A systematic review of immersive technologies for education: effects of cognitive load and curiosity state on learning performance

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Abstract

Immersive technologies (*im*T) is claimed to have many benefits for learning, such as the ability to optimize learners' cognitive load (CL) as well as their curiosity states (intrinsic motivation) (CS-IM). From 2802 studies, we selected only 31 studies with a reliable study-design for investigating the impact of Virtual Reality (VR) and/or Augmented Reality (AR) on learning performance with respect to measurements of cognitive load and/or curiosity state. To this end, we built an analytical gird for probing positive, negative, null, or uninterpretable relationships between the learning performance and CL or CS-IM measures. The 24 studies focusing on CL show that the *im*T benefit for learning depends on technology with CL advantage for AR and with CL disadvantage for VR. For the 15 studies with a focus on CS-IM, the results are inconclusive and inconsistent due to large methodological differences in measuring this facet of the learning experience. Of the 8 studies investigating both CL and CS-IM, very few studies documented causal links between these two learning-related constructs, and the reported results were contradictory. The role of variables such as the type of knowledge taught, the type of learning, or the level of prior knowledge of the learners is examined. However, these variables did not yield significant insight into the relationships between the *im*T-learning performance and the learner experience in terms of CL and/or CS-IM. Recommendations for future research to address the identified gaps are provided for advancing the field of *im*T for learning.

Keywords (from the imposed list)

- Adult learning
- Augmented and virtual reality
- Media in education
- Post-secondary education
- Evaluation methodologies

1. Introduction

The digital transformation of schools is now seen as a promising way to meet the major educational challenges of the 21st century, such as increasing the equality of opportunity at school through pedagogical methods that meet a diversity of learning needs. Due to their versatility, there is a growing interest in immersive technologies (***im*****T**) such as virtual reality (**VR**) and augmented reality (**AR**). The main draw of these technologies for education is in offering learning environments previously unavailable in classroom setting. For example, simulators for learning of critical or risky human activities have been quickly adopted in training programs for aeronautics, medicine, or safety domains (Jensen & Konradsen, 2018). With technological progress, such digital imitations of real situations have increasingly and continuously become higher realism-fidelity, allowing the coupling of tangible interfaces to virtual environments (as in VR) and vice versa (as in AR) while also integrating complex social interactions (e.g., in a collaborative task with multiple users). This has allowed increases and improvements in the immersive experience of users, that in turn has led to VR/AR spreading into the full spectrum of learning domains. imT's increased affordability and enhanced usability have made them popular (Radianti et al., 2020). It is often claimed that immersive properties of technologies lead learners to be more motivated and more likely to engage their cognitive resources due to the creation of an optimal and sustainable flow experience (Radu, 2014; Skulmowski & Xu, 2022). However, is it settled science that that VR and AR universally increase learning effectiveness regardless of the learning domain, the type of learning, the learning context, and the learners' characteristics? Are VR and AR truly able to better engage students in learning?

Recent results from earlier systematic reviews are not supportive of such a conclusion and are often even misleading. First, regarding AR intervention, out of 28 selected studies on online learning, Alzahrani (2020) reported some promising benefits of AR use. While AR allowed for increased learning (in kinesthetic, collaborative, and creative domains), improved learning experience (e.g., engagement, motivation, attention/focus), Alzahrani et al. points out disadvantages such as information and cognitive overload due to a lack of AR practice. Most importantly, this review highlighted the weakness of findings due to studies being limited in terms of research design and evidential validity (non-randomized trials, small sample sizes, unbalanced samples, and non-validated measures). Selecting based on a set of stringent criteria, Buchner et al. (2022) analyzed 58 studies wherein AR is shown to be less cognitively demanding and contributive towards higher performance. However, the authors also suggest that these results are based on media comparisons, which have been criticized for ignoring the process of skill and knowledge acquisition.

Second, regarding *VR-based intervention*, from 18 selected studies, Di Natale et al. (2020) pointed out the lack of evidence for the effectiveness of VR for learning, despite encouraging early results (improved learning and promoting students' motivation and engagement). Beside of this, a meta-analysis on 35 Randomized Controlled Trials (RCT) and quasi-experimental studies (CT) indicates that VR with head-mounted displays (HMD VR) is more effective than other less immersive learning approaches (e.g., video, PPT) but with a small effect size (B. Wu et al., 2020). Moreover, this beneficial effect was achieved primarily for K-12 learners, and specifically in the areas of science education, in knowledge and skill development.

Third, studying interventions based on VR and AR, Newman et al. (2022) concluded from the 13 included studies on neuroanatomy education that the use of AR does not always result in a learning gain and is sometimes irrelevant. Previous systematic reviews reported mixed results for remote learning: from 24 studies assessing the learning performance, only 11 were positive (7 negative and 6 inconclusive) while the six other interventions measuring student engagement were all positive (Nesenbergs et al., (2021) . This later consensus on learner engagement experience fits with two other systematic reviews revealing a positive effect of using VR or AR technologies on student motivation (Fan et al., 2020; W. Huang et al., 2022).

1.1 Research question

From the overall results, early systematic reviews clearly reported strength-of-evidence limitations in studies conducted with VR or AR while the most recent reviews reported mixed results according to *im*T use (VR vs. AR), knowledge-domain, educational context, students' prior knowledge, and outcome measure (learning performance vs. learner experience).
To gain insight, our systematic review focuses on the RCT and quasi-experimental studies investigating the effectiveness of *im*T (VR or RA) for education by limiting to adult learners and distinguishing various outcome measures. The main co-variables identified previously are also taken into account (i.e., knowledge domain, learning outcomes, type of knowledge and learner expertise). As the main claims about imT assets for learning are related to cognitive demand and student motivation, we questioned the impact of *im*T on the relationships between, on the one hand, learning performance, and, on the other hand, student's cognitive load and/or motivation. In other words, our initial research question is *Do imT impact learning performance and/or the learner experience in terms of cognitive load and motivation?*

1.2 Background

1.2.1 Definition of Immersive Technologies (imT)

A recurring problem in the educational research using *im*T is the heterogeneity in the definition of the notion of immersion.
According to technical view, immersion is often defined as the measure of the sensory richness (or vividness) and interactivity delivered by a system and its capacity to isolate the user from the real world (Arnaldi et al., 2018; Slater & Wilbur, 1997). In this sense, immersion is a quantifiable and system-dependent feature (*i.e*., it is possible to rank the different systems according to their own immersive character). Thus, the more a system delivers a sensory rendering close to the real conditions, and/or the more sensory channels which are involved, and, at the same time, the greater the interactivity, the more the system will be considered as immersive. On the other hand, interactivity (*i.e*., the degree of freedom that the user can act on the system in real time) is not always considered as a dimension of immersion. According to a psychological view, the term "immersion" is often used to designate the psychological feeling of being enveloped and present in the virtual environment. To distinguish it from the technological definition, authors use "feeling of presence" to name the subjective perception of immersion induced by the immersive system (Slater & Wilbur, 1997; Witmer & Singer, 1998). Thus, virtual reality (VR) or augmented reality (AR) are considered more immersive systems than traditional multimedia devices like video on a computer. Coupling of VR/AR with a HMD or CAVE is also identified as more immersive than simulations or 3D worlds displayed with desktop, laptop, tablet, or smartphone displays. These latter devices are sometimes called "Low-immersive" as opposed to more immersive devices, sometimes called immersive virtual reality (iVR) or immersive augmented reality (iAR) in some articles (Suh & Prophet, 2018).
The present paper focuses on imT, namely VR and AR, excluding associated devices such as HMD 360° video. We have therefore adopted a technological vision of immersion.

1.2.2 Learning performance and Learner experience

For assessing educational effectiveness, learning outcomes are classically used and include objective measures (*i.e*., learning performance in terms of accuracy and speed) and/or subjective measures of learner experience (*i.e*., feelings of learning, cognitive and affective perceptions). Today, the most elaborate theoretical frameworks of learning integrate both kinds of measures in their conceptualization to pinpoint the dynamic aspects of flow during learning. Two well-known of these respectively focus on one of two (not exclusive) dimensions, cognitive load and intrinsic motivation, which are claimed to be enhanced by the imT use, respectively the *Cognitive-Load-Theory* (**CLT**; Sweller, 1988) and the *Learning progress* hypothesis (**LPH**; Murayama et al., 2019).

1.2.2.1 Cognitive load for learning performance through CLT

CLT proposes that learning, like any task, requires cognitive resources which must not exceed the student's resources available in working memory, otherwise cognitive overload will result. The cognitive load (**CL**) depends on the complexity of the task, the individual's cognitive resources and the way the task is presented (Sweller et al., 2019). According to this theory, optimal learning conditions are met when task complexity and task presentation do not exceed learner's resources. Learners' previous knowledge in long-term-memory is a resource: the more that the knowledge one desires to learn is close to previous knowledge, the lower the cognitive load is. In other words, learner's prior knowledge or expertise impacts the CL allocated to the task (Tricot & Sweller, 2014). CLT distinguishes positive load, i.e., intrinsic cognitive load (ICL), from negative loads i.e., extraneous cognitive load (ECL). The former refers to cognitive resources necessary mobilized for the learning achievement and depend on the complexity of the task (elements interactivity) and the learner's prior knowledge. The ECL correspond to cognitive resources involved in processing unnecessary information during learning (for example decorative information on the learning material). As a result, the total CL correspond to the addition of the ICL and the ECL, and an increase in the ICL (if it does not exceed the individual's capacity) or a decrease in the ECL are desired effects during learning.

It should be noted that a previous version of this theory distinguished a third type of CL, germane cognitive load (GCL), related to knowledge acquisition.

There are several validated measures of self-perceived CL exist such as Leppink cognitive load scale (Leppink et al., 2013) or NASA TLX (Hart & Staveland, 1988). In addition, several studies use electroencephalography (EEG) or reaction time to the secondary task to measure the learner's CL.

