al. [96]	Between subjects	Landmark and route based navigational task	VR driving system with Logitech g-steering wheel controller	None	Eye-tracking	Navigation with insufficient landmarks and difficult routes increase pupil size and cognitive load
Alessa et al. [77]	Between & Within Subjects	Assembly Maintenance Task	XR Headset (Microsoft HoloLens)	Paper based instructions	EEG	AR increased mental workload during high demand tasks
Aksoy et al. [76]	Within Subjects	Visual N-Back Task	XR Headset (HTC Vive)	Desktop	EEG	Visual ERP P3 is similar in both desktop and VR but the N1 peak amplitude is higher in VR environment
Atici-Ulusu et al. [97]	Within Subjects	Assembly Line Diffusion Task	XR Headset (Sony Smart Eyeglass Sed-1)	Paper based instructions	EEG	AR glasses significantly reduced operators' cognitive load compared to standard procedures
Baceviciute et al. [98]	Between Subjects	Reading task: knowledge and transfer tests	XR Headset (HTC Vive)	Physical booklet for reading	EEG	Increased cognitive load in VR condition
Baceviciute et al. [78]	Between Subjects	Knowledge retention and transfer tests	XR Headset (HTC Vive)	None	EEG, Eye-tracking	Auditory representation of text had lowest cognitive demand
Barrett et al. [79]	Between Subjects	Category learning task	XR Headset (HTC Vive)	Desktop	Eye-tracking	Longer fixations and response times in the VR condition indicating higher cognitive load
Bernal et al. [99]	Within Subjects	Tetris Game	XR Headset (Valve Index)	None	EEG	The VR helper event reduced cognitive load while boosting visuospatial engagement. Findings support adaptive VR for workload optimization
Chang et al. [81]	Within Subjects	Desert survival decision making game	XR Headset (HTC Vive Pro Eye)	None	EEG	Embodied and gestural VR agents influenced neural load. Alpha activity showed embodied agents decreased attentional demand while gestures increased it
Chiossi et al. [82]	Within Subjects	Visual monitoring task & N-Back Task	XR Headset (HTC Vive Pro)	None	EEG	Alpha/theta measures supported real-time VR adaptations, with performance benefits depending on adaptation type

Table 4. Cont.

Author	Design	Task	3-D Technology	Control	Psychophysiological Measure	Learning Outcome/ Performance Outcome
Dan & Reiner [14]	Within Subjects	Origami Folding Test	Origami folding demo in 3-D stereoscopic environment	Origami folding demo in 2-D video	EEG	The cognitive load index (CLI) was lower for the 3-D instruction group
Dan & Reiner [15]	Between Subjects	Origami Folding Test	Instructor presented in 3-D stereoscopic glasses (NVIDIA)	Instructor presented in 2-D glasses	EEG	Cognitive load was higher in the 2-D condition and higher in the harder folding task
Drouot et al. [83]	Within Subjects	Dual task paradigm	XR Headset (Microsoft HoloLens 2)	Desktop	Eye-tracking	Lower blink rate and higher mental workload in 3-D condition
Elkin et al. [100]	Between & Within Subjects	Paediatric Resuscitation Task	XR Headset (Oculus Rift)	None	EEG	Feasible to measure cognitive load in real time during VR resuscitation simulations
Ghani et al. [101]	Within Subjects	Exergame rehabilitation task	Tiltboard game connected to a computer screen	None	EEG	N1 component had a reduced amplitude with increased cognitive workload
Hebbar et al. [102]	Within subjects	Flight simulation task	XR Headset (HTC Vive Pro Eye)	None	EEG, Eyetracking	Pupil diameter, fixation rate, and EEG indices increased with workload, while engagement decreased, validating these measures for cognitive load assessment in VR flight scenarios
Kazemi et al. [103]	Between Subjects	Locomotion methods in a navigation task	XR Headset (Oculus Quest 2)	None	EEG	Teleportation and standing showed the highest workload. Joystick and seated the lowest
Kisker et al. [104]	Between Subjects	Delayed Matching to sample Task	XR Headset (HTC Vive Pro 2)	Real objects & Desktop	EEG	Cognitive load was higher for 2D than VR or real 3D, with VR closely matching real-world processing Higher mental workload in VR condition
Kakkos et al. [105]	Within Subjects	Flight simulation task	XR Headset (Oculus rift)	Desktop	EEG	
Kirschner et al. [106]	Within Subjects	Task engagement with Man Machine Interfaces (MMIs)	Cave Automatic Virtual Environment (CAVE)	None	EEG	Man-machine interfaces (MMIs) can be used to adapt training protocols based on participant P300 measures of mental workload
Klotzsche et al. [107]	Within Subjects	Change detection task	XR Headset (HTC Vive)	None	EEG, Eye-tracking	Increased load related to reduced performance, contralateral delay activity (CDA), and lateralized alpha power during retention

Table 4. Cont.

Author	Design	Task	3-D Technology	Control	Psychophysiological Measure	Learning Outcome/Performance Outcome
Kober et al. [108]	Between Subjects	Spatial navigation task	3-D screen	2-D screen	EEG	Task-related alpha decrease in parietal areas for the more immersive C
Krugliak & Clarke [109]	Within Subjects	Face processing task	XR Headset (Microsoft HoloLens)	Photos, computer screen	EEG	Cognitive processes like the face inversion effect occur and can be successfully investigated using 3-D technology
Lee et al. [110]	Within Subjects	Healthcare Observation Task	XR Headset (HTC Vive Pro Eye)	None	Eye-Tracking	Task-evoked pupillary responses (TEPRs) reliably indexed increases in cognitive load with task difficulty and correlated with self-reported effort
Liu et al. [49]	Within Subjects	Sample to match face identification task	XR Headset (HTC Vive)	Monoscopic images	Eye-tracking	Smaller pupil diameters when viewing faces stereoscopically indicating lower load in 3-D condition
Liu et al. [57]	Between Subjects	Textual and visual cue response task	XR Headset (HTC Vive)	None	Eye-tracking	Visual cues in immersive environments can increase cognitive load but appropriate use of visual cues can guide learners
Luque et al. [85]	Within Subjects	Dual Task Paradigm (pedestrian crossing + auditory oddball)	XR Headset (Oculus Quest 2)	None	EEG	Higher workload in dual conditions and oddball conditions
Magosso et al. [111]	Within Subjects	Arithmetic task, reading task, and immersion in virtual plane cabin	Cave Automatic Virtual Environment (Shutter glasses)	Desktop	EEG	Increased mental effort in immersive VR environment
Makransky et al. [2]	Between and Within Subjects	Virtual laboratory simulation: retention task and transfer task	XR Headset (Samsung Gear VR)	Desktop	EEG	During the second simulation, cognitive workload was higher in the VR condition than the 2-D condition
Mondellini et al. [86]	Within Subjects	N-Back Task	XR Headset (HTC Vive Pro)	Desktop	EEG	The mental workload index decreased in VR condition, indicating lower cognitive load than 2-D condition
Nenna et al. [87]	Within Subjects	Arithmetic task, pick & place task, dual task, and physical actions	XR Headset (HTC Vive Pro)	None	Eye-tracking	Greater pupil size in VR condition

Table 4. Cont.

Author	Design	Task	3-D Technology	Control	Psychophysiological Measure	Learning Outcome/ Performance Outcome
Parong & Mayer [88]	Between Subjects	Biology lesson: retention task, transfer task	XR Headset (HTC Vive)	Desktop	EEG	No statistically significant difference between 2-D and 3-D conditions in cognitive overload but authors argue VR more distracting
Petukhov et al. [112]	Within Subjects	Real life and virtual skiing	XR Headset (HTC Vive)	Desktop	EEG	There were more stable neuropatterns in VR environment and real environment compared to the desktop
Reiner & Gelfeld [113]	Between Subjects	Motor cube hitting task	Stereoscopic Shutter glasses	None	Eye-tracking	Pupil-based indices reliably tracked changes in mental workload
Sagehorn et al. [91]	Within Subjects	Stimulus discrimination task	XR Headset (HTC Vive Pro 2)	Desktop	EEG	Higher frontal midline theta in 2-D condition indicative of higher cognitive load
Schirm et al. [114]	Within Subjects	Listening Comprehension Task	XR Headset (HTC Vive Pro Eye)	None	Eye-tracking	Eye-tracking metrics reliably distinguished higher load from foreign/unfamiliar speech and lower load from native/familiar speech in a VR setting
Suarez et al. [93]	Within Subjects	XR motor task training: Coordination, peg transfer, grasping	XR simulator (LapSim)	None	EEG	Training with VR improves performance and reduces cognitive load
Sumardani & Lin [115]	Within Subjects	Reading about the International Space Station(ISS)	XR Headset (Unknown)	None	EEG	Attention better in reading, likely VR caused cognitive overload
Tian et al. [116]	Between Subjects	Visual task	XR Headset (HTC Vive)	Desktop	EEG	Energy of alpha and theta and subjective load was higher in the VR group
Tremmel et al. [117]	Within Subjects	N-Back Task	XR Headset (HTC Vive)	None	EEG	Cognitive workload during an interactive VR task can be estimated via scalp recordings
Volmer et al. [94]	Between Subjects	N-back task & button pressing procedural task	Spatial Augmented Reality (SAR) projected onto a dome shape	Desktop	EEG	Spatial augmented reality (SAR) baseline reduced cognitive load compared to desktop monitor.
Yang & Wang [24]	Within Subjects	Studying molecular shapes task	AR implemented on android tablets	None	Eye-tracking	Simpler/static visualizations better, increase total fixation duration (TFD) linked to learning gain in post-test

Table 4. Cont.

Author	Design	Task	3-D Technology	Control	Psychophysiological Measure	Learning Outcome/Performance Outcome
Zacharis et al. [118]	Within Subjects	Viewing of 3 different environments	3-D Active Glasses	Desktop	EEG	A real stereoscopic environment had the least mental effort compared to a 2-D and 3-D environment
Zacharis et al. [119]	Within Subjects	Observation of changes in objects position	3-D Active Glasses	Desktop	EEG	No difference in cognitive load between conditions
Zhao et al. [95]	Between Subjects	Photography Task	Augmented reality photography application	2-D photography application	EEG	AR group had more alpha activation and active engagement

3.2. RQ1: Learning and Performance Is Enhanced by 3-D Technologies

A total of 27 papers in our dataset investigated performance and task-related outcome measures as indicators of learning or cognitive load via 3-D technology. Overall, there appeared to be improvements in performance across a variety of tasks, in 55.6% (15/27) of the cases (See Figure 2), in 3-D conditions on their own or versus 2-D counterparts [14,15,24,49,57,77,78,80,87,89,91–95]. Some papers had specific findings regarding improved 3-D performance, such as in a surgical training task where individuals had improved performance using a virtual reality laparoscopic simulator (VRLS) over time [93]. Learning outcomes were also improved in an instance where cues, annotations, and arrows were added to an immersive 3-D environment [57] and in an experiment using VR manipulation of a robotic control arm, in which participants preferred and performed better in the task using action based controller systems compared to a button control system [87].

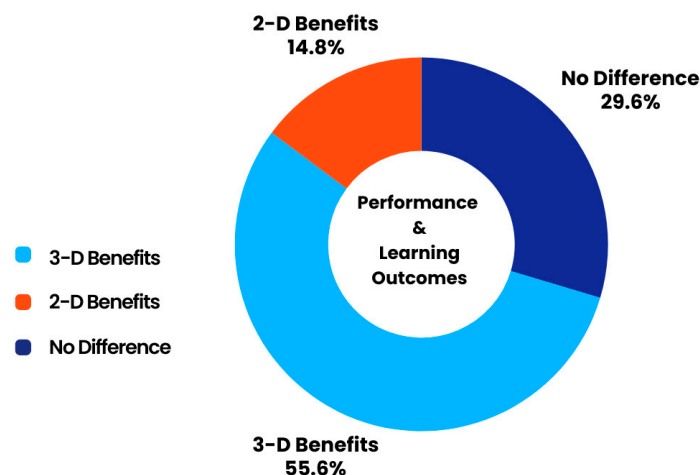


Figure 2. Performance and learning outcomes: A visual synthesis of the table above (27 papers) in terms of which of the papers indicate improvement in learning outcomes using 3-D technology (55.6%, 95% CI: 37.3–72.4%); found no differences between 3-D learning outcomes on their own or compared to a control (29.6%, 95% CI: 15.9–48.5%); indicate a control or 2-D condition having better learning outcomes than the 3-D condition (14.8%, CI: 5.9–32.5%). Note: Chiossi et al. [82] tested adaptive vs. non-adaptive VR. Since effects were mixed in this study, it was categorized as no-difference in 3-D vs. 2-D conditions.