From such a CL conception, imT can be used to reduce ECL while optimizing ICL. As mentioned before, the load benefit is reported for AR in a more extensive way compared to VR (Buchner et al., 2022; Newman et al., 2022). In contrast, the load benefit remains undocumented by a dedicated review on VR–based learning studies, even if an increased irrelevant load (due to the command complexity and/or stimuli richness of 3D environments) is identified by subjective review (e.g., Makransky & Petersen, 2021). Consequently, we reviewed VR and AR studies with a focus on their impact on learning performance and distinguishing the useful (ICL) and irrelevant (ECL) loads.

1.2.2.2 Intrinsic motivation for learning performance through LPH

LPH is derived from curiosity-based learning model (Oudeyer et al., 2016) which stresses the relationships between the learner's intrinsic motivation (**IM**) or curiosity states (**CS**) and their learning performance. IM is defined as "the inherent tendency to seek out novelty and challenges, to extend and exercise one's capacities, to explore, and to learn." (Ryan & Deci, 2000). It is a natural phenomenon associated with exploratory behaviors and spontaneous interest, that is to say, states of curiosity. In general, CS-IM is related to the performance of an activity for the personal pleasure induced by its performance, as opposed to extrinsic motivation, which is characterized by behaviors performed for reasons external to the task being performed, such pressures or rewards. Literature shows that students who are intrinsically motivated learn more, perform better academically, have better retention rates in short- and long-term memory, and are more persistent when difficulties arise (Oudeyer et al., 2016). The importance of these intrinsic learning behaviors is explained by LPH, which describes the self-reinforcing positive feedback loop between information-seeking behaviors and knowledge acquisition (Murayama et al., 2019; Oudeyer et al., 2016). Specifically, these models suggest that a reward resulting from knowledge acquisition (i.e., learning progress) fosters CS-IM for information-seeking behaviors. LPH explains that predictions made by the learner will modulate a perceived intrinsic reward from the acquisition of knowledge which verifies those predictions.

Often, imT are seen as boosting students' motivation and curiosity. In a systematic review, W. Huang et al. (2022) argued that one of the main benefits of AR and VR is to foster learners' motivation for learning. Yet, even though the literature tends to emphasize this positive effect, a recent literature review showed that too many limitations in current empirical studies, such as small sample sizes and not always standardized measures, prevent reliable conclusions from being drawn about the effect of imT on learners' motivation and CS-IM (Di Natale et al., 2020).

1.2.2.3 Cognitive Load and Intrinsic motivation relationships

As viewed, CL as well as CS-IM are two dimensions of learning widely explored for explaining the imT effects on learning performance. As a result, some studies have attempted to investigate the links between CL and motivational states (particularly, the CS) in order to better understand their mediating effects on learning performance with imT-based instructional settings (W. Huang et al., 2022; Makransky & Petersen, 2021). These studies are still few and far between, and formalizations of the relationship between curiosity and CL remain unclear or poorly articulated. A systematic review of these studies should shed some insights on this issue, and by a rebound effect could explain the differential effects of AR and VR on learning performance.

1.2.3 Knowledge-domain, learning outcomes, type of knowledge and expertise

Recent literature reviews on the use of imT for learning highlight differences in the pedagogical context between studies on the topic, including learning domain, learning outcomes, type of knowledge taught, and learner's prior knowledge or expertise (Hamilton et al., 2021; Radianti et al., 2020).

Concerning the learning domain, most systematic reviews on the subject show that sciences, engineering and health education are the most recurrent domains in the literature (Di Natale et al., 2020; Hamilton et al., 2021). However, none of the reviews investigated the differences in outcomes across these different domains.

According to Anderson and Krathwohl's (2001) taxonomy for learning, teaching and assessment, all knowledge can be divided into four categories on a continuum, from the most concrete to the most abstract: factual knowledge ("bits of information"), conceptual knowledge ("more complex, organized knowledge forms"), procedural knowledge ("knowledge of how") and metacognitive knowledge ("students' knowledge and control of their own cognition"). In addition, some authors consider factual and conceptual knowledge as a subcategory of declarative knowledge. Several recent literature reviews show that imT, including VR, can teach both declarative and procedural knowledge, with contradictory learning results (Hamilton et al., 2021; Radianti et al., 2020). It seems that VR has an advantage over less immersive learning methods for declarative learning (Hamilton et al., 2021) while its effects are demonstrated as inconsistent for procedural learning (Makransky & Petersen, 2021). However, no systematic reviews have explored whether the effectiveness of AR relates to the type of knowledge to be learned.

Similarly, several types of learning outcomes are studied in the literature around imT. The most frequently observed learning outcomes are retention learning (storing new information in LTM), transfer of learning (ability to use the learning material in a new context) and skill acquisition but perceived learning and behavioral changes can also be mentioned. Previous reviews showed that the learning outcome considered is rarely explained (Hamilton et al., 2021; Merchant et al., 2014) and no systematic review of the literature takes this factor into account in its analysis of the effectiveness of imT.

Finally, the importance of the learner's expertise (level of prior knowledge) is emphasized in both CL and IM theories (Murayama et al., 2019; Sweller et al., 2019). However, to our knowledge, none of the literature reviews explicitly take this dimension into account in their analysis.

1.3 Operationalized research questions

Based on the state of the art conducted on the initial question, "Do imT impact learning performance and/or the learner experience in terms of CL and motivation? ", three operational research questions, along with five sub-questions, were formulated to guide this literature review (see Table 1).

ID	Operationalized research questions
RQ1	What is the effect of imT on learning performance, mediated by CL?
RQ2	What is the effect of imT on learning performance, mediated by CS-IM?
RQ3	What are links between CL and CS-IM variables?
	Research sub-questions
a	Do the main effects depend on the types of imT?
b	Are the main effects influenced by knowledge-domain?
c	Are the main effects influenced by type of knowledge?
d	Are the main effects influenced by learning outcomes?
e	Are the main effects influenced by prior learner expertise?

Table 1: Operationalized research questions and associated sub-questions

2. Method

An a priori protocol was designed and registered with PROSPERO (registration number: CRD42022335531). The checklist of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was applied to guide the systematic review process.

2.1 Search strategy

The initial database searches were conducted between April and June 2022 using Scopus, Web of sciences and PsycInfo. In addition to the database searches, a hand search of relevant journals and grey literature were also conducted to ensure all relevant works were included in the review. According to the research question, we used the following query: *Immersive Technologies AND Learning AND (Cognitive Load OR Curiosity States)*. Table 2 details the keywords used associated with the different search terms of the key phrase.

Categories	Research Keywords
Immersive technologies	Immersion; immersive; virtual reality; augmented reality; mixed reality; virtual environment; virtual world; digital world; virtual; head mounted display
Learning	Learning; training; schooling; student; higher education; education; teaching; instruction
Cognitive load	Cognitive load; cognitive load theory; dual task; working memory; overload; germane load; germane cognitive load; intrinsic load; intrinsic cognitive load; extraneous load; extraneous cognitive load
Curiosity states	Curiosity; intrinsic motivation; epistemic curiosity; motivational beliefs; interest + intrinsic motivation; curiosity + intrinsic motivation

Table 2 : Research keywords used for the identification stage

A total of 2802 papers were found (including two additional studies identified in the gray literature), as presented in Figure 1. All duplicates were removed, which reduced the results to 1967.

2.2 Eligibility criteria

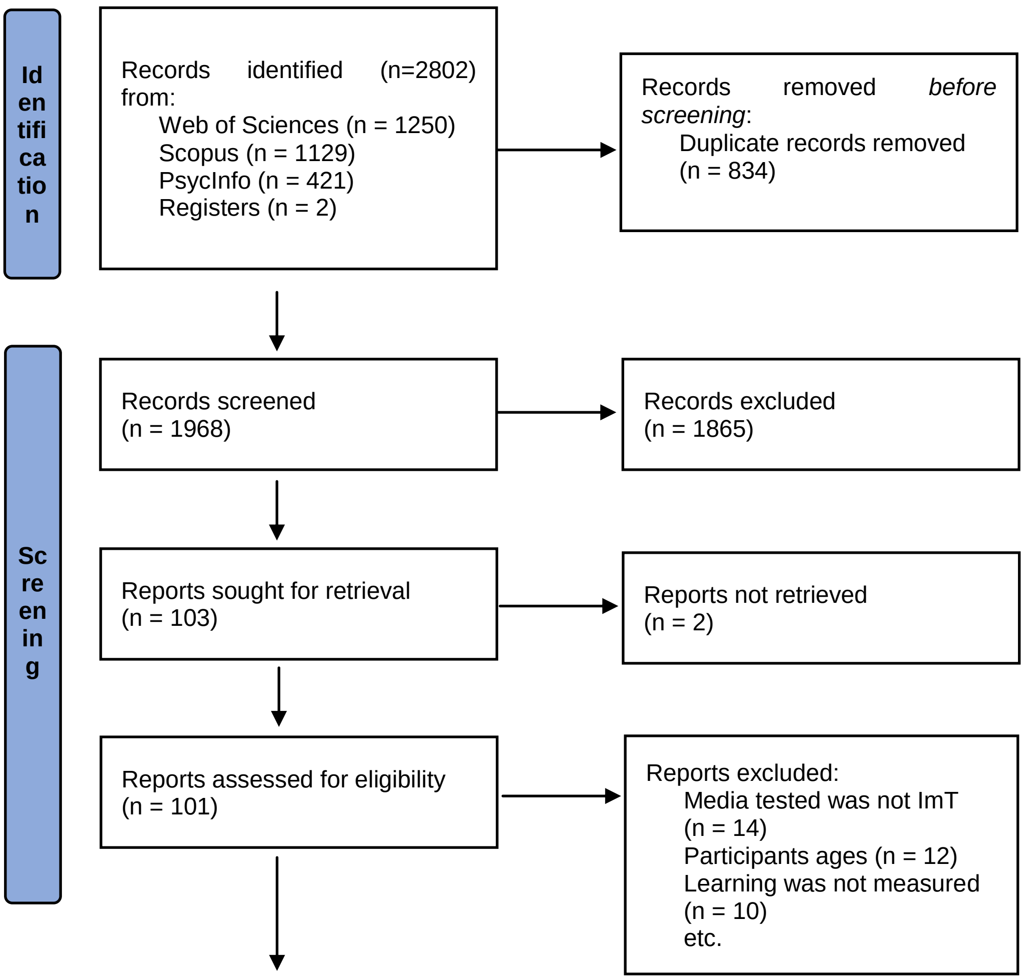
In this systematic review, we included all studies about the effect of imT on learning performance and CL or CS-IM variables. No restrictions were set regarding the publication date, but the included studies had to be in English and follow a true experimental design (i.e., randomized controlled trial or controlled trial) with at least ten participants per group. Furthermore, studies that included k-12 or the elderly and were not journal or conference papers were excluded. Table 3 present details of inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
Must use immersive technologies (VR or AR)	Immersive technologies were not used
Must be about learning and measure learning gain	Learning was not the main goal of using immersive technologies
Must consider/measure cognitive load or curiosity states (IM, engagement, etc.) variables	Neither cognitive load nor curiosity states were measured
Must adopt a true experimental design and more than ten participants per group	Non true experimental design
	Participants were K12 or elderly
	Not journal or conference papers (e.g., books, thesis, etc.)

Table 3 : inclusion and exclusion criteria

2.3 Screening and study selection

The screening process started with removing irrelevant papers. Articles were first excluded based on titles and abstracts (n = 1865) resulted in 103 articles to go through to the next stage of full-article review. The title-abstract screening process was carefully evaluated by three authors on ten percent of the articles, including all studies included by the first reviewer. Where there was uncertainty or disagreement among the reviewers, consensus was reached through discussion. The full-text review of the remaining papers results to 30 papers including 31 studies included for the systematic review. The main reasons for the exclusions are presented in the PRISMA flowchart Figure 1.



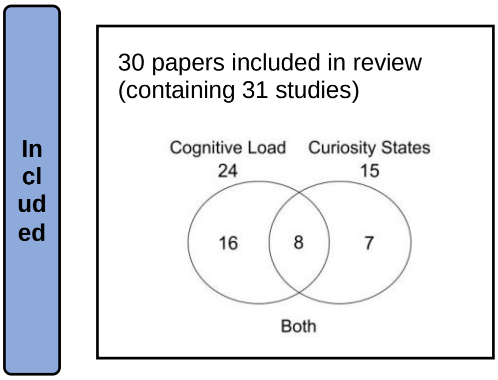
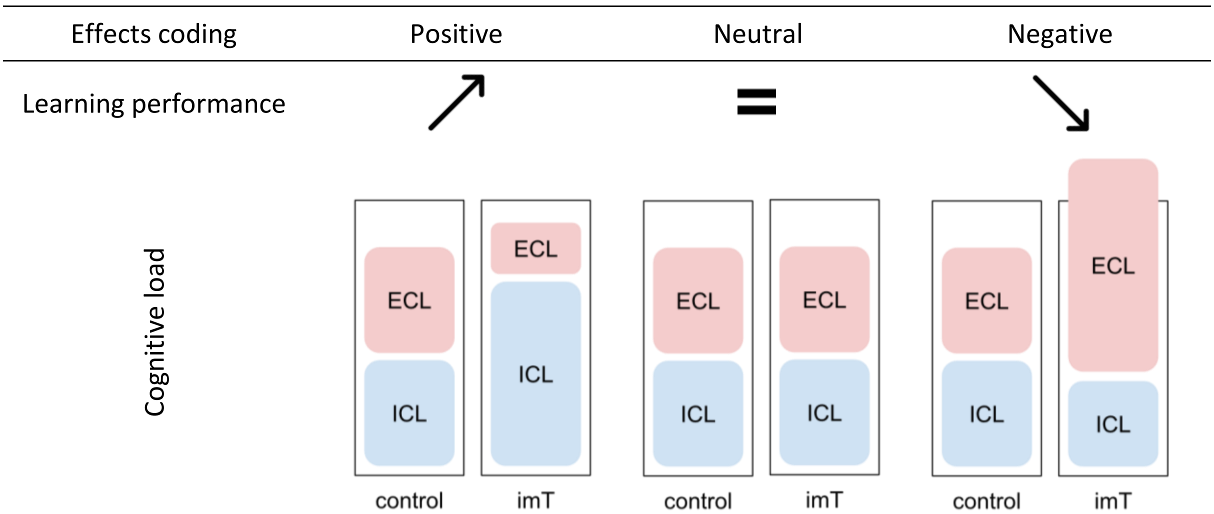


Figure 1 : PRISMA flowchart

2.4 Data extraction

To answer to the different research questions, a coding sheet was developed to extract different information. First, data about study characteristics was extracted including authors, publication year, sample information (size, mean age, expertise level, education level, etc.) and type of experimental design (randomized or non-randomized controlled trial). Information about imT used were also extracted, including type and characteristics of imT and comparative medium used (e.g., HMD VR, video, PPT). Moreover, types of learning outcomes measured (retention, transfer, perceived learning or skill acquisition), type of knowledge assessed (based on the Anderson and Krathwohl's (2001) taxonomy), field of learning activity, learner expertise and assessment method were considered.
The authors also examined the variables and definitions of CL or CS, how they are measured, and whether CL and CS-IM are connected in the article. Finally, experimental results CL and CS-IM were retrieved, with associated effect sizes.
It should be noted that the nature of the effect of the technology on CL or CS-IM (positive, neutral, or negative) was determined by taking into account the learning outcomes. Figure 2.a details the expected and consistent effects with CL and IM theories, while Figure 2**Erreur ! Source du renvoi introuvable.**.b shows the inconsistent or unexplainable effects.



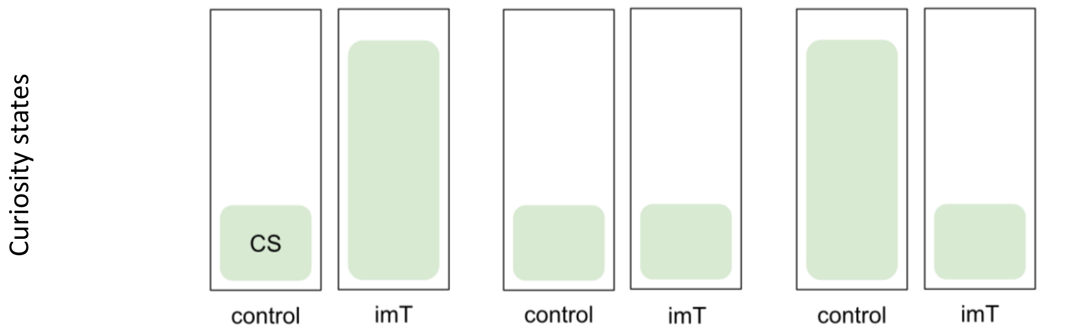


Figure 2.a : Grid for analyzing the expected effects of imT on learning mediated by cognitive load and states of curiosity, consistent with cognitive load and motivation theories

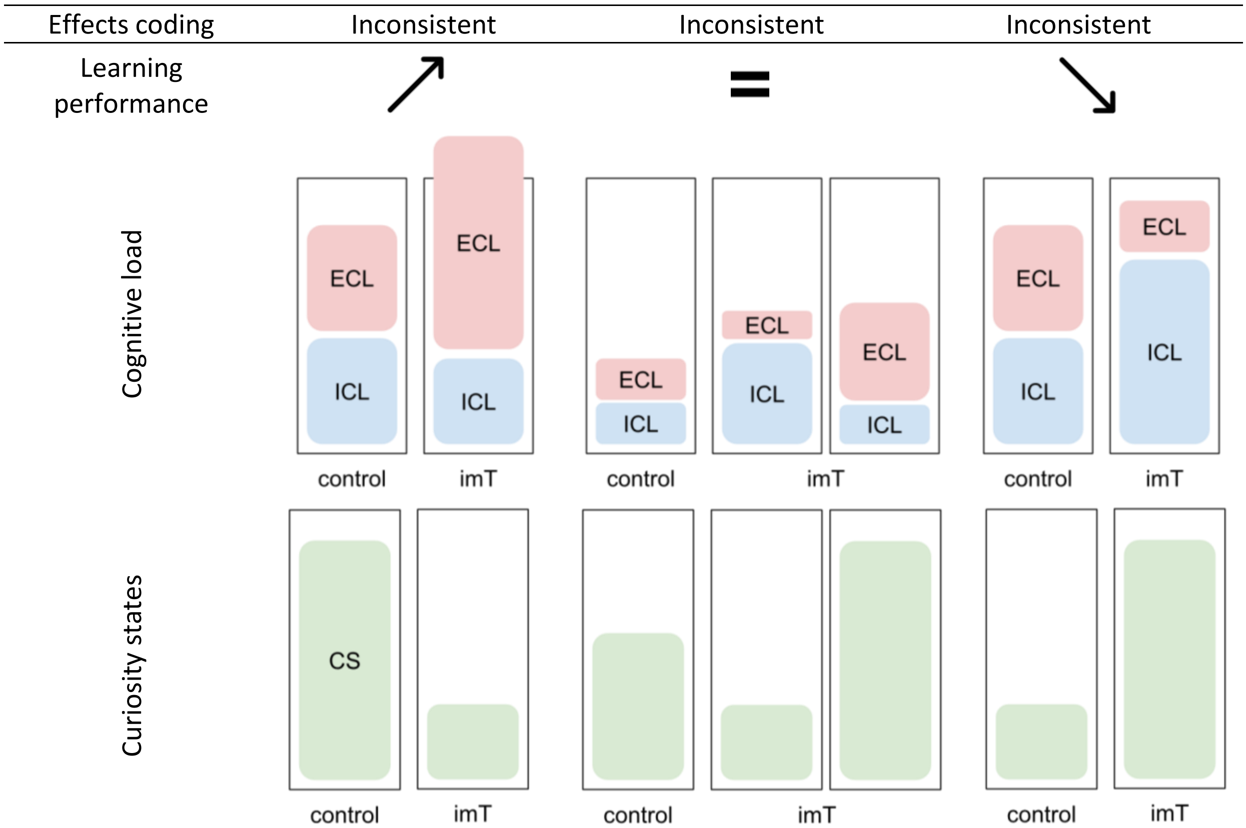


Figure 2.b: Grid for analyzing the unexpected effects of imT on learning mediated by cognitive load and states of curiosity, consistent with cognitive load and motivation theories

2.5 Assessment of quality

The quality of the studies was rated using the SIGN (Harbour & Miller, 2001) ratings of levels of evidence. This evaluation method proposes an estimate of the strength of available evidence provided by a study, based on the methodological design and the evaluation of possible biases. Because literature reviews and non-experimental studies were rejected in our selection process, the best possible score for the extracted studies was 1++ (RCT with very low risk of bias) and the worst possible score was 2- (non-RCT with a high risk of confounding or bias and a significant risk that the relationship is not causal).