Alternatively, 29.6% (8/27) of the studies found no significant difference between 3-D and 2-D interventions in terms of accuracy or specific learning outcomes [76,78,79,81,82,84,86,90].

However, in 14.8% (4/22) of the cases, a 2-D approach was beneficial over a 3-D approach [23,83,85,88]. A specific finding by Drouot et al. [83] was a worse performance in a simple assembly task in AR but no difference in performance between a complex assembly task using a computer and the same task using AR.

3.3. RQ2: Task Dependent Psychophysiological Measures on Levels of Cognitive Load

The data show that, within this dataset, there appear to be benefits for using 3-D technologies when it comes to learning and performance outcomes. However, to investigate how task performance impacted cognitive load, we analyzed our dataset for psychophysiological correlates of behavior in 3-D contexts. Table 4 shows the papers from our dataset that emphasized task-dependent psychophysiological measures (specifically EEG and eye-tracking) for CL in 2-D and 3-D environments. To address how cognitive load was quantified, we investigated how psychophysiological measures of cognitive load and/or mental effort were explored in selected experimental paradigms. Furthermore, we looked at how the difficulty of and variation in task demands impacted cognitive processing, cognitive load, or mental effort (Figure 3a). Figure 3b compares cognitive load indices in five different experiments that used varied 3-D vs. 2-D tasks. The five selected studies were the only studies from the full dataset that shared cognitive load indices that were statistically comparable and could be used as an illustration of varying levels of cognitive load between 2-D and 3-D groups.

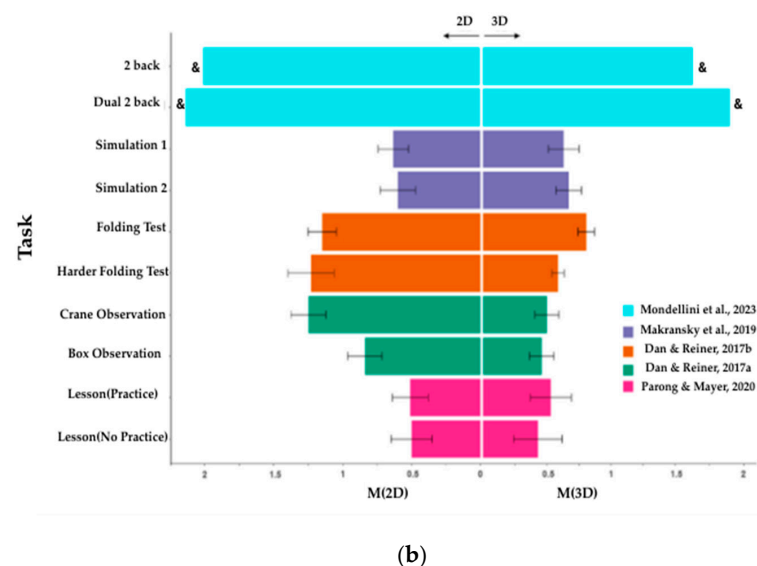
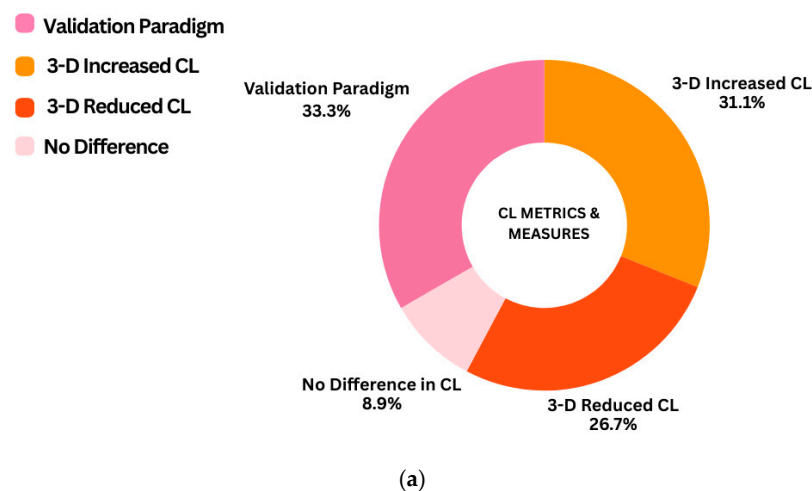


Figure 3. (a) Heterogenous cognitive load metric and measures (RQ2). The papers had diverse experimental designs and heterogeneous findings; therefore, to analyze findings specific to this research

question, we divided the papers in Table 4 into different themes. A total of 14/45 (31.1%, 95% CI: 19.5–45.7%) of the studies reported that 3-D technologies increased cognitive load, 12/45 studies showed decreased cognitive load using 3-D technology (26.7%, 95% CI: 16–41%), and 4/45 studies found no difference in cognitive load between 3-D and control conditions (8.9%, CI: 3.5–20.7%). A large group of papers (15/45) focused on validating specific paradigms using EEG or eye-tracking in combination with 3-D technologies to identify, investigate, and make conclusions about cognitive load and mental effort (33.3%, 95% CI: 21.4–47.9%). Note: A study by Petukhov et al. [112] used processing power and presence as an argument for reduced cognitive load in 3-D conditions and was therefore added to that category. **(b) Mean cognitive load indices differences in 2D and 3D tasks.** This figure highlights the tasks (y-axis) described in a subset of five papers from Figure 3a which focused on cognitive load-based indices ([2,14,15,86,88]). These indices illustrate differences in mental workload between 2-D and 3-D conditions using studies that utilize the cognitive load index (CLI) metric (M, x-axis) and mental workload indices. The indices include the CLI, which is the ratio derived from absolute frontal theta (Fz)/parietal alpha (Pz) and a normalized cognitive workload metric that ranges from 0 to 1. The higher the CLI ratio or workload (closer to 1), the more mental effort is being utilized, and the closer the mean CLI or workload is to 0, the less load/mental effort is being utilized. The 2-D conditions are projected towards the left and the 3-D methods towards the right. &: The study by Mondellini et al. [86] used median values instead of the mean and did not share values for standard deviation (SD); therefore, error bars are missing. Error bars in the figure represent the standard deviation (SD) of the mean cognitive load indices.

From the papers using the indices (Figure 3b), Makransky et al. [2] used a workload metric derived from EEG as their measure of cognitive load in a 2×2 mixed design task where participants were divided into a group that learned from a simulation with text and another group that learned with text and narration. The simulation was presented either first on a PC (2-D) and then with VR (3-D) or vice versa, and participants were tested based on their retention and transfer of knowledge. The workload metric was reported to range from 0 to 1 (0–0.4 being bored, 0.4–0.7 being optimal workload, and 0.7–1 being overloaded). There was no difference between the 2-D and 3-D conditions regarding the cognitive workload in the first simulation, but there was a higher cognitive workload in the second. In Dan and Reiner's [14] study, the participants had to perform various versions of a simple folding test in which they made an origami box or a harder folding test in which they made a crane after receiving instructions in either 2-D or 3-D. There was a higher mean CLI with the 2-D instructions compared to 3-D, especially in the harder folding test.

Similarly, in another study by Dan and Reiner [15], the authors purport that a 3-D digital avatar of an instructor explaining a folding task resulted in greater learning than a 2-D alternative. The authors found that the cognitive load index (CLI) was higher in the 2-D condition than in the 3-D condition. The higher CLI indicates that a 2-D presentation requires more mental effort than a 3-D condition. Parong and Mayer [88] used EEG-derived measures of cognitive workload to assess differences in cognitive load and engagement during a biology lesson presented in either a PowerPoint (2-D) format or through IVR (3-D). They concluded that IVR creates more cognitive distraction, but their workload metric did not show a significant difference between the PPT group and the IVR group and both groups' scores ranged in the reported ideal workload levels for learning and engagement during a task. Mondellini et al. [86] used a mental workload index (MWLI) that was calculated by dividing the frontal midline theta by the central parietal alpha and their findings indicate that the use of a HMD in a n-back task and a dual n-back task has a lower MWLI compared to the same task in desktop, which is indicative of lower mental load.

Overall, our dataset pertinent to RQ2 (See Table 4) contain slightly more papers showing an increase in cognitive load in 3-D conditions [2,77,79,81,83,85,87,98,103,105,108,111,115,116].

The authors qualified these results by suggesting that the increase in cognitive load in the 3-D conditions was due to greater cognitive processing, increased feelings of presence, and higher stimulation in the more immersive environments. Other researchers found that the cognitive load and mental effort were reduced in 3-D environments [14,15,49,86,91,93–95,97,99,104,112]. There were also studies that found no significant differences in cognitive load between 3-D and alternative conditions [64,72,94,95]. Some papers had nuanced findings, such as that by Zacharis et al. [118], who found that there was higher mental effort involved in 2-D and 3-D conditions compared to a real-life condition.

A large portion of papers focused on validating psychophysiological measures like EEG and eye-tracking as temporally specific and robust tools in measuring mental effort and cognitive load when used in combination with 3-D research contexts [24,57,78,82,96,100–102,106,107,109,110,113,114,117].

There was also the characteristic finding of increased theta activity related to greater cognitive processing and mental effort for the 3-D condition [77,103,105,116,119]. For alpha activity, Tian et al. [116] found higher activity in a VR group compared to a 2-D group, which is related to decreased cognitive load, and Kober et al. [108] found a task-related power decrease in parietal alpha during the more immersive VR condition of their task, which indicates more cortical processing in the 3-D condition. Klotzsche et al. [107] validated the presence in a VR task of lateralized alpha activity and contralateral delay activity (CDA: a lateralized ERP component) as a characteristic response to encoding of working memory visual stimuli. In another ERP study, the group using VR had a higher peak amplitude of N1 and P1 at frontal regions [76], which could be indicative of earlier attentional processes, especially regarding visual stimuli, being more greatly activated and visual attentional resources being recruited.

In eye-tracking studies, there was a greater pupil size in a condition which was more difficult [87,114] and elicited higher cognitive workload in VR [96]. In an AR assembly task, there was a lower blink rate and higher pupil size compared to a 2-D condition, which is indicative of a higher cognitive load [83]. Some studies found longer fixation durations in VR tasks under higher workload conditions [102] or compared to a 2-D condition [79]. Furthermore, there was greater fixation duration when visual stimuli cues were presented outside of the fovea, which is also indicative of greater cognitive effort [57]. In a stereoscopic condition, the pupil diameter was smaller in a stereoscopic condition compared to a monoscopic condition during a face identification task [49].

4. Discussion

4.1. Overview

3-D technologies have been shown to enhance engagement, presence, and spatial interaction—factors widely recognized as essential for deep learning and motivation. However, the cognitive processing required to support such engagement can vary significantly between learners and tasks. A certain degree of cognitive load is both expected and beneficial for learning. Yet, beyond a certain point—unique to each individual—it can become overwhelming, counterproductive, and lead to cognitive overload.

Primarily, the findings from selected papers of this review show that cognitive load as measured by learning outcomes tends to decrease in certain 3-D learning environments (See Figure 2). Additional benefits of using 3-D technologies included enhancement of spatial awareness, presence, and embodiment in learning environments. These benefits were linked to reported improvements in performance in some studies [14,15,24,49,57,77,78,80,87,89–95], although the underlying mechanism behind this was not clear. Our systematic study shows that lower levels of cognitive load or mental effort may be important contributors towards enhanced performance. Alternatively, some studies found 3-D settings to be more distracting

and argued that 2-D settings were better for improving learning outcomes and reducing cognitive load [2,68,78,85]. The argument proposed is that IVR is more distracting and thus impacts focus and retention of information [2]. The high level of engagement elicited by interactive features in IVR and other 3-D technologies may increase extraneous cognitive load, diverting attention away from learning relevant information [83].