3. Results

3.1 Descriptive results

As mentioned before, the systematic review analysis was performed on 30 papers (29 journal articles and 1 conferences proceeding) including 31 studies, all experimental (RCT).
Results shown that 24 (77%) studies investigated the CL, 15 (48%) studies investigated the CS-IM, but amongst them, 8 (26%) of them addressed both (Figure 1). Additionally, 19 (61%) studies used VR while 11 (35%) used AR and only one compared both technologies (Figure 4). Studies were conducted in different countries, with an average number of 80 participants per study and an average participant age of 23 years. Most part of studies included university students with various levels of expertise on the knowledge domain targeted: 14 studies included learners with no prior knowledge on the topic, 10 included learners with prior knowledge (intermediate level) and the rest (n=7) were not clear on the expertise of the learners (see table 4). Finally, different measures of learning were used, on different types of knowledge and learning domains (Table 4). Retention (n=25), transfer (n=9), and skill acquisition (n=5) were the most used learning outcomes. Most of the included articles studied declarative (factual or conceptual) and procedural knowledge. Moreover, the most studied learning areas were science and medicine.

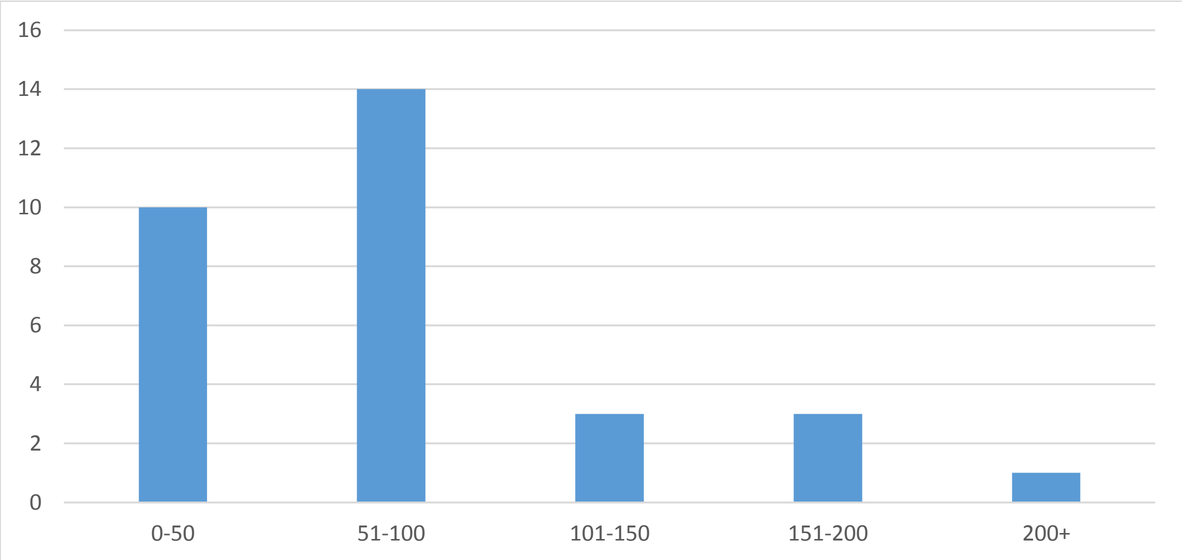


Figure 3 : Number of studies by sample size and type of experimental design

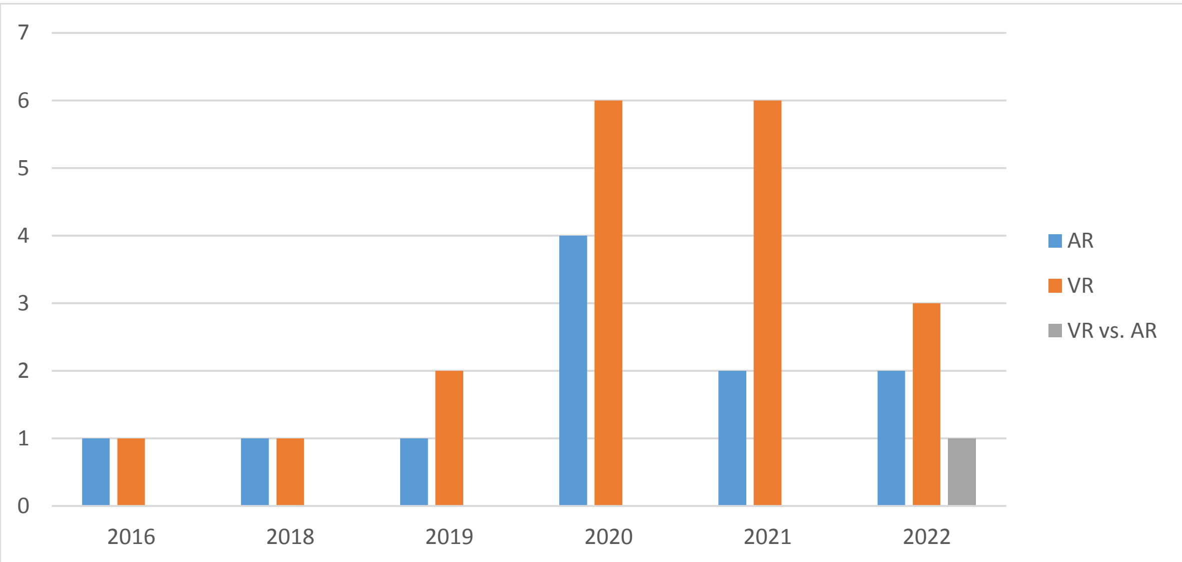


Figure 4: Distribution of publications over time and by technology

Features	n	%
Learning domain		
science	18	58%
medicine	4	13%
art	2	6%
safety	2	6%
history	2	6%
language	2	6%
engineering	1	3%
Makeup design	1	3%
Learning outcomes		
retention	25	60%
transfer	9	21%
skills acquisition	5	12%
perceived learning	2	5%
behavioral change	1	2%

Features	n	%
Knowledge Type		
declarative	23	70%
factual	4	12%
conceptual	6	17%
both	13	36%
procedural	7	21%
ALL	2	6%
unsure	1	3%
Level of expertise		
novice	14	45%
intermediate	10	32%
unsure	7	23%

Table 4 : Distribution of studies by a) learning area b) learning outcomes c) types of knowledge and d) level of expertise of learners

3.2 RQ1 - What is the effect of imT on learning performances, mediated by cognitive load?

Among the 24 studies on CL and learning, 7 (29%) founded that the use of imT has a positive influence on CL during learning, 5 (21%) founded a negative effect, and 6 (25%) showed that imT have no impact on learner's CL mediated by learning compared to other media. In addition, 6 studies (28%) showed an irrelevant effect of imT on CL mediated by learning performance. See Table 6 for more details.

For example, Turan et al. (2018) compared mobile AR (mAR) with books for geomorphology learning on 95 university students. Authors found that mAR decreases learners' CL and increases learning performance. Similarly, HMD VR seems to have a positive impact on CL and calligraphy skills acquisition of 80 engineering students in comparison to Slides show (Yang et al., 2021). At the opposite, in a RCT on 52 university students, Makransky, Terkildsen, et al. (2019) showed decreased retention of laboratory learning associated with increased workload brain activity when learners used HMD VR rather than desktop VR, especially if they had a first session with desktop VR.

These overall results did not support the claim that immersive technologies have a systematic positive effect on CL taking into account learning.

Twelve (50%) studies examined the impact of VR on CL and eleven (46%) focused on AR. Only 3 (25%) studies of the 12 that investigated VR conditions on CL and learning found a positive effect (Baceviciute et al., 2021; Makransky & Klingenberg, 2022; Yang et al., 2021). Among other studies (75%, n=9), 2 reported that VR had no effect (17%), and 5 reported a negative impact of VR on CL and learning (42%) (Figure 5.a). For instance, in a study involving 80 students, an HMD VR condition was compared to video condition for learning historical facts; HMD decreased transfer learning, and the EEG measure showed that video condition yielded a better cognitive engagement (Parong & Mayer, 2021b). Hence, VR was found to have a negative on learning-related CL. To our knowledge, this result is not currently highlighted in any systematic review.

Regarding AR, no study found a negative effect on CL, 3 reported no effect (27%) and 4 (36%) a positive effect of this type of imT on learners' CL (Figure 5.b). In their respective RCT studies on 70 students, Kucuk et al. (2016) and Lee & Hsu (2021) found a positive effect on CL (decrease in self-reported overall CL) when using mAR rather than traditional media (pictures and text) or e-books. They also showed an improvement in learning neuroanatomy and makeup design. These results therefore indicates that AR condition leads a positive, or even neutral, effect on learning-related CL, which fitted with the results previously mentioned in systematic reviews (Buchner et al., 2022; Newman et al., 2022).

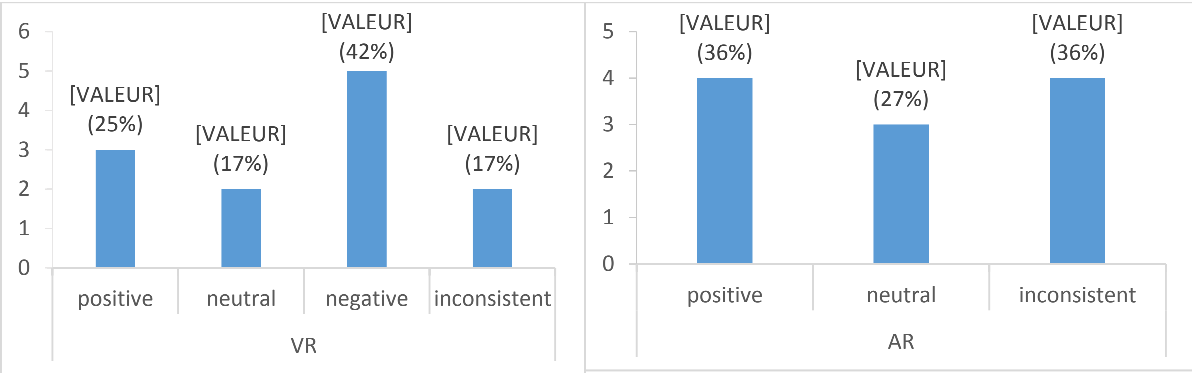


Figure 5: Effect of immersive technologies (a. VR, b. AR) on learning mediated by cognitive load

It should also be noted that only one study compared the use of AR and VR, for the "Lightning" learning (Tugtekin & Odabasi, 2022). No significant differences between the two imT in learning or CL were obtained in this study. Overall, of the AR and VR devices, only AR has shown promising results in improving CL for learning.

Regarding the learning activities, this conclusion does not seem to be influenced by the knowledge domain. Most studies (n=19, 61%) focused on retention of information rather than transfer of learning (n=7, 23%) or skill acquisition (n=3, 10%). The findings appear to depend on the types of imT (VR or AR): VR often had a negative effect on learners' CL for both retention (n=4, 44%) and transfer tasks (n=3, 60%). Conversely, AR optimized (n=2, 22%) or at least did not harm (n=3, 33%) CL in retention tasks, but no conclusion can be made regarding transfer (only two studies). See Figure 6 for more details

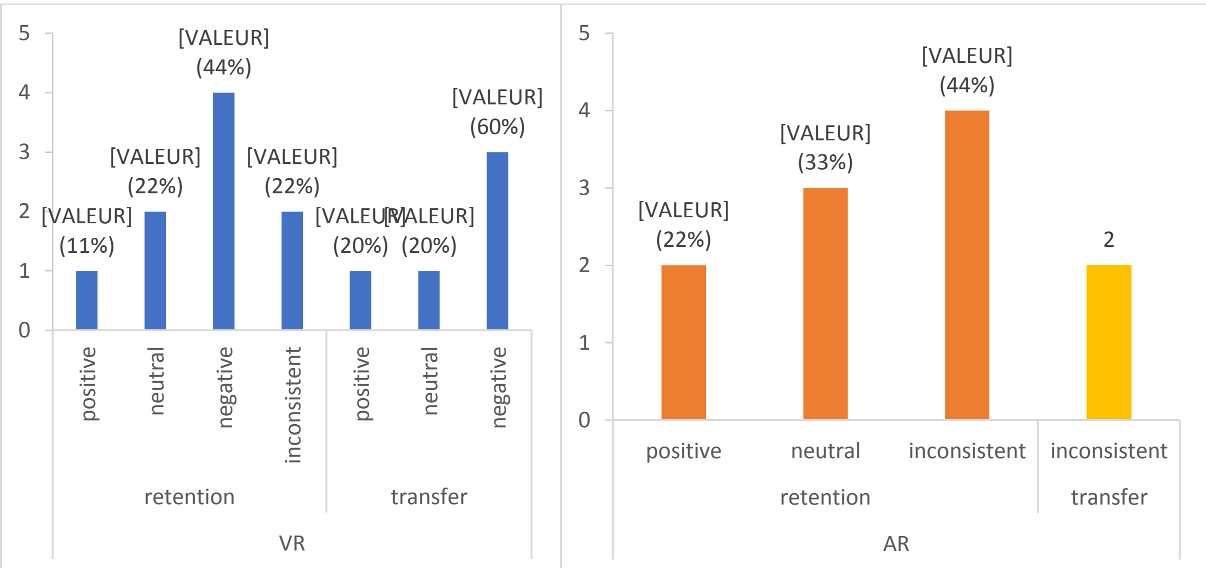


Figure 6: Effect of immersive technologies on cognitive load-mediated learning as a function of learning type. a. VR and b. AR

Regarding type of knowledge taught, studies on effect of imT on CL during procedural learning were too rare (n=6, 24%) and contradictory (3 positive and 3 negative) to draw any conclusions. For declarative learning (n=18, 72%), once again, results depended on imT type (VR or AR): VR mostly induced less appropriate CL and learning (n=3, 38%) whereas AR mostly elicited a positive (n=2, 22%) or neutral effect (n=3, 33%) on CL and learning (see Figure 7).

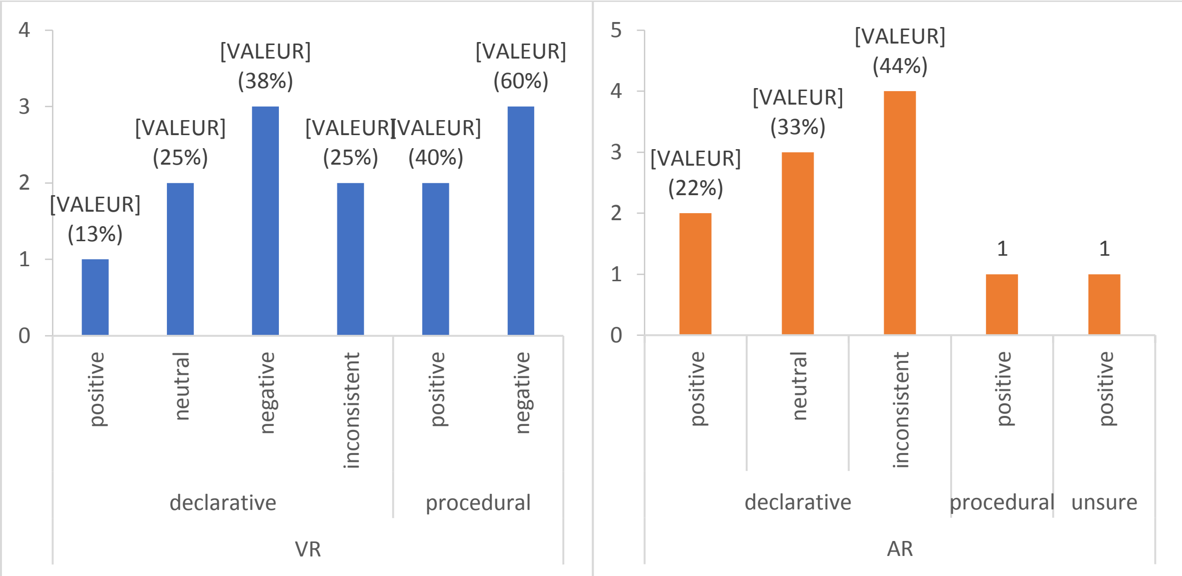


Figure 7: Effect of immersive technologies on CL-mediated learning as a function of knowledge type. a. VR and b. AR

Finally, imT did not often has a negative effect on the CL and learning of learners with prior knowledge on the learning activity (Figure 8): 3 (33%) studies showed a positive effect and only one (11%) showed a negative. On the other hand, for novice students, AR frequently optimized CL and led to better learning (n=3, 60%) while the opposite is shown for VR, which had the more often a negative effect on learning and CL (n=3, 50%).

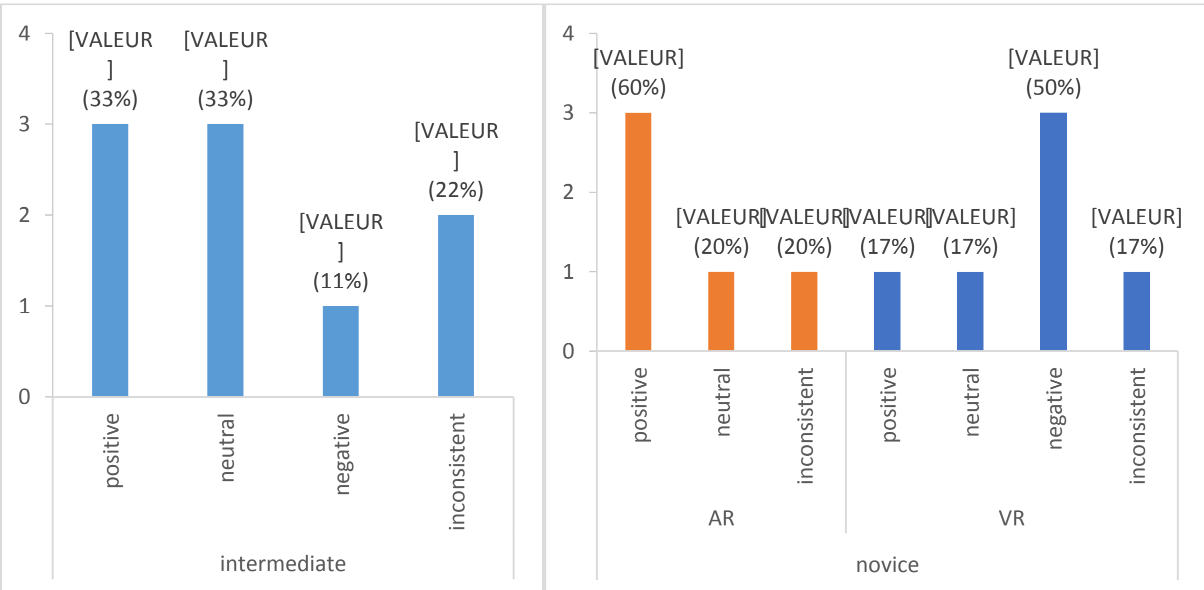


Figure 8: Effect of immersive technologies on cognitive load-mediated learning as a function of learners' level of expertise (a. intermediate and b. novice)

The overall results stressed that consideration of pedagogical context is important in assessing the impact of imT on learning-mediated CL: AR was often reported as beneficial for declarative learning, for retention, and irrespective of learner's expertise in the domain addressed, whereas VR was often reported as suboptimal for teaching declarative knowledge, for retention or transfer activities, and for novice learners.

3.3 RQ2 - What is the effect of imT on learning performance, mediated by curiosity states?

Results of the selection process led to 15 (48%) studies on CS-IM (see Table 4).