Despite improved performance in some 3-D learning environments, there were also studies that reported an increase in load in 3-D environments (Figure 3a). As mentioned earlier, an important consideration for this review and future research is the definition of cognitive load—some mental load and processing is a necessary aspect of learning and helps to commit items to long term memory [120]. Therefore, a level of cognitive load may be essential to engage with learning materials, but the problem arises when there is cognitive overload. A further question arises as to what point is an ideal level of cognitive workload and at what point cognitive overload occurs. Some workload indices [65] use a 0 to 1 scale, with 0.4–0.7 being an optimal amount of load. However, there is a lack of consensus on what optimal cognitive workload really is or what the cut-off ranges are. Further issues may arise in defining how these optimal levels may deviate between participants [121,122].

These conflicting results highlight the complexity of measuring cognitive load and suggest that finer details might be obscured by the heterogeneity and limitations of the methodologies used. To address these challenges and gain a clearer understanding, our study emphasizes the importance of employing high-temporal-resolution measurement technologies in 3-D learning research. This approach is critical as it captures the dynamic fluctuations of cognitive load, offering a more nuanced insight that is often missed by subjective assessment methods like the NASA-TLX test [123]. Since the amount of working load continuously changes, self-reported overall scores such as those acquired with the NASA-TLX test can easily be misinterpreted. The focus on integrating high-resolution technologies such as EEG and eye-tracking into 3-D learning research is relatively recent, which is why our dataset is small and has great variety in its study designs. These diverse experimental designs and technologies used in the analyzed studies are contributors to high heterogeneity in the findings of our dataset.

There are other reasons as to why the results were more heterogeneous than expected, beyond the varied task designs and study outcomes. The 3-D technologies utilized were assessing various contributors towards learning outcomes and goals, i.e., not only was cognitive load being assessed but also immersion and presence in learning settings. Immersion in 3-D technology involves a user being deeply engaged with the spatial and sensory aspects of the virtual environment, as well as the technology's ability to deliver a realistic and interactive experience [124]. While closely related, presence also reflects the subjective experience of the user in the environment [21,124,125]. We did not initially hypothesize a connection between immersion and presence and deeper learning outcomes. However, it has been shown in the previous literature that feelings of presence in a learning environment enhance realism, motivation, and engagement with the learning materials [22,107,126]. This raises the possibility that enhanced presence and immersion in 3-D learning environments might influence cognitive load. Future research will need to establish this link and further explore the connection between presence, immersion, and cognitive load.

A prominent finding from this review was that 3-D technologies may be especially useful in contexts where spatial skills are recruited. This is demonstrated in the Dan and Reiner [14] study that reveals a better performance and a lower cognitive load in a 3-D setting compared to a 2-D setting. This was further illustrated in a similar study performed by Dan and Reiner [15], which found a lower CLI with 3-D instruction in an origami folding task. A qualification of this finding is that the benefits of 3-D modes of instruction may be

more pertinent to spatial recognition and abilities. Therefore, the use of a stereoscopic 3-D headset may be good for spatial tasks and learning but less so for non-spatial tasks [19].

Individual spatial ability is also an important factor when employing 3-D technologies in learning settings, which may be a moderating factor in performance outcomes in 2-D vs. 3-D settings [19,104]. This is seen in the literature through a relationship between spatial ability and learning environments, in which high-spatial-ability (HSA) participants performed better in PPT-based learning environments and low-spatial-ability (LSA) participants benefitted from VR-based learning environments [78]. This is in line with previous research that has shown greater benefits of 3-D visualizations for individuals with lower spatial ability [14]. The aspect of spatial ability as a factor that may impact performance when using 3-D interventions is something that needs to be taken into consideration when considering the role it may have in affecting mental effort and cognitive load in learners.

To foster deeper learning processes and the use of appropriate instructional materials, there should be considerations of alignment of the type of learning with the presentation of the material. In other words, if declarative knowledge is being tested and individuals must learn facts through text, then traditional methods such as slideshow presentations may be suitable and less distracting for the learner. However, with materials that require greater visualization and depth-related information, it may be better to consider 3-D approaches and technologies to bolster learning.

In the studies that we analyzed, there was not always an alignment of the projection of learning materials (i.e., monoscopic vs. stereoscopic) with the type of knowledge or material being presented. For example, reading a text in VR did not directly qualify as 3-D learning. However, simulating driving using VR may be a more apt context and use of this technology [81]. Misalignment of technologies with learning objectives, such as using VR for reading text or employing 2-D screens for spatial tasks, could cause extraneous load for learners [14,127]. The disruption of the learning process can increase the intrinsic load, which affects the experience of the complexity of the content. Consequently, the combined effect of increased extraneous and intrinsic load can lead to cognitive overload, thereby impairing learning outcomes [120].

4.2. Differences in Cognitive Load as Reflected by Psychophysiological Measures

The relationships between multi-dimensional learning environments and high-temporal resolution measures of cognitive load were explored through EEG and eye-tracking measures in this systematic review. The findings showed slightly more papers reporting increased cognitive load in 3-D conditions (Figure 3a). This increase could be attributed to several factors, such as heightened engagement and cognitive processing being required in 3-D environments, which can enhance attentional mechanisms [2,4]. As focus and attention intensify during a task, so does the activation of cognitive load markers, which reinforces the notion that a certain level of increased engagement and cognitive load is necessary for encoding and learning [24]. However, it is cognitive overload that can be detrimental to the learning process [120,128]. Conversely, cognitive load indices show a trend toward reduced cognitive load in 3-D environments, which suggests that, under certain conditions, 3-D technologies may optimize cognitive processing and reduce unnecessary mental effort compared to 2-D presentations (Figure 3b; [121]).

4.2.1. EEG

Aksoy et al. [76] used ERPs to observe P1, P3, and N1 waveforms in response to a n-back task. They looked at peak amplitudes and latencies of these components in a VR environment (3-D) vs. a desktop environment (2-D). The authors found a significantly stronger N1 peak amplitude (highest point relative to baseline) at the frontal region in the

VR condition than in the desktop condition. The peak amplitude being stronger in a VR condition can be indicative of novelty and saliency of the virtual environment but also greater cognitive load and mental effort [129–132]. Alternatively, Ghani et al. [101] found a decrease in amplitude of the N1 component with increasing difficulty, which could mean a reduction in N1 amplitude is related to preventing focus on task–irrelevant information. The contradictory findings from these studies show that components such as N1 activate in different ways depending on the task design and theoretical perspectives.

Aksoy et al. [76] also found a stronger P1 peak and mean amplitude at the occipital region in the VR condition, which indicates that there was increased attention in the visual areas. The P1 component in general is related to early visual attention and sensory processes [133]. Higher P1 activation in the VR condition could be indicative of greater cognitive load. Sun et al. [23] found a higher P2 for lower-spatial-ability (LSA) participants in a PPT condition compared to a VR condition. This P2 component is linked to selective attention and evaluation of stimulus relevance [134], and a higher P2 in the PPT condition could indicate higher cognitive load for LSA participants. Later components such as the P3 response are also linked to cognitive load in that increases in cognitive load can lead to a higher P3 amplitude and latency [135]. This was also investigated by Kirchner et al. [106], who used variations in P3 latency to assess changes in task load and task engagement.

Variations between the ERP components in 2-D and 3-D conditions can indicate that the attentional and cognitive processes are different between two projection modalities, and studying these differences may lend insight into how early attentional processes are enhanced through different modes of visualization. Although ERPs can highlight differences due to spatial aspects of different projection modalities in 2-D vs. 3-D technologies, it is essential to consider other non-spatial factors, such as the physical experience of wearing a headset versus using a desktop. Future studies should aim to disentangle these influences to provide a clearer picture.

Other studies primarily focused on fluctuations in alpha and theta band rhythmic activity. Several authors indicated that higher theta activity is indicative of greater processing and load [2,14,15,23,82,88,89,91–93,103,105,116]. These increases in theta activity are not solely an indicator of cognitive load but also a measure of recruitment of cognitive resources, attention, and cognitive processing [42]. An example is the study by Sloubonov et al. [92] in which they used EEG in a spatial navigation task in a 2-D vs. 3-D VR presentation and found a stronger sense of presence in the 3-D setting, along with a higher frontal midline (FM) theta in the 3-D condition, which is indicative of greater recruitment of resources in the 3-D condition. Suarez et al. [93] found that, at the end of surgical training, the frontal theta power decreased, which is indicative of a reduction in cognitive workload, and that the central parietal alpha increased, which indicates a decrease in attentional load. This is indicative of lower cognitive load as performance and learning improves over time [136–138].

Alpha responses were more variable and task-dependent than theta responses. Kober et al. [108] found a decrease in alpha in a VR condition, which is indicative of greater cognitive load and cortical processing. While a reduction in alpha activity corresponds to higher cognitive demands, it also signifies enhanced task engagement, which is beneficial unless it leads to cognitive overload. Fluctuations in theta and alpha band activity can be indicators of task-dependent engagement and activation of deeper learning processes. Other studies looked at cognitive load and mental workload by using frontal theta/parietal alpha ratios as measures of which modalities (2-D vs. 3-D) increased mental workload [2,14,15,86,88]. These ratios offer a normalized and standardized index which can be an accessible and comparable means of analyzing mental workload. For instance, Mondellini et al. [86] used

a mental workload index (MWLI) to demonstrate a lower load in a single and dual n-back task in a VR environment compared to a desktop environment.

Overall, this review indicates a slightly higher number of published papers describing cognitive load in 3-D conditions (Figure 3a), but the papers that used a cognitive load or workload index showed a trend towards reduced cognitive load in 3-D conditions (Figure 3b). These variable findings suggest that further research is needed to determine when projection technologies increase cognitive load and to identify the most suitable validated cognitive load indices for measuring these differences. Additionally, it is crucial to distinguish whether the increased load enhances task engagement, learning, and cognitive processing or is indicative of cognitive overload.

4.2.2. Eye-Tracking

Eye-tracking was used in this review to investigate the cognitive processing and mental load during experimental tasks. Metrics like increased pupil diameter, decreased fixation times, and faster saccades were indicative of higher levels of cognitive load. Several studies in this review found an increase in pupil size in a 3-D condition, which is reflective of increased cognitive load [83,87,96,102,110,114]. However, in this context, it is relevant to mention that the usability of pupil diameter metrics is questionable when using headsets in an experimental setup. The projection of light close to the eyes affects the pupil size and could mask cognitive load-imposed changes. Recent work, however, has demonstrated possible solutions: Lee et al. [110] corrected for light-induced reflexes using photosensor data and modeling approaches, thereby restoring the sensitivity of pupillometry to cognitive load in VR training, which may represent a promising way forward in headset-based experiments.

Research focused on eye-tracking using VR headsets by Baceviciute et al. [78] found that participants that spent more time fixating and had increased saccadic activity experienced greater cognitive load and mental effort. Ultimately, eye-tracking measures can give information on the levels of cognitive processing, load, and mental effort imposed by 3-D technologies [72,139]. Additionally, eye-tracking is an informative method in assessing what parts of a visual scene individuals are attending to and, consequently, which parts of a virtual scene may be cognitively overloading or distracting.

4.3. Does 3-D Technology Improve Learning?

We tried to answer the question of whether 3-D technology can be implemented into learning settings to improve skills and performance. Our findings indicate that one should be careful not to introduce the use of 3-D technologies in learning settings only based on advancements in technology. Rather, they should be aligned to the learning task and learning goals and based on prevention of cognitive overload for the user. Technologies that reduce cognitive load and mental effort are especially helpful in delaying or preventing the overload condition. However, too much reduction can result in diminished cognitive processing and lowered learning outcomes.

Based on the current literature, it is hard to pinpoint which elements of 3-D technology are responsible for inducing or reducing cognitive load. For instance, in VR, elements that can influence extraneous cognitive load but which are also beneficial include immersion, stereoscopic presence, interaction with the digital content and environment, feedback, and a mix of visual and auditive cues [2,6]. On the other hand, elements like disconnection from one's physical surroundings and the frequent occurrence of cyber-sickness influence the learning experience in a negative way [140].

Therefore, when utilizing 3-D technologies to improve performance or learning outcomes, it is necessary to apply them to the appropriate learning settings and to optimize

the paradigms to make the experience comfortable for the user. A certain level of mental effort or load is optimal and enhances outcomes, but too much strain or distracting visual stimuli may be redundant and overload the user.