A main result is that 10 studies (67%) found inconsistent correlation between CS-IM and learning variations**.** Only 3 studies (20%) found a positive effect (Jin et al., 2022; Makransky, Borre-Gude, et al., 2019; Makransky & Klingenberg, 2022) of imT on CS-IM and learning and 2 (13%) others found no effect (see Figure 9)**.** For example, a study on biology lessons given on the human bloodstream compared HMD VR and PPT media on 61 participants. Results showed that PPT groups scored higher in retention and transfer score (only significant for transfer) than VR groups which reported a significant higher enjoyment during lessons (Parong & Mayer, 2021b). Surprisingly, this suggested a decorrelation between CS-IM and learning.

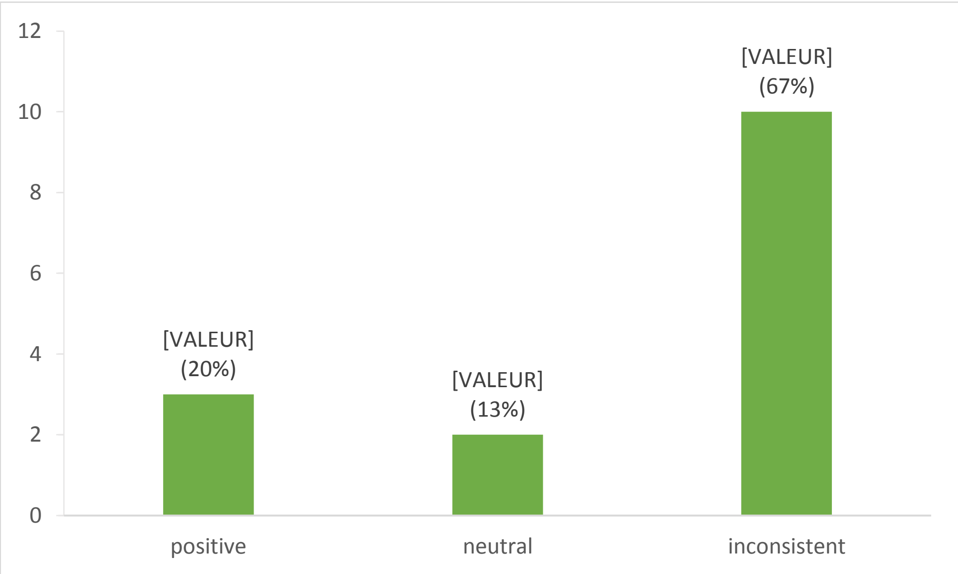


Figure 9: Effect of immersive technologies on learning mediated by curiosity states

Therefore, at this step, it is difficult to conclude about the nature of the effect of imT on CS-IM. Note that no studies show a negative effect of imT, suggesting that their use does not reduce learners' IM and learning performance.

The considerable number of papers concluding with a decorrelation or a negative correlation between CS-IM and learning performance can be explained in several ways. First, unlike CL, the term "curiosity state", like motivation, is polysemous and can refer to varied factors such as intrinsic motivation, motivation to learn, perceived enjoyment or situational interest (Murayama et al., 2019). These polysemous terms translate into different theoretical frameworks, leading studies to assess a state of curiosity not directed towards the learning activity itself, which may explain the contradictory and inconsistent results of the different articles.

In a related way, another explanation is the diversity of measurement scales used. Even if the most used scale was the interest/enjoyment subscale of IM Index (Deci et al., 1994), seven different scales were used to measure CS-IM in selected studies. In addition, twelve studies (80%) adapted the original scales for their research. Although this is common practice, most of these studies (n=8, 67%) did not provide details of how the scales were modified (see Table 5). This leads to large methodological differences between the scale-based measures, which may explain the inconclusive results reported in the current systematic review. In addition, several articles used scales that do not clearly measure IM, such as the Index of Learning Styles (ILS) (Soloman & Felder, 2005) used in two studies, whereas much more common and validated scales for measuring motivation can be used (e.g., IMI of Deci et al., 1994). Regarding the three studies reporting a positive relation between the curiosity and learning imT's improvements, they have in common to use Intrinsic Motivation

Inventory (IMI) scale (Deci et al., 1994) with using only the subscale of Interest/enjoyment as prescribed by the authors for assessing IM. Taken together, these observations would mean that the inconsistent results for the relationships between CS-IM and learning come from methodological issues, especially measurement of IM such as no standardized measures or misuses of standardized questionnaires.

Features	n	%
Original scale used or adapted		
Interest/Enjoyment of IMI scale	9	45%
Perceived Enjoyment (Tokel and İsler, 2015)	4	20%
Own scales	2	10%
Index of Learning Styles (ILS)	2	10%
Knogler et al. (2015)	1	5%
Huang et al. (2010)	1	5%
Makransky and Petersen (2019)	1	5%
Type of adaptation		
No information	8	67%
Selecting items	2	17%
Wording	1	8%
Translating	1	8%

Table 5: CS-IM measurement scales used and types of accommodations made.

Finally, it is possible that these inconsistent results concerning IM are due to other factors related to the use of imT, not considered in the studies, such as CL for example. Thus, the effect of variations in CS-IM on learning due to imT use could be masked by effects on CL.

It is also noteworthy that only two studies (13%) investigated the effect of AR on CS. In view of the major differences found between the two types of imT for CL, it would be interesting to investigate extensively the RA on intrinsically motivated learning behavior. This lack of studies on AR may also suggest that this imT on motivation is expected as negligible compared to the effects on other variables such as CL. The current review highlights the negative effect of VR on CL and learning. It may be that this poor CL offsets the effects on motivation.

3.4 RQ3 - What are links between cognitive load and curiosity states variables in imT context?

Eight articles (26%) studied the link between CL and CS-IM in learning mediated by imT (see Table 6).

Two of them showed that the use of AR allows a more adapted CL and a better learning of Makeup design or electronics laboratory skills compared to less immersive media (e-books or manuals), but that there was no effect on motivation (Lee & Hsu, 2021; Singh et al., 2019). In a similar vein, one paper showed that VR, for teaching historical facts, had a negative effect on CL, and that this technology led to poorer learning than video media, while motivation did not change between conditions (Parong & Mayer, 2021b). These results are confirmed by another study by Parong et Mayer (2021b) on human blood system learning, in which they compared the use of VR to PPT for 60 novice students. The results showed that the PPT group had a better transfer score, but more importantly that this score was explained by a better CL. They also showed that VR had little influence on CS-IM (increased PE but not IM or interest) and that this influence did not affect learning performance. These results indicated a link between CL and learning that is consistent with the CLT hypotheses (Sweller et al., 2019). However only one study directly investigated this link with correlational statistics (Parong & Mayer, 2021b). In particular, AR could induce a more optimal CL, leading to better learning while VR induces unnecessary CL that could explain poor learning performance. On the other hand, all these articles shown no or negligible effect of imT on CS, which can be explained by the previously reviewed results of the current literature review.

On the contrary, Makransky et Klingenberg (2022) study highlighted that VR provides better learning of naval safety than a traditional course with a personal trainer, but the researchers confirmed previous findings where imT's effect on learning is depending on the induced CL. On the other hand, they also highlighted the positive effect of VR on IM and perceived enjoyment, suggesting then a positive correlation between curiosity state and learning performance (not directly evaluated statistically). In addition, an RCT on human body learning showed that using VR rather than 360-degree video promoted perceived enjoyment and IM, but did not affect learning retention or transfer, and did not reduce perceived mental demand and effort (Zhao et al., 2020).

Although all these studies did not statistically investigate the relationships between CL, motivation and learning elicited by imT, they provided some probes of these relationships, especially a simultaneous enhancement of CL and learning. However, these probes are not sufficient and further correlation or inferential studies are needed to understand these relationships.

Finally, two studies performed structural equation modeling (SEM) to actually explore the relationships between cognitive and curiosity variables in science learning with HMD VR (W. Huang et al., 2022; Petersen et al., 2022). In the first (50 participants), the results showed that a highly immersive VR HMD setup, compared to a less immersive one, does not affect learner CL but increases motivation to learn. The resulting SEM model showed that VR technical features positively impacted motivation mediated by VR psychological variables (presence and agency). In turn, motivation reduced ECL and promoted perceived ICL which has a positive effect on learning (see Figure 1010) (W. Huang et al., 2022).

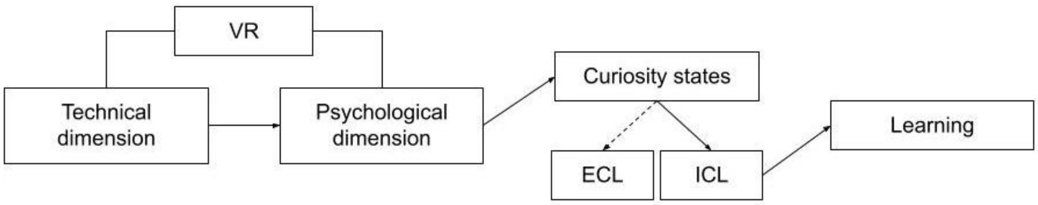


Figure 10: W. Huang et al. (2022) structural model of the imT effect on learning performance, mediated by CL and CS

The second study (Petersen et al., 2022) divided 153 students into 4 groups, varying the sensory richness (HMD vs. desktop screen) and interactivity (control vs. passive) of the setup and examined differences between conditions on retention, CL, and curiosity state (IM and interest) variables. Results showed no significant differences on declarative learning, a significant increase in extrinsic CL in the interactive conditions, and an increase in situational interest in the groups using HMD. The SEM (see Figure 11) revealed a direct link between curiosity states and learning and that imT features (sensory richness and interactivity) had a positive effect on CS-IM mediated by presence. Moreover, resulting model indicated that extrinsic CL imposed by the imT negatively impacts CS, also mediated by sense of presence. However, this model focused on the CL induced by the environment and did not consider the CL imposed by the learning activity, which could have a direct causal link with CS-IM (as it was put forward in the previously mentioned study).