4.4. Limitations

The papers included in this study utilized a diverse range of experimental designs, which resulted in significant heterogeneity in their outcomes and findings. This variation made it challenging to directly compare the results across different studies. Due to this, there may be a risk of bias in the synthesis of the findings. In addition, the papers discuss various forms of cognitive load but do not all deeply delve into an analysis of cognitive overload. For instance, our findings did not reveal cognitive overload in instances of 3-D technology use, but rather an increased cognitive load. This is not out of the ordinary, since a certain level of load is crucial for learning and attention. This point of overload was not found in our review, and future studies should seek to effectively delineate when increases in cognitive load cross a threshold to become cognitive overload. Also, due to the relatively recent nature of this type of research, the total number of papers included in this review was limited to 51. Other factors like our strict definitions of what constitutes 3-D and virtual reality also played a role in the final paper selection.

While this review concentrated on psychophysiological measures of cognitive load, it did not address biophysical safety concerns, such as electromagnetic exposure and thermal effects during prolonged use of EEG or VR/AR headsets, and their possible indirect influences on cognitive load. Emerging research underscores these risks. For instance, Uluaydin and Şeker [141] modeled thermal effects and SAR levels in smartphone-based VR headsets under 4G/5G, and Rupp [142] demonstrated that microclimate temperatures within modern VR goggles can rise to levels ($>38^{\circ}\text{C}$) that users find uncomfortable—particularly during active or extended sessions. Future cognitive load studies employing immersive technologies—for extended educational sessions—should consider integrating real-time monitoring of the specific absorption rate (SAR) and thermal accumulation to ensure safe and comfortable user experiences.

4.5. Future Directions

Although this review focuses on EEG and eye-tracking approaches following established workload frameworks [65], future studies should seek to use high-temporal-resolution psychophysiological techniques to pinpoint when cognitive load transitions into overload, and how these thresholds may differ between traditional 2-D and immersive 3-D learning settings.

In this regard, fuzzy and neuro-fuzzy models and well-tuned classical machine learning approaches have achieved accuracies in the 85–95% range in related EEG tasks—including workload classification and closely related fatigue/drowsiness detection—especially when EEG is fused with autonomic signals such as those measured with electrocardiograms (ECGs) and electrooculograms (EOGs) [143,144]. These methods enable soft-boundary classification between optimal and overloaded states, accommodating the dynamic and non-binary nature of cognitive states. Applied to continuous EEG indices such as the frontal theta or the theta/alpha ratio, such adaptive modelling could operationalize an “optimal load interval” in immersive learning tasks, enhancing sensitivity to subtle threshold crossings beyond fixed cut-offs.

Future research could also explore multi-sensor fusion approaches, where EEG is combined with complementary biopotential measures—such as ECG for autonomic state monitoring [145,146] and surface electromyography (sEMG) for motor-load estimation [147,148]—to better differentiate cognitive from physical demands in inter-

active or embodied learning tasks. Although such methods were not applied in the studies reviewed here, evidence from multimodal neuroergonomics indicates that integrating complementary channels in real-life scenarios can improve real-world applicability and reduce confounds inherent in purely cognitive or purely motor indices [149]. In parallel, emerging work in electrical impedance tomography (EIT) shows that scalp-level impedance imaging can reconstruct 3-D changes associated with evoked brain activity and, given its high temporal resolution, could be adapted toward near-real-time visualization of workload distributions across cortical regions [150].

In addition, spatiotemporal deep learning architectures—such as the LSTM-U-Net framework recently applied to electrical absorption monitoring [151]—could be adapted for EEG data streams to jointly model spatial patterns across channels and temporal dependencies across time. This approach may enable the detection and possibly even forecasting of transitions between optimal load and overload states, allowing adaptive systems to adjust task demands before cognitive overload fully occurs—rather than only responding after a fixed threshold is crossed.

Future investigations should aim for greater methodological alignment across studies to reduce heterogeneity in their results [2,8], and to clarify which learning domains benefit most from 3-D immersive technologies [19,23,24]. In contexts that seek to enhance presence, embodiment, and spatial engagement, immersive 3-D tools may offer distinctive advantages, but their deployment should be matched carefully to the content type, learner profile, and cognitive load tolerance to avoid counterproductive overload [152].

5. Conclusions

3-D technologies can be utilized in learning and performance-based settings to increase the acquisition of knowledge, retention of information, and enhancement of skill and to increase feelings of embeddedness and presence. Technologies like EEG and eye-tracking are invaluable research tools in understanding how individuals interact, process, and learn from diverse technologies in learning tasks. In instances of engaging with spatial tasks and visualization-based performance, 3-D technologies reveal benefits over traditional 2-D methods in reducing cognitive load. The use of new visualization technologies should not be considered as a replacement of traditional methods but rather an extra tool for enhancing learning, visualization, and presence. Future studies should continue to investigate individual differences in learning and performance-based outcomes in 2-D vs. 3-D settings by using psychophysiological techniques as methods of validation.

Author Contributions: Conceptualization, R.K., D.S. and B.P.H.; methodology, R.K., D.S. and J.V.; validation, R.K., D.S., J.V. and B.P.H.; formal analysis, R.K. and B.P.H.; investigation, R.K.; data curation, R.K.; writing—original draft preparation, R.K.; writing—review and editing, D.S. and B.P.H.; visualization, R.K. and B.P.H.; supervision, D.S. and B.P.H.; project administration, D.S.; funding acquisition, D.S. All authors have read and agreed to the published version of the manuscript.

Funding: This project received no external funding.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: All data analyzed during this systematic review are contained within the published articles cited in the reference list. No new data were generated for this study. Detailed information extracted from the included studies is presented within the manuscript.

Acknowledgments: Felix Weijdemans, librarian, Veterinary Faculty, Utrecht University (The Netherlands) is acknowledged for his expert help with the search strategy.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

3-D/3D	Three-Dimensional
2-D/2D	Two-Dimensional
AR	Augmented Reality
CTML	Cognitive Theory of Multimedia Learning
CDA	Contralateral Delay Activity
CL	Cognitive Load
CLI	Cognitive Load Index
CLT	Cognitive Load Theory
ECG	Electrocardiogram
EEG	Electroencephalography
EOG	Electrooculogram
ERPs	Event Related Potentials
fMRI	Functional Magnetic Resonance Imaging
GSR	Galvanic Skin Response
HMD	Head Mounted Device
HRV	Heart Rate Variability
HSA	High Spatial Ability
IVR	Immersive Virtual Reality
LSA	Low Spatial Ability
LSTM	Long Short-Term Memory
MOT	Multiple Object Tracking
MWLI	Mental Workload Index
MR	Mixed Reality
PPT	PowerPoint
STEM	Science, Technology, Engineering, Mathematics
RCTs	Randomized Controlled Trials
VR	Virtual Reality
VRLS	Virtual Reality Laparoscopic Simulator
XR	Extended Reality

Appendix A. Search Strategy

Inclusion and Exclusion Criteria:

Inclusion: (Must mention some kind of 3-D technology AND Cognitive load or performance based on reaction, learning, memory, skill acquisition AND must use some kind of psychophysiological or neuroimaging recording and testing technique as validation of objective/brain measures), must be an experimental type design.

Exclusion: Must be newer than 2009, must be in English, must have full text available, must include healthy controls, must not be a review or abstract.

Pubmed search terms:

("cognitive load*" [Title/Abstract] OR "mental effort*" [Title/Abstract] OR "mental load*" [Title/Abstract] OR "Working Memory" [Title/Abstract] OR "Memory Load" [Title/Abstract] OR "Memory Capacity" [Title/Abstract] OR "Working Memory Capacity" [Title/Abstract]) AND ("Virtual Reality" [Title/Abstract] OR "Augmented Reality" [Title/Abstract] OR "Mixed reality" [Title/Abstract] OR "3D" [Title/Abstract] OR "3-D" [Title/Abstract]) AND ("electroencephalography" [Title/Abstract] OR "EEG" [Title/Abstract] OR ("eye tracking technology" [MeSH Terms] OR "eye tracking technology" [Title/Abstract] OR "eye tracking" [Title/Abstract] OR "eyetracker" [Title/Abstract] OR "eyetracking" [Title/Abstract] OR "neuroimaging" [Title/Abstract] OR "psychophysio*" [Title/Abstract]) AND ("hu-

mans"[MeSH Terms] AND "english"[Language] AND 2009/01/01:2025/03/31[Date - Publication])) AND ((humans[Filter]) AND (english[Filter]))

Eric search terms:

((Cognitive Load or Cognitive Workload or Cognitive Effort or Cognitive Overload or Mental overload or Mental Effort or Mental workload or working memory load or working memory overload or working memory capacity or memory capacity or memory load or memory overload) and (Virtual Reality or Augmented Reality or Mixed Reality or 3D or 3-D or Virtual or Augmented or projection or 3D projection or 3-D projection or key-view or rotation) and (EEG or Electroencephalography or Eye-tracking or eye tracking or Psychologic* or neuroimaging or imaging or neuro* or psychophysiological or psychological assessment)). mp [mp = abstract, title, heading word, identifiers]

Psycinfo search terms:

((Cognitive Load or Cognitive Workload or Cognitive Effort or Cognitive Overload or Mental overload or Mental Effort or Mental workload or working memory load or working memory overload or working memory capacity or memory capacity or memory load or memory overload) and (Virtual Reality or Augmented Reality or Mixed Reality or 3D or 3-D or Virtual or Augmented or projection or 3D projection or 3-D projection or key-view or rotation) and (EEG or Electroencephalography or Eye-tracking or eye tracking or Psychologic* or neuroimaging or imaging or neuro* or psychophysiological or psychological assessment))

Scopus Search terms: TITLE-ABS-KEY ("cognitive load*" OR "mental effort*" OR "mental load*" OR "working memory" OR "memory load" OR "memory capacity" OR "working memory capacity") AND TITLE-ABS-KEY ("virtual reality" OR "augmented reality" OR "mixed reality" OR "3D" OR "3-D") AND TITLE-ABS-KEY ("electroencephalography" OR "EEG" OR "eye tracking" OR "eyetracker" OR "eyetracking" OR "neuroimaging" OR "psychophysio*") AND (PUBYEAR > 2008 AND PUBYEAR < 2026) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (DOCTYPE, "ar"))

Web of Science search terms:

TS = ("cognitive load*" OR "mental effort*" OR "mental load*" OR "working memory" OR "memory load" OR "memory capacity" OR "working memory capacity")

AND TS = ("virtual reality" OR "augmented reality" OR "mixed reality" OR "3D" OR "3-D")

AND TS = ("electroencephalography" OR "EEG" OR "eye tracking" OR "eyetracker" OR "eyetracking" OR "neuroimaging" OR "psychophysio*")

AND LA = (English)

AND PY = 2009–2025

Appendix B

Table A1. Data Extraction Table.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Reduced Mental Load in learning a motor visual task with virtual 3D method [14]	Dan, Reiner	Journal of Computer Assisted Learning	2017 (a)	14	10 M, 4 F	Within Subjects	Folding Test	Participants watched origami folding demos in 2-D or 3-D and then participated in a folding test	3-D Origami	2-D Origami	Stereoscopic 3-D headset	2-D video	EEG	2	Cognitive Load Index	NASA-TLX	Findings suggest benefit of the 3-D presentation vs. 2-D presentation
The Effect of a virtual reality learning environment on learners' spatial ability [23]	Sun, Wu, Cai	Virtual Reality	2019	28	13 M, 15 F	Between Subjects	Auditory test (single stimulus paradigm)	Discriminate standard from non-target tone	VR based learning group	Presentation Slides learning group	XR Headset (Google Card-board)	Presentation Slides	EEG	1	ERP: N1 & P2	Learning outcome test, spatial ability test, astronomy knowledge test	Low Spatial Ability participants had reduced cognitive loads and improvement in performance in VR-based learning environment. High Spatial Ability learners did not show differences in their cognitive load between the 2-D & 3-D environments, but they had less learning performance in the VR-based environment.

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Frontal Alpha Oscillations and Attentional Control: A Virtual Reality Neuro-feedback Study [80]	Berger and Davelaar	Neuroscience	2017	22	14 M, 8 F	Between Subjects	Stroop Task	Used neuro-feedback training to train alpha responses in a cognitive control task	3-D Neuro-feedback	2-D Neuro-feedback	XR Headset (Oculus Rift Development Kit 2)	2-D Screen	EEG	1	Mean correct response times & accuracy on Stroop task	N/A	Increase in frontal alpha was associated with enhanced attentional processing. Learning slopes were higher in participants who received 3-D feedback. Alpha oscillations can be a useful measure of cortical processing and efficiency.
Investigating the Redundancy principle in immersive reality environments: An eye-tracking & EEG Study [98]	Baceviciute, Lucas, Terkildsen, Makransky	Journal of Computer Assisted Learning	2021a	73	44 F, 29 M	Between Subjects	Knowledge retention & transfer tests	After exposure to three different conditions: written, auditory, and redundant, participants knowledge retention and transfer was tested	Redundant (written + auditory)	2 Groups: Written, auditory	XR Headset (HTC Vive)	N/A	Eye-tracking and EEG	2	Self-reported Cognitive Load Scales (Ayrnes; Cierniak; Salomon; Leppink; Paas; Ayres), EEG measurements (Theta + Alpha), Eye-Tracking (fixation & Saccades)	Pre-test survey, post-test questionnaires, Retention & Transfer test scores	There was more mental effort required for the auditory group; there are benefits of redundant learning content in an IVR context as opposed to a standard context

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Changes in brain activity of trainees during laparoscopic surgical virtual training assessed with electroencephalography [93]	Suarez, Gramann, Ochoa, Toro, Mejia, Hernandez	Brain Research	2022	16	9 F, 7 M	Within Subjects	Motor training and then post tests for tasks: coordination, peg-transfer, and grasping	Use of XR technology to train in surgical/motor tasks	Use of XR technology to perform 3 basic tasks	N/A	XR simulator (LapSim)	N/A	EEG	1, 2	EEG: changes in Frontal Midline Theta and Central Parietal Alpha, NASA-TLX questionnaire	Performance in coordination, grasping & peg transfer	The EEG data indicate that brain rhythms are linked to distinct cognitive processes regarding training and the acquisition of skills. Training in VR reduced frontal midline theta and increased performance. Furthermore, there was a positive correlation with central parietal alpha and improved performance

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
An intelligent Man-Machine-Interface-Multi Robot Control adapted for Task engagement based on single trial detectability of P300 [106]	Kirchner, Kim, Tabie, Wohrle, Maurus, & Kirchner	Frontiers in Human Neuroscience	2016	6	6 M	Within Subjects	Task engagement with Man-Machine Interfaces (MMI)	Participants controlled robots and their task engagement and task load was assessed	Subjects control several simulated robots, subjects needed to complete 30 tasks	N/A	A virtual environment using MARS (Machina Arte Robotum Simulans) in 3-D and 2-D. The Man Machine Inteface (MMI) makes use of a Cave Automatic Virtual Environment (CAVE)	N/A	EEG	2		Changes in the inter-stimulus interval (ISI), Changes in P300 related activity	MMIs can be used to adapt training protocols based on participants' ERP(P300) measures for mental workload.
Efficacy of a Single-Task ERP Measure to Evaluate Cognitive Workload During a Novel Exergame [101]	Ghani, Signal, Niazi, Taylor	Frontiers in Human Neuroscience	2021	16	11 F, 13 M	Within Subjects	Exergame Rehabilitation Task	Participants had to play a tilt ball game on a balance board that was controlled through an android phone. The task was varied on three levels of difficulty	Three levels of difficulty (easy, medium, hard)	N/A	Computer screen projection while playing on tilt board	N/A	EEG	2	ERP (N1)	Task performance parameters: goals scored, difficulty level; Subjective Ratings of Difficulty	The amplitude of the N1 ERP component decreased significantly with an increase in task difficulty

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Remediating learning from non-immersive to immersive media: Using EEG to investigate the effects of environmental embeddedness on reading in Virtual Reality [78]	Baceviciute, Terkildsen, & Makransky	Computers & Education	2021b	48	27 F, 21 M	Between Subjects	Real Reading vs. Embodied Reading in VR followed by a Knowledge Test and Transfer Test	Participants had to read information about sarcoma cancer either in a real-reading condition or VR reading condition and were tested on their learning outcomes afterwards	Educational Text from a physical booklet	Identical Text in virtual booklet	XR Headset (HTC Vive)	Physical Booklet	EEG	1, 2	mental effort (Paas Scale), extrinsic cognitive load measure, intrinsic cognitive load, germane load	N/A	XR promotes knowledge transfer, but no significant difference in knowledge retention. EEG measures suggested that cognitive load was increased in XR
EEG-based cognitive load of processing events in 3D virtual worlds is lower than processing events in 2D displays [15]	Dan & Reiner	International Journal of Psychophysiology	2017b	17	11 M, 6 F	Between Subjects	Folding Test	Participants watched origami folding demos of an instructor in 2-D or 3-D and then participated in a folding test where they either needed to fold an origami box or origami crane.	First folded a box after 2-D instruction, then a crane after 3-D instruction	First folded a box after 3-D instruction, then a crane after 2-D instruction	3-D NVIDIA glasses	2-D Video	EEG	1, 2	Cognitive Load Index (Frontal Theta & Parietal Alpha)	VZ-2 paper folding test to assess spatial ability	Cognitive load of visually processing 2-D video was higher than in 3-D virtual worlds. During both the easier task of box folding and the harder task of crane folding, the cognitive load index was lower for all participants in the 3-D world and most for those with lower spatial ability

Table A1. Cont.

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Towards real world neuroscience using mobile EEG and augmented reality [109]	Krugliak & Clarke	Scientific Reports	2022	8	4 F, 4 M	Within Subjects	Face processing tasks: Computer-based face processing task; viewing of upright and inverted photos of faces along the walls of a corridor; viewing of virtual faces along a corridor (upright and inverted)	The assessment of the characteristic face inversion effect was investigated in conjunction with a head mounted AR device	Task 1: Computer Based, Task 2: mEEG + photos, Task 3: mEEG + XR	N/A	XR Headset (Microsoft Hololens)	N/A	EEG	2	Epoch based analysis, GLM based analysis	N/A	There was an increased low-frequency power over posterior electrodes for inverted faces compared to upright faces demonstrating the characteristic face inversion effects. This study revealed that these face inversion effects can be identified during free moving EEG paradigms. The authors argue that EEG and XR are a feasible approach to studying cognitive processes in various types of environments.

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A comparative experimental study of visual brain event related potentials to a working memory task: virtual reality head-mounted display versus a desktop computer screen [76]	Aksoy, Ufo-diamma, Bateson, Martin, Asghar	Experimental Brain Research	2021	21	7 F, 14 M	Within Subjects	N-back task	A working memory task in which participants needed to remember visual stimuli from a sequence either 1 trial back (1-back) or 2 trials back (2-back) in either a VR or desktop condition	Single Wall VR condition	Desktop	XR Headset (HTC Vive)	Desktop	EEG	1, 2	Anterior N1, Posterior P1 and P3 ERPs	response time, accuracy rate of 1-back and 2-back tasks.	The P3 waveform was similar in the XR condition and the desktop environment. N1 peak amplitude was higher in the XR HMD environment.

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Enhancing Cognitive Function Using Perceptual-Cognitive Training [89].	Parsons, Magill, Boucher, Zhang, Zogbo, Bérubé, Scheffer, Beauregard, and Faubert	Clinical EEG & Neuroscience	2014	20	Not Reported	Between Subjects	3D Multiple Object Tracking(MOT)	Participants performed a 3-D MOT with or without training	Training	Non-active Control	Neurotracker (glasses)	N/A	EEG	1	EEG: Alpha, Beta, Gamma and Theta power	. MOT session scores, Integrated Visual and Auditory Continuous Performance Test, selected subtests from the Wechsler Adult Intelligence Scale, Delis-Kaplan Executive Functions System Color-Word Interference Test	3D-MOT can improve cognitive function and can have an effect on attention, working memory, and visual information processing speed as demonstrated by EEG measures. 3-D MOT training can have improved cognitive outcomes compared to non-active control group.
Estimating Cognitive Workload in an Interactive Virtual Reality Environment Using EEG [117]	Tremmel, Herff, Sato, Tetsuya, Rechowicz, Yamani, Krusien-ski	Frontiers in Human Neuroscience	2019	15	4 F, 11 M	Within Subjects	N-back task in virtual environment	Participants had to virtually move colored balls that were presented n-trials before and move them to the target area	Three experimental blocks in randomized order: 0-back, 1-back, 2-back	N/A	XR Headset (HTC Vive)	N/A	EEG	2	Differences in average spectral amplitude of EEG bands across workload levels, Task performance	N/A	Cognitive workload during an interactive XR task can be estimated via scalp recordings

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Being present in a real or virtual world: A EEG study [112]	Petukhov, Glazyrin, Gorokhov, Steshina, Tanyrverdiev	International Journal of Medical Informatics	2020	5	ALL M	Within Subjects	Real life skiing and virtual skiing	Five experienced skiers first performed a controlled downhill skiing task while wearing EEG equipment and afterwards performed virtual downhill skiing task using a headset, and a simulated downhill skiing task using a desktop	Downhill skiing task followed by virtual downhill skiing task and desktop skiing task	N/A	XR Headset (HTC Vive)	Desktop	EEG	2	Frontal Activation Pattern Analysis and measure of cognitive expenditure during task	Electrocardiogram, Electrooculogram, Electromyogram, respiration analysis	This study revealed greater stable neuropatterns present in the virtual and physical environment compared to the desktop application. The authors argue that similar brain activity in the virtual and physical environments could help to understand the sense of presence in XR. In all cases (desktop, XR, physical) there was a high level of activation in the frontal lobe, which was indicative of processing of sensory and cognitive information.

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Cortical correlate of spatial presence in 2D and 3D interactive virtual reality: An EEG Study [108]	Silvia Erika Kober, Jurgen Kurzmann, Christa Neuper	International Journal of Psychophysiology	2011	30	15 F, 15 M	Between Subjects	Spatial Navigation Task	Participants performed the task in a desktop condition on a small screen that was less immersive or a XR condition on a large screen that was more immersive while their EEG data was recorded	Single Wall XR condition	Desktop VR condition	3-D screen	Desktop	EEG	2	Task Related Power Analysis	Regional activity and connectivity, Presence Ratings	There was a greater feeling of presence in the more immersive XR condition and there was an increased parietal activation compared to the less immersive desktop condition. In terms of the decreased presence experience there was a stronger functional connectivity between frontal and parietal brain regions

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Adding immersive virtual reality to a science lab simulation causes more presence but less learning [2]	Makransky, Terkildsen, Mayer	Learning & Instruction	2019	52	22 M, 30 F	Between Subjects and within subjects	four different versions of a virtual laboratory simulation followed by Knowledge & Transfer tests	The participants learning outcomes were measured post simulation and they were assessed on their retention of information through a knowledge test and their ability to transfer their learning to another context through a transfer test	Part 1 (Between Subjects): Text; Part 2 (Within Subjects): VR -> Desktop	Part 1 (Between Subjects): Text + Narration; Part 2 (Within Subjects): Desktop -> VR	XR headset (Samsung GearVR)	Part 2: Desktop	EEG	2	Workload metric	Performance on tests, participant questionnaire, self-report survey	The study shows that immersive instructional media may indeed be fun and increase presence but does not necessarily increase student learning. High-immersion XR can increase processing demands on working memory and decrease knowledge acquisition. The authors argue that this should be taken into account before utilizing immersive XR for instructional learning

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Cognitive and affective processes for learning science in immersive virtual reality [88]	Jocelyn Parong, Richard Mayer	Journal of Computer Assisted Learning	2020	61	40 F, 20 M, 1 Other	Between Subjects	A biology lesson which varied in terms of the instructional media and the practice testing administered to participants	Participants were tested on their learning outcomes through retention and transfer post-tests administered after the lesson which was either virtual reality or desktop	VR	Desktop	XR headset (HTC Vive)	Desktop	EEG	2	EEG, Heart Rate Variability, Skin Conductance	Retention Score, Transfer Score, self report	Participants performed better on transfer tests after viewing a biology lesson in a PowerPoint as opposed to in IVR. IVR was rated as more distracting based on self-report measures and EEG-based measures than the PowerPoint. IVR led to more distraction, which was linked to weaker performance on learning outcomes
Stereoscopic perception of women in real and virtual environments: A study towards educational neuroscience [118]	Zacharis, Mikropoulos, Priovolou	Themes in Science & Technology Education	2013	36	36 F	Within Subjects	Stereoscopic perception of women were observed in three different environments to observe the electric brain activity	These women either had to view a real environment, a 2-D environment, or a 3-D and a stereoscopic environment	Real desktop, 2-D virtual desktop, 3-D virtual desktop	N/A	Desktop with active 3-D glasses (Sony)	Desktop without active 3-D glasses	EEG	2	Theta, Alpha, Beta and Gamma activity	N/A	Brain activity was similar in the real and 3-D environments compared to 2-D. The real (stereoscopic) environment required the least mental effort compared to the other two environments

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Impacts of Cues on Learning and Attention in Immersive 360-Degree Video: An Eye-Tracking Study [57]	Liu, Xu, Yang, Li, Huang	frontiers in psychology	2022	110	74 F, 36 M	Between Subjects	Textual and visual, cue response task	Participants watched a 360-degree video on an intracellular environment and then were assigned to 4 conditions: • No cues • Textual cues in the field of vision (FOV) • Textual cues outside of the FOV • Textual cues outside of the FOV with visual cues	textual cues in the initial FOV (TCIIF) group, textual cues outside the initial FOV (TCOIF) group, textual cues outside the initial FOV + visual cues (TCOIF + VC) group	No cues (NC) group	XR headset (HTC Vive), Eye-Tracker (Tobii Pro)	N/A	Eyetracking	1, 2	Main eye movement indicators: total fixation duration, fixation duration on annotation areas of interest (AOIs), fixation duration on initial FOV AOIs and fixation heatmaps	spatial ability tests, prior knowledge test, semi-structured interview	Due to limited field of vision in immersive environments, visual cues in the field of vision (FOV) help guide the learner. However, visual cues and annotations may increase cognitive load, therefore appropriate use of visual cues is necessary for instructional design in immersive environments.