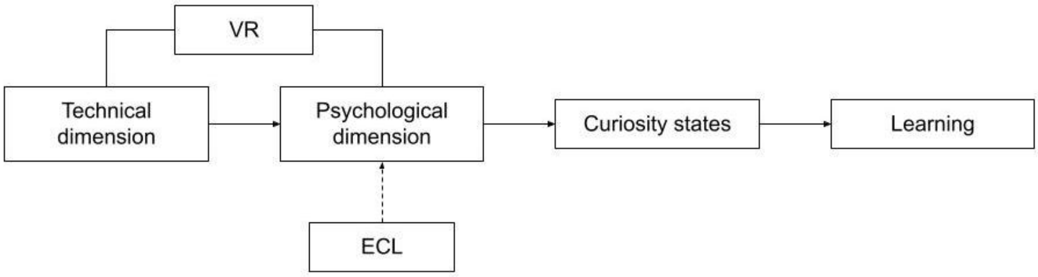


Figure 11: Petersen et al. (2022) structural model of the imT effect on learning performance, mediated by CL and CS

As a result, these two SEM based studies provided some evidence for the existence of links between CL and curiosity variables in imT-mediated learning. They also provided insight into the causal links between the two concepts that were previously hypothesized in several papers (Feldon et al., 2019; Makransky & Petersen, 2021; Skulmowski & Xu, 2022). However, the number of causal studies is too small to determine the real nature of the links between CL and CS, and their influence on learning performance: although similar on some points (mediating role of presence), the two models exhibited different configurations of causal links shared between the three variables.
Therefore, further studies, similar to W. Huang et al. (2022) and Petersen et al. (2022), are needed to understand the role of CL and motivation on learning performance mediated by imT**.**

Table 6 : Summary table of characteristics and results of included studies. (The shaded area includes items measuring both cognitive load and curiosity states. CL = cognitive load, CS = curiosity states, IM = intrinsic motivation, ML = motivation to learn, PE = perceived enjoyment.)

Authors (year)	Participants; expertise level	Study design; imT vs. comparative medium	Learning design	Main results
Altmeyer et al. (2020)	50 university students; novice	RCT; mAR vs. Tablet	Science; conceptual; retention and transfer	The application of tablet-based AR for learning electrical circuits with the addition of spatial continuity yields higher immediate conceptual knowledge gains, but no significant differences from the traditional method were found for transfer or CL (adapted from Leppink et al., 2013).
Baceviciute et al. (2021)	48 university students; novice	RCT; HMD VR vs. Book	Medicine; declarative; retention and transfer	Reading in VR led to better transfer performance than real reading, but no significant differences were found for retention. VR was also associated with an increase of ECL (Cierniak et al., 2009), a decrease of ICL (Ayres, 2006) and an increase of general EEG mental load.
Burgues et al.(b) (2020)	154 French university students; novice	RCT; HMD VR vs. Tablet (with and without control)	Art; factual; retention	VR does not lead to better art learning than the tablet and does not seem to affect CL (own scale), but system interactivity, in VR or with the tablet, leads to better art retention.
Elford et al. (2022)	34 higher education students; novice	RCT; mAR vs. 2D drawings	Science; conceptual; retention	The results showed no significant effect between the use of AR and books on the learning of molecular structures and CL (adapted from Leppink et al., 2013).
Frederiksen et al. (2020)	31 post-doctoral medicine students; novice	RCT; HMD VR vs. Desktop VR	Medicine; procedural; skills acquisition	HMD VR simulation for laparoscopic surgery training induces higher CL (secondary-task reaction time) and results in worse performance than desktop VR for novices. The HMD VR environment causes additional ICL and ECL.
Frithioff et al. (2020)	24 university students; intermediate	RCT; Ultra High Fidelity VR vs. Desktop VR	Medicine; procedural; retention	Ultra-high fidelity VR simulation compared to conventional screen-based VR simulation for temporal bone surgery training results in lower comprehension and higher CL (relative reaction time) in medical learners.
Geng et Yamada (2020)	21 Asian non-native learners; intermediate	RCT; mAR vs. Images	Language; declarative; retention	The results showed that there was no significant difference in CL (Leppink et al., 2013) between the two conditions and that perceived CL was related to learning performance and was likely to be affected by LM.
Kapp et al. (2020)	56 university students; intermediate	RCT; HMD AR vs. Tablet	Science; conceptual; retention	The use of HMD AR for spatial continuity compliance does not affect learning performance in laboratory of physics or the CL (adapted from Leppink et al. 2013 and presented by Thees et al., 2020b) of students.
Keller et al. (2021)	30 university students; unsure	RCT; mAR vs. text and pictures	Science; declarative; retention	mAR for organic chemistry learning did not significantly influence learners' CL (Klepsch et al., 2017). Learning performance and CL were not correlated.
Kucuk et al. (2016)	70 university students; intermediate	RCT; mAR vs. 2D pictures, graphs, and text	Medicine; declarative; retention	The use of mAR for learning anatomy leads to a better performance associated with a lower CL (Paas and Van Merriënboer, 1994) than traditional media (text, graphics, and images).
Makransky et al. (2019)	52 university students; unsure	RCT; HMD VR vs. desktop VR	Science; conceptual and procedural; retention and transfer	Using an HMD VR science lab simulation resulted in greater presence, but less learning and greater cognitive overload (EEG), compared to desktop VR.
Thees et al. (2022)	107 German university students; intermediate	RCT; HMD AR vs. Tablet (traditional setup)	Science; conceptual; retention and transfer	The results indicated that the separate display condition (without AR) could outperform the AR condition with respect to learning gains and CL (adapted from Klepsch et al., 2017)
Thees et al. (2020)	74 German university students; intermediate	RCT; HMD AR vs. Desktop (traditional setup)	Science; conceptual; retention	No effect of spatial continuity in AR on conceptual knowledge around electronic measurement equipment and ICL (adapted from Leppink et al., 2013) was found. On the other hand, the results indicate a significant reduction of ECL in the AR condition compared to conventional teaching methods.
Tugtekin et Odabasi (2022)	349 undergraduates' students; intermediate	RCT; desktop AR vs. HMD VR (with different multimedia principles)	Science; declarative; retention and (retention, achievement, and comprehension performances)	The results indicate no significant differences on learning or CL (Kılıç and Karadeniz, 2004, and secondary task reaction) between the two media conditions (AR vs. VR). In contrast, the authors demonstrate that multimedia principles affect participants' objective CL in AR and VR.

Turan et al. (2018)	95 university students; novice	RCT; mAR vs. Book	Science; declarative; retention	AR for geography learning improved performance and reduced overall self-reported CL (Paas and Van Merriënboer, 1994) levels compared to traditional book-based learning. These results are consistent with the semi-structured interviews, in which students reported that AR increased their performance and decreased their CL levels.
Yang et al. (2021)	80 engineering students; intermediate	RCT; HMD VR vs. PPT	Engineering; procedural; skills acquisition	VR allows for better acquisition of operational skills and reduces CL (adapted from Hwang, Yang, et al., 2013) compared to traditional teaching methods.
W.Huang et al. (2022)	50 university students; unsure	RCT; HMD VR vs. Lower immersive HMD VR	Science; declarative; retention	VR has a positive impact on LM but not on CL (both scales were revised from validated instruments). LM reduces CL and increases generative processing which increases learning.
Lee et Hsu (2021)	70 Taiwan vocational senior high school students; novice	RCT; mAR vs. E-book	Makeup design; unsure; unsure	Using AR to teach makeup resulted in better learning performance (large effect size), less mental effort (large effect size; modified from that Hwang, Yang, et al., 2013) but no difference in LM (adapted from Hwang, Yang, et al., 2013) compared to the e-book approach.
Makransky et Klingenberg (2022)	28 non-WEIRD sample of professional seafarers; intermediate	RCT; HMD VR vs. Personal trainer	Safety; procedural; perceived learning and behavioral change	Teaching security resulted in non-WEIRED learner's higher PE (Tokel & İsler, 2015), LM (Deci et al., 1994), perceived learning and behavioral change and lower CL (Andersen and Makransky, 2021) than learning with personal trainer (large effect size).
Parong et Mayer (2021)	80 university students; novice	RCT; HMD VR vs. Video	History; factual; retention and transfer	HMD VR led to worse performance on learning outcomes than video, particularly for transfer. No significant effects were shown for emotional states (situational interest, LM and PE; authors scale), and self-reported CL (authors scale).
Parong et Mayer (2021)	61 university students; novice	RCT; HMD VR vs. PPT	Science; declarative; retention and transfer	The VR group showed poorer transfer performance, associated with an increase in ECL (own scales). VR had little influence on CS-IM (increased PE but not IM or interest; own scales) and that this influence did not affect learning performance.
Petersen et al. (2022)	153 university students; novice	RCT; HMD VR vs. desktop VR vs. video	Science; declarative; retention	The different media conditions did not affect participant retention, but the interactivity led to an increase in their ECL (Andersen and Makransky, 2021) and the sensory richness promoted their interest (Knogler et al., 2015) but not IM (Makransky and Petersen, 2019). ECL has a negative effect on situational interest and IM, mediated by sense of presence
Singh et al. (2019)	60 engineering students; novice	RCT; AR vs. manuals	Science; procedural; skill acquisition	AR allow a better laboratory skills learning (large effect) than traditional methods, associated with a decrease in CL (medium effect; adapted from Hwang, Yang et al., 2013). No effect on LM (adapted from Hwang, Yang et al., 2013) was found even if student's opinion revealed that learning in VR is more interesting, convenient and allow better understanding
Zhao et al. (2020)	75 university students; unsure	RCT; HMD VR vs. 360° video	Science; declarative; retention and transfer	HMD virtual reality for biology learning has no effect on learners' CL (NASA-TLX; Hart and Staveland, 1988) and performance but increase their IM (adapted from Ryan, 1982) with a large effect size.
Burgues et al.(a) (2020)	61 French university students; novice	RCT; HMD VR vs. Tablet (with and without control)	Art; factual; retention	VR had no impact on intrinsic motivation (adapted from Deci et al., 1994) but better learning performance was found if the system was interactive (medium/significant effect).
Jin et al. (2022)	54 Chinese university students; novice	RCT; HMD VR vs. Multi-touch table system	History; factual; retention	Study showed that learning with HMD VR resulted in better learning retention and greater learning motivation (adapted from Huang et al., 2010) than learning with multiple touch tablet.
Klingenberg et al. (2020)	89 first year undergraduate students; novice	RCT; HMD VR vs. Desktop VR	Science; factual, conceptual, procedural, and metacognitive; transfer and retention	No effect difference between HMD and desktop VR on learning performance scores, IM, and perceived enjoyment (adapted from Deci et al., 1994) was found in the first posttest but a significant difference in favor of HMD in the second posttest for IM and PE (large effect size), indicating that the student preferred HMD VR "when they had a frame of reference after trying both media conditions."
Makransky et al. (2019)	105 engineering students; intermediate	RCT; HMD VR vs. Desktop VR vs. manual	Safety; factual, conceptual, procedural, and	The VR conditions lead to a significant increase in IM (large effect; adapted from the IMI, Ryan in 1982) and perceived enjoyment (large effect; adapted from Tokel and İsler in 2015) compared to traditional textbook