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From 2D to VR Film: A Research on the Load of Different Cutting Rates Based on EEG Data Processing [116]	Tian, Zhang and Li	information	2021	40	27 M, 13 F	Between Subjects	Visual Task	Participants watched the film in either a 2-D or 3-D (VR) condition at three different cutting rates	XR Group	2-D Group	XR Head-set(HTV Vive)	Desktop	EEG	2	Alpha, Beta, and Theta Frequency bands and power values, NASA-TLX	PANAS questionnaire	EEG analysis and topographical maps showed that the energy of the alpha, beta, and theta waves of the XR film group were higher than the 2D film group. The NASA-TLX results also show that the subjective load of the XR film group was higher than that of the 2D film group
Cognitive load and attentional demands during objects' position change in real and digital environments [119]	Zacharis, Mikropoulos, Kalyvioti	Themes in Science & Technology Education	2016	36	ALL F	Within Subjects	Observation of changes in object position and attentional demand in real and digital environments	Participants were placed into three different environments: real, 2-D, and 3-D while they observed before and after changes in objects position	Real Environment (Before & After), Virtual Environment (Before & After), Virtual environment using 3-D Glasses (Before & After)	N / A	Desktop with active 3-D glasses	Desktop	EEG	2	Theta, Alpha, Beta, and Gamma frequency and power analysis	Performance in different environments	Cognitive load associated with the task was higher in all environments before the change of the objects position. The cognitive load appeared to reduce after the change

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Mental Workload Drives Different Reorganizations of Functional Cortical Connectivity Between 2D and 3D Simulated Flight Experiments [105]	Kakkos, Dimitrakopoulos, Gao, Zhang, Qi, Matsopoulos, Thakor, Bezerianos, Sun	IEEE Transactions on neural systems and rehabilitation engineering	2019	33	33 M	Within Subjects	Flight simulation with three levels of mental workload	Participants were assigned to both the simulation session in a desktop condition and in a XR condition	XR interface	2-D interface	XR headset (Oculus Rift)	Desktop	EEG	2	Frequency Analysis (Delta, Theta, Alpha, Beta, Gamma), Workload Metric, Task difficulty performance	Network Topology Analysis, Functional connectivity, Classification using support vector machine (SVM) analysis	The study validated different levels of workload in a simulation setting and found differences in 2-D vs. XR conditions. XR interface had higher mental workload. Theta band edges had higher overall connectivity in XR condition with increasing mental load. This may be a result of higher presence, and active cognitive processing in the XR condition

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The impact of 3D and 2D TV watching on neurophysiological responses and cognitive functioning in adults [84]	Jeong, Ko, Han, Oh, Park, Kim, Ko	European Journal of Public Health	2015	72	40 F, 32 M	Between Subjects	Administered various neurocognitive tests, i.e., simple reaction time (SRT), choice reaction task (CRT), digit classification task (DC)	Participants did neurocognitive tests while physiological measurements were being taken in either a 2-D TV watching condition or 3-D TV watching condition	3-D TV watching	2-D TV watching	3-D stereoscopic TV (with polarized glasses)	Regular TV	EEG	1	Mean electrical activity across Theta, Alpha, beta, gamma, delta bands in frontal and occipital regions	Psychophysiological Measures: heart rate, respiratory rate, electromyography, galvanic skin response, temperature; neurocognitive measures: simple reaction time (SRT), choice reaction time (CRT), color word vigilance (CWV), digit classification (DC), digit addition (DA), digit symbol substitution (DSS), memory forward digit span (FDS), backward digit span (BDS), and finger tapping test (FT); Simulator Sickness Questionnaire	Contrary to belief that 3-D TV watching is harmful and may negatively affect neurocognitive outcomes, findings reveal it is equivalent to its 2-D counterpart with no dangers to cognitive functioning or differences between the two conditions in neurocognitive outcomes

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EEG Alpha Power Is Modulated by Attentional Changes during Cognitive Tasks and Virtual Reality Immersion [111]	Magosso, Crescenzio, Ricci, Piastra, and Ursino	Computational Intelligence & Neuroscience	2019	EXP 1: 30, EXP 2: 41	EXP 1: 10 F, 20 M, EXP 2: 9 F, 32 M	Within Subjects	EXP 1: Arithmetic Task & Reading Numbers Task EXP 2: Immersion in a VR airplane cabin--relaxation without VR, first static immersion in the VR, interactive exploration of VR, and second static immersion in the VR.	EXP 1: participants had to solve arithmetic operations vs. mentally read the arithmetic operations (order randomized). EXP 2: participants passively and actively exploring a VR environment. Twenty-four participants additionally performed arithmetic task in VR	separate participants for each exp	N/A	Cave Automatic Virtual Environment(CAVE) with shutter glasses	Desktop	EEG	2	Alpha Power Computation as a function of task demands	N/A	Attention to immersive XR environments and an arithmetic task both create a significant ERD compared to a previous relaxation phase, especially in parietal-occipital regions which is indicative of mental effort/cognitive load. XR environments have a sense of realism and attention-grabbing influence as reflected in alpha rhythms The use of XR with objective physiological measures is a useful tool in studying various aspects of cognition and behavior

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An Augmented Reality Based Mobile Photography Application to Improve Learning Gain, Decrease Cognitive Load, and Achieve Better Emotional State [95]	Zhao, Zhang, Chu, Zhu, Hu, He & Yang	International Journal of Human Computer Interaction	2022	28	7 M, 21 F	Between Subjects	Photography Task	Participants performed the task in a 2D mobile photography app vs. a 3D XR photography application	AR App	2-D App	Android mobile AR application (Huawei LYA-AL00)	Android mobile application (Huawei LYA-AL00)	EEG	1, 2	Cheng Scale, Comparison of pre to post performance test score	Emotional State Indicators	Both groups improve their knowledge of photography. However, ARMPA participants perform better and have the most learning gain. From these findings the authors propose that AR has lower cognitive load and according to their brain analyses the AR group has greater interest for students

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Comparing virtual reality, desktop-based 3D, and 2D versions of a category learning experiment [79]	Robin Colin Alexander Barrett, Rollin Poe, Justin William OCamb, Cal Woodruff, Scott Marcus Harrison, Katerina Dolguikh, Christine Chuong, Amanda Dawn Klassen, Ruilin Zhang, Rohan Ben Joseph, Mark Randal Blair	Plos One	2022	179	N/A	Between Subjects	Category Learning Task	Participants performed a category learning task in either a 2-D projection, 3-D projection on a desktop, or 3-D projection using XR	3-D Stimuli using XR	3-D Stimuli using Desktop & 2-D Stimuli using Desktop	XR Head-set (HTC Vive)	Desktop	Eye-tracking	1, 2	Improvements in Accuracy, Fixation Counts & Average Fixation Duration	Response Time, Optimization, and information sampling	There were no significant differences in learning outcomes between the three groups but there were longer fixations in the XR condition and longer response times

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Cognitive workload evaluation of landmarks and routes using virtual reality [96]	Usman Alhaji Abdurrahman, Lirong Zheng, Shih-Ching Yeh	Plos One	2022	79	36 M, 43 F	Between Subjects	Landmark Route & Navigational Task	Assessment via a XR driving system whether there's an effect of landmarks and routes on navigational efficiency and learning transfer	Part 1:Sufficient Landmarks and Easy routes Part 2: Insufficient Landmarks and Easy Routes	Part 1: Sufficient Landmarks and Difficult routes Part 2: Insufficient Landmarks and Difficult routes	XR Driving System with Logitech G-27 Steering wheel controller	N/A	Eye-tracking	2	Fixation rate, blink rate, blink duration, cognitive workload obtained through combining information on pupil size, eye gaze, heart rate, performance, into classifiers (support vector machine (SVM), artificial neural networks (ANNs), naïve Bayes (NB), K-nearest neigh-bor (KNN), and a decision tree (DT))	Mean Task Completion Time	Sufficient landmarks increase navigational efficiency. Navigation with insufficient landmarks increased pupil size

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Augmented reality on industrial assembly line: Impact on effectiveness and mental workload [83]	Mathilde Drouot, Nathalie Le Bigot, Emmanuel Bricard, Jean-Louis de Bougrenet, Vincent Nourrit.	Applied Ergonomics	2022	27	22 M, 5 F	Within Subjects	Dual Task Paradigm: Main Assembly Task and Auditory stimulus Detection Task	Assembly tasks: picking, positioning, tool uses, and handling and to be as accurate while doing a secondary beep detection task	AR Complex, AR Simple	Computer Complex, Computer Simple	XR Headset (Microsoft Hololens 2)	Desktop	Eye tracking	1, 2	Pupil size, Blink rate, Blink duration, NASA-TLX,	Reaction Time	Lower blink rate and higher mental workload when using XR
Visual short term memory-related EEG components in Virtual Reality set-up [107]	Felix Klotzsche, Michael Gaebler, Arno Villringer, Werner Sommer, Vadim Nikulin, Sven Oh	Psychophysiology	2023	26	14 M, 12 F	Within Subjects	Change Detection Task	The visual memory of varying loads was tested in a change detection task with bilateral stimulus arrays of either two or four items while varying the horizontal eccentricity of the memory arrays	XR Group	N/A	XR Headset (HTC Vive)	N/A	Eye tracking, EEG	2	Blink rate, saccades, alpha activity, memory performance, CDA power	Contralateral Delay Activity Analysis	Increasing memory load resulted in diminished memory performance and we observed both a pronounced CDA and a lateralization of alpha power during the retention interval. Findings encourage the use of XR to measure EEG signals related to visual short-term memory and attention (e.g., the CDA or the lateralization of alpha power)

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A Multimodal Approach Exploiting EEG to Investigate the Effects of VR Environment on Mental Workload [86]	Marta Mondellini, Ileana Pirovano, Vera Colombo, Sara Arlati, Marco Sacco, Giovanna Rizzo, and Alfonso Mastropietro	International Journal of Human-Computer Interaction	2023	27	16 M, 11 F	Within Subjects	N-Back Task	Working memory task with varying levels of load; participants were asked to indicate if the image was the same as the one presented ‘n’ trials ago. There was also a dual task version with visual + audio stimuli	XR Group	Desktop Group	XR Headset (HTC Vive Pro)	Desktop	EEG	1, 2	Mental Workload Index, NASA-TLX	Performance assessment	No significant differences between XR and desktop in terms of mental workload or performance assessments
Does stereopsis improve face identification? A study using a virtual reality display with integrated eye-tracking and pupilometry [49]	Liu, Laeng, Czajkowski	Acta Psychologica	2020	32	19 F, 13 M	Within Subjects	sample to match face identification task	Stereoscopic vs. monoscopic images of faces were presented and accuracy of face identification was assessed in frontal, intermediate and profile views	Stereoscopic & Monoscopic images	N/A	XR headset (HTC Vive) + SMI Eye-tracker	N/A	Eyetracking and pupilometry	1, 2	Gaze information, pupil size variation	Response time	The accuracy rate was higher in the stereoscopic condition compared to the monoscopic condition for both frontal and intermediate views.

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Enhanced Interactivity in VR-based Telerobotics: An Eye-tracking Investigation of Human Performance and Workload [87]	Federica Nenna, Davide Zanardi, Luciano Gamberini	International Journal of Human Computer Studies	2023	24	13 M, 11 F	Within Subjects	an arithmetic task, a pick-and-place task, physical actions, a dual-task	5 tasks using VR—arithmetic calculations in virtual environment; pick and place items using a robotic arm—one task via a button, the other by manually moving the arm in VR; in the dual task both arithmetic and pick and place task performed simultaneously	VR Group	N/A	XR Headset (HTC Vive Pro Eye Headset)	N/A	Eyetracking	1	NASA-TLX, Pupil Size Variation	Operation time, Error rate	Improved performance and reduced cognitive load in a XR-based action control system
Modulation of cortical activity in 2D versus 3D virtual reality environments: An EEG study [92]	Sloubonov, Ray, Johnson, Slobounov, Newell	International Journal of Psychophysiology	2015	EXP 1: 12, EXP 2: 15	6 M, 6 F; 8 M, 7 F	Within Subjects	3-D Spatial navigation Task	Navigation in a 3-D or 2-D projected virtual corridor	EXP 1: 3-D TV; EXP 2: 3-D VR moving room	EXP 1: 2-D TV; EXP 2: 2-D VR moving room	3D television with CrystalEyes stereo glasses	N/A	EEG	1, 2	EEG frontal midline Theta Power Analysis	Postural Movement Analysis; accuracy of the task performance, number of trials-and time needed to complete the test	VR has a higher sense of presence, especially in 3-D conditions compared to 2-D. Navigation performance was better in 3-D condition compared to 2-D condition. FM-theta was higher in encoding rather than retrieval

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A comparative analysis of face and object perception in 2D laboratory and virtual reality settings: insights from induced oscillatory responses [91]	Merle Sagehorn, Joanna Kisker, Marike Johnsdorf, Thomas Gruber, Benjamin Schöne	Experimental Brain Research	2024	55	38 F, 17 M	Within Subjects	Face & Object Perception & (Car) Standard Stimulus Discrimination paradigm	Viewing of face stimuli and car stimuli in either 2-D or 3-D version and then pressing of button to identify target and then feedback on whether response was correct or not	XR Condition	PC condition	XR Headset (HTC Vive Pro 2)	Desktop	EEG	1, 2	Posterior induced alpha band response (iABR) and mid-frontal induced theta band response (iTBR), Response Times	Induced Beta Band response (iBBR)	Cognitive load higher in 2D setting, as midfrontal theta was higher and faster reaction times in virtual condition
Tracking visual attention during learning of complex science concepts with augmented 3D visualizations [24]	Fang-Ying Yang, Hui-Yun Wang	Computers & Education	2023	32	15 M, 17 F	Within Subjects	AR Chemistry Learning App	3 different 3-D visualizations in AR app: static, dynamic and interactive 3D modes with descriptions of molecular shapes and instructions on how to interact with them. After playing with AR app and doing activities participants could take post-test.	XR group	N/A	App developed on Unity and download on Android Tablet	N/A	Eye-tracking	1, 2	Total Fixation Duration(TFD), Average Fixation Duration(AFD), Saccade Duration(SD)	Pre & Post test results	Students significantly increased their understanding of study concepts after AR learning. Interactive 3D mode captured attention in basic stages but dynamic modes were better in advanced stages. Higher fixation durations for static and interactive modes

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Impact of Visual Game-Like Features on Cognitive Performance in a Virtual Reality Working Memory Task: Within-Subjects Experiment [90]	Eric Redlinger, Bernhard Glas, Yang Rong	JMIR Serious Games	2022	20	6 F, 14 M	Within Subjects	Visual Working Memory Task	Participant sees a screen with 4 distractor images in the corners and a center image. In order to proceed the participant needs to identify which image was present previously in the center—1-back condition.	XR condition	N/A	XR Headset (HTC Vive)	N/A	EEG	1	Task Performance: Accuracy & Reaction Time	Spectral EEG power	Visually distracting 3D background has no observable effect on reaction speed but slight impact on accuracy
Cognitive processes during virtual reality learning: A study of brain wave [115]	Dadan Sumardani, Chih Hung Lin	Education & Information Technologies	2023	9	4 M, 5 F	Within Subjects	Attention differences between reading activity and virtual reality activity	Reading material about the International Space Station (ISS) and experiencing virtual reality simulation about the ISS	XR Learning	Reading	Unknown	Reading Material	EEG	2	Resting State EEG	Meditation in EEG vs. XR	Reading had higher level of attention than XR Learning

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Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Dynamic Cognitive Load Assessment in Virtual Reality [100]	Rachel Elkin, Jeff M. Beaubien, Nathaniel Damaghi, Todd P. Chang, and David O. Kessler	Simulation & Gaming	2024	12	6 F, 6 M	Mixed (within & between subjects design)	VR paediatric resuscitation task	Participants acted as team leader in four immersive VR emergency scenarios (status epilepticus vs. anaphylaxis) with low vs. high distraction manipulations, requiring airway management, medication administration, and stabilization.	Novice paediatric residents (PGY1–2)	Expert paediatric emergency fellows/attendings	XR Headset (Oculus Rift)	None (all scenarios delivered in VR)	EEG & ECG	2	EEG + ECG (denoised with accelerometry); combined into a composite workload index using previously validated classifier models; NASA-TLX; Performance: Time to critical action, number of errors.	ECG	Feasible to measure CL unobtrusively in real time during VR resuscitation simulations; experts showed lower CL than novices, consistent with NASA-TLX
Understanding Pedestrian Cognition Workload in Traffic Environments Using Virtual Reality and Electroencephalography [85]	Francisco Luque, Víctor Armada, Luca Piovano, Rosa Jurado-Barba, Asunción Santa-maría	Electronics	2024	12	2 F, 10 M	Within Subjects	VR pedestrian crossing with embedded auditory oddball (dual-task paradigm).	Participants performed road-crossing decisions in a VR traffic environment while simultaneously completing an auditory oddball task to assess attentional load	Dual task (VR Crossing + oddball)	N/A	XR Headset (Oculus Quest 2)	None	EEG	1, 2	P3 amplitude, Early-CNV, time-to-arrival estimation	NASA-TLX	There is value of virtual environments to explore cognitive load

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Identification of Language Induced Mental Load from Eye Behaviors in Virtual Reality [114]	Johannes Schirm; Andrés Roberto Gómez-Vargas; Monica Perusquía-Hernández; Richard T. Skarbez; Naoya Isoyama; Hideaki Uchiyama; Kiyoshi Kiyokawa	Sensors	2023	EXP 1: 30 EXP 2: 15	EXP 1: 9 F, 21 M EXP 2: 1 F, 14 M	Within Subjects	Listening Comprehension Task	Participants listened to four speech samples (native vs. foreign; familiar vs. unfamiliar) to vary mental load.	participants under higher cognitive load (listening to unfamiliar/foreign language speech)	Same participants under lower cognitive load (listening to familiar/native speech)	XR Headset (HTC Vive Pro Eye)	None	Eye-tracking	2	Gaze points, gaze targets, pupil size, focus point, fixation frequency, saccades	NASA-TLX	Eye-tracking metrics (pupil size, fixations, focus offset) reflected changes in cognitive load during the VR listening task
Visual information processing of 2D, virtual 3D and real-world objects marked by theta band responses: Visuospatial processing and cognitive load as a function of modality [104]	Joanna Kisker, Marike Johnsdorf, Merle Sagehorn, Thomas Hofmann, Thomas Gruber, Benjamin Schöne	European Journal of Neuroscience	2024	99	61 F, 38 M	Between Subjects	Delayed Matching to Sample Task	Participants viewed abstract objects in 2D (PC), VR, or real-world (3D print) and judged whether pairs were identical or different, while EEG theta band responses were recorded to compare sensory vs. cognitive processing across modalities.	VR condition (virtual 3D objects presented via HMD)	PC condition (2D objects on a monitor), RL condition (real-world 3D printed objects)	XR Headset (HTC Vive Pro 2)	Desktop	EEG	2	Discrimination performance, induced Theta band response (iTBR)	Evoked Theta Band Response (eTBR)	Cognitive load was higher for 2D than VR or real 3D, with VR closely matching real-world processing

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Comparative Analysis of Teleportation and Joystick Locomotion in Virtual Reality Navigation with Different Postures: A Comprehensive Examination of Mental Workload [103]	Reza Kazemi, Naveen Kumar & Seul Chan Lee	International Journal of Human-Computer Interaction	2024	60	20 F, 40 M	Between Sub-jects	Navigation Task	Locomotion in VR navigation through joystick and teleportation methods and postures: sitting and standing	Telepor-tation (seated + standing)	Joystick (seated + standing)	XR Headset (Oculus Quest 2)	None	EEG	2	Alpha & Theta Band Activity	NASA-TLX, ECG	Teleportation locomotion and standing posture both increased mental workload compared to joystick and seated conditions. Joystick + seated produced the lowest workload and better task performance, while teleportation + standing showed the highest workload.
The impact of virtual agents ‘multi-modal communication on brain activity and cognitive load in Virtual Reality [81]	Zhuang Chang, Huidong Bai, Li Zhang, Kunal Gupta, Weiping He, and Mark Billinghurst.	Frontiers in Virtual Reality	2022	11	1 F, 10 M	Within Sub-jects	VR desert survival decision making game	Participants ranked 15 survival items in col-laboration with a virtual agent in VR, across three IVA commun-ication conditions (voice-only, embodied with gaze, gestural with pointing).	Virtual agents with em-bodied multi-modal commun-ication— speech + gaze (Em-bodied Agent) or speech + gaze + pointing (Gestural Agent).	Virtual agent with voice-only commun-ication	XR Headset (HTC Vive Pro Eye)	None	EEG	1, 2	Alpha Band Activity (Spectral power + ERD/ERS), Survival Ranking score	NASA-TLX, Co-presence question-naire	Embodied and gestural VR agents influenced neural load; alpha activity showed embodied agents eased attentional demand while gestures increased it, though survival ranking performance was unaffected

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
A Neurophysiological Evaluation of Cognitive Load during Augmented Reality Interactions in Various Industrial Maintenance and Assembly Tasks [77]	Faisal M. Alessa, Mohammed H. Alhaag, Ibrahim M. Alharkan, Mohamed Z. Ramadan, and Fahad M. Alqah-tani.	Sensors	2023	28	28 M	Mixed (between + within)	Piston pump assembly / maintenance task	Participants performed pump maintenance (gearbox repair = high demand; seal check = low demand) using either AR-based or paper-based instructions.	AR-based instructions	Paper based instructions	XR Headset (Microsoft HoloLens)	Paper Manuals	EEG	1, 2	Theta, alpha, beta band activity; total task time	NASA-TLX	AR increased mental workload (theta, alpha; beta), especially during high-demand tasks, but reduced completion time versus paper
Event Related Brain Responses Reveal the Impact of Spatial Augmented Reality Predictive Cues on Mental Effort [94]	Benjamin Volmer, James Baumeister, Stewart Von Itzstein, Matthias Schlesewsky, Ina Bornkessel-Schlesewsky, and Bruce H. Thomas.	Transactions on Visualization and Computer Graphics	2023	23	2 F, 21 M	Between Subjects	N-Back task and button pressing procedural task	Button-pressing sequences with instructions shown via monitor or SAR (baseline highlight or predictive cues: ARC, ARROW, LINE, BLINK, COLOR), while performing a dual-task auditory oddball to index mental effort.	SAR with predictive cues (ARC, ARROW, LINE, COLOR, BLINK).	1. Monitor-based (2D screen instructions). 2. SAR baseline without predictive cues.	Spatial Augmented Reality (SAR) projected onto a dome shape	Desktop	EEG	1, 2	Mismatch negativity (MMN), P3 component, Response times, accuracy	EOG	Using spatial AR predictive cues improves task performance and can lower cognitive load, but not all cues are equal—ARC and ARROW balance speed and low brain effort best, while LINE is fastest but not the most cognitively efficient