			metacognitive; retention and transfer	learning. Although there was no effect of iVR and VR on retention score, these media were more effective on transfer than the text condition, especially for iVR (medium effect size).
Makransky et al. (2016)	189 university students; unsure	RCT; desktop VR vs. Real demonstration	Science; declarative; retention and skill acquisition	Using VR to prepare students for microbiology laboratory courses is no more effective, in terms of learning performance or IM (Interest/ Enjoyment Scale from the IMI Ryan in 1982), than traditional face-to-face tutoring.
Makransky et Lilleholt (2018)	104 European university students; unsure	RCT; HMD VR vs. Desktop VR	Science; declarative and procedural; perceived learning	Even if students preferred using HMD rather than desktop VR with a large effect size observed for IM (adapted from Ai-Lim Lee et al. in 2010)) and enjoyment (adapted from Tokel and İsler in 2015), no differences was found for learning outcomes.
Pande et al. (2021)	28 university students; unsure	RCT; HMD VR vs. Video	Science; declarative; retention and skill acquisition	Results showed a positive but non-significant effect of HMD VR on long-term biology learning and no effect on IM and perceived enjoyment (Monteiro et al., 2015) compared to video.

4. Discussion

The purpose of this systematic review on 32 studies was to inform the growing research field on imT and learning, especially focusing on the CL and CS-IM as well as their relationships within immersive devices.

Regarding our first research question, the present results revealed that the CL-related learning benefits from imT occurred more often with AR systems while unnecessary CL was more often reported for VR based ones. This opposite result with respect to type of imT (AR versus VR) is consistent with previous systematic reviews based on AR (Buchner et al., 2022; Newman et al., 2022) and added a new idea for VR, which, until now, had not been subjected to a systematic review process. This imT discrepancy can be explained by their technological features. AR allows adding some virtual elements to the real learning situation, sometimes even guaranteeing the principles of CLT. On the contrary, the use of VR implies a much richer virtual environment both in terms of sensory rendering and interaction, which can cause cognitive overload. At the same time, the AR advantage for CL is mostly observed by studies addressing retention and declarative knowledge, and further studies are needed to cover the multiple facets of learning such as learning transfer and procedural learning. In addition, amongst the studies on declarative learning and retention, there were inconsistent results regarding the advantage of imT for CL. When studies failed to establish a relationship between CL and learning, they generally proposed several primary explanations. The first was the appearance of a "floor effect" linked to a learning activity that was too easy for the learners (Sweller et al., 2019). If the complexity of the task was not high enough, the associated variations in CL could be too small and not visible (Altmeyer et al., 2020; W. Huang et al., 2022; Thees et al., 2022). It is therefore necessary to control for this complexity in future empirical studies on the subject, so that it is neither too low (floor effect) nor too high (cognitive overload). Another explanation could be the measurement of CL, which was sometimes insufficiently sensitive and often self-reported (Lee & Hsu, 2021). In the future, it would be wise to rely on already validated scales (e.g., Leppink et al., 2013) and incorporate objective measures of load such as EEG or reaction time to a secondary task to properly measure and capture CL. Furthermore, Huang concluded that the lack of a direct causal link between CL and learning performance could be due to retention testing. According to him, the skills to be learned that were impacted by VR use and thus associated with changes in CL were not assessed, explaining the lack of correlation between CL and learning. Finally, it should be noted that user experience, especially in VR, is subject to many inter-individual variabilities such as spatial abilities or video game experience, which may explain unexpected results, especially in studies with small samples. Overall, we can only conclude that AR studies have provided promising results for learning by optimizing learners' CL while VR seems to impose an unnecessary load that can impair declarative retention.

For the second research question, the results do not allow us to conclude a grounded effect of *im*T on CS-IM. Most of the studies indicated effects that were inconsistent with self-determination theories. It is possible that these results are due to a misunderstanding of the concepts of CS-IM due to the polysemy of the term (Murayama et al., 2019). Another explanation could be the diversity of the scales used, and their lack of validity. Indeed, the current literature review showed that some of the studies that found inconsistent results between motivation and learning performance used adapted or non-validated scales. This argument is supported by the studies that found consistent correlations between motivation and learning, which in most cases used the validated Interest/Enjoyment Scale of the Intrinsic Motivation Inventory (Deci et al., 1994). We suggest using validated scales for future empirical studies, such as the Intrinsic Motivation Inventory (Deci et al., 1994) and to specify the changes made if this is the case. In addition, some authors have identified a distraction effect associated with VR use (W. Huang et al., 2022). Learners were likely to invest more in fun and enjoyment than in the learning task, which could explain the inconsistent correlations between motivation and learning. Finally, it is also possible that other uncontrolled variables, such as

CL, are responsible for these inconsistent results. In any case, further studies on this issue are needed, especially for AR. As a result, there is a need for more methodologically rigorous research on this issue, taking care to understand the variables of CS-IM and to assess them properly.

About the third research question, results highlighted the existence of links between cognitive and motivational variables, but do not allow to provide a grounded conclusion about their nature. Although several studies included measures of CL and CS-IM in their paper, only two explored the causal links between these three variables (W. Huang et al., 2022; Petersen et al., 2022). Both studies showed different causal relationships between the two variables, with CS-IM determining CL in one case while in the other, CL influenced attendance which determined learner motivation. These contrasting results are also found in the literature on CL and motivation in contexts other than imT-mediated learning. On the one hand, CLT assumes that a sufficient level of motivation is required for the learner to invest the cognitive effort necessary to complete the task (Sweller et al., 2019). Similarly, studies show that curiosity enhances cognitive engagement and reduces perceived effort (Milyavskaya et al., 2021), in particular by reducing the perceived unnecessary load often imposed by virtual environments (Skulmowski & Xu, 2022). These results support that CL is positively influenced by CS-IM. On the contrary, Feldon et al. (2019) highlights the negative effect of CL on motivation. Indeed, the cognitive effort expected could decrease the motivational beliefs of learners and their motivation to learn. Thus, CL could be perceived as a motivational cost. In any case, the authors point out a lack of studies on the subject. Furthermore, unlike W. Huang et al. (2022), Petersen et al.'s (2022) model did not address the role of ICL. Yet, both types of loads could influence motivation in diverse ways. A reduction in ECL could predict more motivation (Feldon et al., 2018), maintaining a greater sense of presence as argued by W. Huang et al. (2022), whereas ICL should be favored to allow for better motivation (X. Huang, 2017). Finally, both models only explored the role of VR on CL and CS. It is important to understand the role of AR, which may differ from VR with respect to these links. For example, it could be that the mediating role of presence is intrinsic to VR use, as this factor is much more associated with this technology than with AR. Therefore, this critical issue deserves further research to better understand the role of these two-learning experience-related constructs in imT-based learning.

For the present literature review, a new operational method has been specially developed to analyze the effects of *im*T on learning, mediated by CL and CS (Figure 2). This operational and reusable grid relies on the principle of a required concomitance of an actual improvement in objective learning performance and an actual improvement in CL or CS-IM to claim that the learning benefit of i*m*T is due to a benefit on CL or CS-IM. This principle excludes subjective measures of learning performance, but does not exclude objective measures of CL or CS-IM (e.g., respectively, physiological indicators such as pupil dilation or EEG signals related to controlled attention, and curiosity-related behaviors such as active exploration or verbal inquiries). The exclusion of subjective learning performance is motivated by studies revealing that self-perceived improvement can be contaminated by metacognitive failures leading the learners to overestimate or underestimate their learning performance especially when they have been invited to self-report their cognitive efforts or their intrinsic motivation for performing the learning activity (e.g., Deslauriers et al., 2019, see for a review: Reber & Greifeneder, 2017). Such a principle ensures a better categorization of the *im*T effects according to the hypotheses of CL and CS-IM driven learning theories minimizing the conclusions risks not being actually evidence-based finding. Therefore, we propose to use this method as a common guiding framework for analyzing the effects of certain media on CL and motivation by considering learning performance, excluding qualitative measures of learning such as intention to learn and perceived learning.

5 Limitations

Some limitations must be mentioned, especially regarding future work. First, the definition of search terms and selection criteria remained subjective, so it is possible that some articles were not included in the search results. Second, as we limited the selection bias by the participation of three readers, the control of the selection process was performed only on a small part of the articles (10% including all articles selected by the first reviewer), which does not completely exclude a selection bias. Finally, non-experimental designs and studies that did not objectively measure learning performance were excluded, which significantly reduced the number of articles selected. However, this allowed us to compare studies that were highly consistent in design.

6 Conclusions

Our method of analyzing the studies revealed that learning with imT improves CL if AR is used rather than VR. Thus, the claim of a better cognitive load produced by imT is only partially confirmed. The claim of an increase in intrinsic motivation by imT is not supported by our analysis, and remains to be better investigated by well-constructed and validated measures of intrinsic motivation. Finally, the links between CL and CS-IM are only barely studied and need to be further investigated to understand their nature, in order to better understand and contextualize the added value of imT for education.

7 Authors contributions

Matisse Poupard: Conceptualization, Methodology, Analysis, Investigation, Data Curation, Writing-Original Draft, Editing, Visualization.
Florian Larrue: Supervision, Validation, Writing - Review & Editing
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