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Designing and Evaluating an Adaptive Virtual Reality System using EEG Frequencies to Balance Internal and External Attention States [82]	Francesco Chiossi, Changkun Ou, Carolina Gerhardt, Felix Putze, and Sven Mayer	International Journal of Human-Computer Studies	2025	24	12 F, 12 M	Within Subjects	Visual Monitoring Task & N-Back Task	Participants performed a visual monitoring task (tracking target avatars) and a 2-back task with colored spheres. The VR system adjusted the number of distractor characters in real time according to EEG signals, either to support internal attention (positive adaptation) or to bias toward external attention (negative adaptation).	EEG-adaptive (positive & negative).	Non-adaptive n-back + visual monitoring baseline.	XR Headset (HTC Vive Pro)	None	EEG	1, 2	Alpha & Theta Band Activity; Accuracy scores, reaction times	NASA-TLX, Gaming Experience Questionnaire (GEQ)	Positive (internal-attention) adaptation improved 2-back accuracy and lowered workload versus negative adaptation; negative adaptation sped responses but hurt accuracy and increased workload. EEG alpha/theta can drive useful real-time VR adaptations

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Cognitive Load Estimation in VR Flight Simulator [102]	P. Archana Hebbar, Sanjana Vinod, Aumkar Kishore Shah, Abhay A. Pashilkar, and Pradipta Biswas.	Journal of Eye movement research	2023	12	12 M	Within Subjects	VR flight simulation (dogfight scenarios against AI-controlled enemy aircraft).	Twelve Air Force test pilots flew VR F-16 simulations, engaging AI aircraft across five scenarios. They controlled the aircraft using HOTAS (Hands-On Throttle and Stick) and fired missiles when targets were in range.	More AI guidance (higher automation support) and shorter radar latency (system responding quickly).	Less AI guidance (lower automation support) and longer radar latency (slower system response).	XR Headset (HTC Vive Pro Eye)	None	EEG, Eye-tracking	2	EEG Spectral power (Theta + Alpha); Ocular Parameters (pupil dilation, gaze fixation)	None	Pupil diameter, fixation rate, and EEG workload indices increased with task difficulty and workload manipulation, while engagement measures decreased, showing these physiological signals reliably estimate cognitive load in VR flight scenarios and support VR simulators for cockpit evaluation
Unraveling the Dynamics of Mental and Visuospatial Workload in Virtual Reality Environments [99]	Gonzalo Bernal, Hyejin Jung, Ilayda Ece Yassi, Nicolás Hidalgo, Yonathan Alemu, Theresa Barnes-Diana, and Pattie Maes.	Computers	2024	34	16 F, 15 M	Within Subjects	VR Tetris Game	Participants played VR Tetris with and without a “helper event” (a ball piece that cleared rows when the stack reached 60%).	Tetris with helper event	Tetris without helper event	XR Headset (Valve Index)	None	EEG	2	Alpha, Beta, Theta spectral activity; performance improvement	Photoplethysmography (PPG), Heart Rate Variability (HRV)	The VR helper event reduced cognitive load and arousal while boosting visuospatial engagement. Performance improved with helper events, supporting adaptive VR for workload optimization

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Measuring Cognitive Load in Virtual Reality Training via Pupilometry [110]	Joy Yeonjoo Lee, Nynke de Jong, Jeroen Donkers, Halszka Jarodzka, and Jeroen J. G. van Merriënboer	Transactions on Learning Technologies	2023	14	12 F, 2 M	Within Subjects	Health care observation task	Participants engaged in a 9-minute VR home-healthcare scenario. In the easy condition, they observed the provider's actions; in the difficult condition, they identified patient symptoms and evaluated the provider's performance.	Difficult Observation Task	Easy Observation Task	XR Headset (HTC Vive Pro Eye)	None	Eye-tracking	2	Task Evoked Pupillary Responses (TEPR); Task score	Paas Scale	TEPRs reliably indexed increases in cognitive load with task difficulty and correlated with self-reported effort

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Estimating mental workload through event-related fluctuations of pupil area during a task in a virtual world [113]	Miriam Reiner, Tatiana M Gelfeld	International Journal of Psychophysiology	2014	31	15 F, 16 M	Between Subjects	Motor task: hitting cubes	Participants used a VR stylus-hand to strike cubes under two conditions: a congruent task (cube size matched weight) and a random task (size-weight association unpredictable).	6 congruent trials, 6 random trials	12 congruent trials, 6 random trials	Stereoscopic Shutter Glasses	None	Eye-tracking	2	Pupil size, Power Spectrum Density (PSD)	None	Pupil-based indices (low/high frequency ratio and high-frequency power) reliably tracked changes in workload. Mental load decreased with repeated congruent trials but increased when task demands became unpredictable, supporting pupil metrics as valid, non-intrusive measures for adaptive VR/BCI systems

Table A1. Cont.

Paper	Authors	Journal	Year	Number of Participants	Gender	Design	Task	Task Description	Experimental Group	Comparison Group	3-D Technology	Control Technology	Psychophysiological Measure	Research Question (RQ)	Cognitive Load Measure	Other Measure(s)	Conclusion
Effects of augmented reality glasses on the cognitive load of assembly operators in the automotive industry [97]	Hilal Atici-Ulusu, Yagmur Dila Ikiz, Ozlem Taskapilioglu & Tulin Gunduz	International Journal of Computer Integrated Manufacturing	2021	4	2 M, 2 F	Within Subjects	Assembly line diffusion task	Operators on an automotive assembly line performed a diffusion task (selecting and sorting materials into carts for assembly preparation).	Assembly with AR glasses	Standard manual procedure with paper instructions	XR Glasses(Sony Smart Eyeglass Sed-1)	Paper instructions	EEG	2	area under the curve ($\mu V \times s$), focusing on frontal/temporal/occipital beta-gamma oscillations (attention, decision-making).	NASA-TLX	AR glasses significantly reduced operators' cognitive load compared to standard procedures. Workers adapted immediately—no extra burden between first and last days—suggesting AR can enhance accuracy and efficiency in assembly preparation without increasing mental effort

Appendix C. Quality Assessment

Table A2. This table illustrates the risk of bias assessment for the included randomized controlled trials (RCTs) using the ROB-2 tool. Each study is evaluated across six domains of bias: randomization process, deviations from intended interventions, missing outcome data, measurement of the outcome, selection of the reported result, and overall bias. The color-coded circles represent the level of risk: blue (low risk), yellow (unclear risk), and red (high risk). This visual synthesis provides an overview of the methodological rigor and potential biases in the studies included in the systematic review.

Study	Bias Arising from the Randomization Process	Bias Due to Deviations from Intended Interventions	Bias Due to Missing Outcome Data	Bias in Measurement of Outcome	Bias in Selection of the Reported Result	Overall Risk of Bias
Dan & Reiner(a)	+	+	+	+	+	+
Kober, Kurzmann, Neuper	+	+	+	?	+	+
Sun, Wu, & Cai	+	+	+	?	+	+
Ghani, Signal, Niazi, Taylor	+	+	+	?	?	+
Makransky, Terkildsen, Mayer	+	+	+	?	+	+
Parong & Mayer	+	+	+	?	+	+
Berger & Davelaar	+	+	+	?	+	+
Baceviciute, Lucas, Terkildsen, Makransky (a)	+	+	+	?	+	+
Liu, Xu, Yang, Li, Huang	+	+	+	?	+	+
Parsons, Magill, Boucher, Zhang, Zogbo, Bérubé, Scheffer, Beauregard, Faubert	+	+	+	?	+	+
Dan & Reiner(b)	+	?	+	?	+	+
Baceviciute, Terkildsen, Makransky(b)	+	+	+	?	+	+
Tian, Zhang, Li	+	+	+	?	+	+
Jeong, Ko, Han, Oh, Park, Kim, Ko	+	+	+	?	+	+
Zhao, Zhang, Chu, Zhu, Hu, He & Yang	+	+	+	?	+	+
Liu, Laeng, Czajkowski	?	+	+	?	+	+
Nenna, Zanardi, Gamberini	?	+	+	?	?	?
Drouot, Bigot, Bricard, Bougrenet, Nourrit	+	+	+	?	?	?
Mondellini, Pirovano, Colombo, Arlati, Sacco, Rizzo, Mastropietro	+	+	+	?	+	+
Abdurrahman, Zheng, Yeh	+	+	+	?	+	+
Barrett, Poe, O'Camb, Woodruff, Harrison, Dolguikh, Chuong, Klassen, Zhang, Joseph, Blair	+	+	+	+	?	+
Redlinger, Glas, Rong	+	+	+	+	+	+
Sagehorn, Kisker, Johnsdorf, Gruber, Schöne	?	+	+	+	+	+
Sumardani & Lin	?	+	+	-	+	-
Luque, Armada, Piovano, Jurado-Barba, Santamaria	?	+	+	+	+	+
Kisker, Sagehorn, Hofmann, Gruber, Schöne	+	+	+	+	+	+
Schirm, Gómez-Vargas, Perusquía-Hernández, Skarbez, Isoyama, Uchiyama	?	+	+	+	?	?
Volmer, Baumeister, Von Itzstein, Schlesewsky, Bornkessel-Schlesewsky, Thomas	?	+	+	+	+	+
Alessa, Alhaag, Al-harkan, Ramadan, Alqahtani	?	+	+	+	+	+
Chang, Bai, Zhang, Gupta, He, Billinghamurst	?	+	+	+	+	+
Lee, De Jong, Donkers, Jarodzka, Van Merriënboer	?	+	+	?	+	?
Kazemi, Kumar, Lee	+	+	+	+	+	+

ROBINS-I Risk of Bias Assessment

Table A3. This figure presents the risk of bias assessment for non-randomized studies included in the systematic review using the ROBINS-1 tool. Each row represents a study, and the columns indicate different domains of bias: confounding, selection of participants, classification of interventions, deviations from intended interventions, missing data, measurement of outcomes, and selection of reported result. The color-coded symbols denote the level of risk: low risk (blue), high risk (red), and unclear risk (yellow). The overall risk of bias for each study is also depicted in the last column.

Study	Confounding	Selection of Participants	Classification of Interventions	Deviations from Intended Interventions	Missing Data	Measurement of Outcomes	Selection of Reported Result	Overall Risk of Bias
Magosso, Crescenzo, Ricci, Piastra, & Ursino	+	+	+	+	+	?	+	+
Kakkos, Dimitrakopoulos, Gao, Zhang, Qi, Mastopoulos, Thakor, Bezerianos, Sun	+	+	+	+	+	?	+	+
Zacharis, Mikropoulos, Priovolou	?	-	+	+	+	?	?	-
Sloubonov, Ray, Johnson, Sloubonov, Newell	+	+	+	+	+	+	+	+
Zacharis, Mikropoulos, Kalyvoti	?	-	+	+	+	?	?	?
Tremmel, Herff, Sato, Tetsuya, Rechowicz, Yamani, Krusienski	+	+	+	+	+	+	+	+
Petukhov, Glazyrin, Gorokhov, Steeshina, Tanyrverdev	?	-	+	+	+	?	?	-
Aksoy, Ufodiana, Bateson, Martin, Asghar	+	+	+	+	+	+	+	+
Kirchner, Kim, Tabie, Wohrle, Maurus, & Kirchner	?	-	+	+	+	+	?	?
Suarez, Grasmann, Ochoa, Toro, Mejia, Hernandez	?	?	+	+	+	+	+	+
Krugliak & Clarke	?	?	+	+	+	+	+	+
Yang & Wang	?	?	+	+	+	+	+	?
Elkin, Beaubien, Damaghi, Chang, Kessler	?	+	+	+	+	+	+	+
Bernal, Jung, Yassi, Hidalgo, Alemu, Barnes-Diana, Maes	?	+	+	+	+	+	+	+
Hebbar, Vinod, Shah, Pashilkar, Biswas	?	+	+	+	+	+	+	+
Chiossi, Ou, Gerhardt, Putze, Mayer	?	+	+	+	+	+	+	+
Atici-Ulus, Ikiz, Taskapilioglu, Gunduz	-	-	+	+	+	+	?	-
Reiner & Gelfeld	?	+	+	+	+	?	?	?

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