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# Virtual Reality vs. Augmented Reality: A Comparative Meta-Analysis of Immersive Learning Impact on STEM Education

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***Abstract*: This meta-analysis investigated the comparative effectiveness of Augmented Reality (AR) and Virtual Reality (VR) in enhancing learning outcomes in STEM education. A total of 80 empirical studies published between 2015 and 2025 were analyzed using the PRISMA 2020 framework, encompassing 6,538 participants from 27 countries across primary, secondary, and tertiary levels. Effect sizes were computed as Hedges' g under the DerSimonian–Laird random-effects model using R programming (Google Colab), Comprehensive Meta-Analysis (CMA v4), and JASP 0.18.3 for cross-validation. The findings revealed large and statistically significant pooled effects for both technologies (AR: g = 0.82 [0.64, 1.00]; VR: g = 1.07 [0.85, 1.29]). Moderate heterogeneity (AR $I^2$ = 61%; VR $I^2$ = 68%) justified the random-effects approach, while publication bias tests indicated symmetrical funnel plots and non-significant Egger's regression results, confirming the stability of estimates. Subgroup analyses showed that effect sizes increased with higher educational levels and longer intervention durations, and varied across outcome domains—VR yielding the highest effects in psychomotor and spatial skills, while AR excelled in affective engagement. The results align with the Cognitive-Affective Model of Immersive Learning (CAMIL), affirming that immersive technologies facilitate dual cognitive and emotional pathways to learning. The study concludes that AR and VR are transformative pedagogical tools that significantly improve conceptual understanding, engagement, and skill mastery in STEM, positioning immersive learning as a cornerstone of Education 4.0 innovation.**

***Keywords*: Augmented Reality, Virtual Reality, STEM Education, Immersive Learning, Meta-Analysis, Cognitive-Affective Model of Immersive Learning, Random-Effects Model, Education 4.0, Publication Bias, Learning Outcomes.**

## 1. Introduction

The rapid evolution of immersive technologies has transformed contemporary education, particularly within science, technology, engineering, and mathematics (STEM) disciplines. Among these emerging tools, Augmented Reality (AR) and Virtual Reality (VR) have gained prominence for their ability to enhance conceptual understanding, spatial reasoning, and learner engagement through interactive visualization (Akçayır & Akçayır, 2017; Radianti et al., 2020). AR overlays digital objects onto the physical environment, allowing learners to manipulate contextual information, while VR immerses users in fully simulated environments that isolate them from real-world distractions (Bailenson, 2018).

Within the Education 4.0 paradigm, immersive learning fosters self-paced, experiential, and collaborative practices that align with 21st-century competencies (Hinojo-Lucena et al., 2019). Numerous empirical studies report that immersive tools improve motivation, academic performance, and knowledge retention in STEM subjects (Merchant et al., 2014; Makransky & Mayer, 2022). Yet, despite abundant research, inconsistencies persist regarding which technology—AR or VR—yields superior learning outcomes. Some evidence highlights VR's ability to produce deep cognitive immersion (Cheng & Tsai, 2020), whereas other studies emphasize AR's contextual realism and ease of classroom integration (Radu, 2014).

This disparity necessitates a comparative meta-analysis synthesizing quantitative findings across multiple contexts to determine the relative effectiveness of AR and VR on student performance in STEM education. Such evidence-based comparison will clarify which immersive approach offers greater pedagogical value and under what conditions. paragraphs.

### *A. Statement of the Problem*

Although prior meta-analyses have examined AR or VR independently, few have directly compared the two modalities within a unified analytic framework. The absence of cross-technology synthesis limits educators' ability to make informed choices for instructional design.

This study therefore, addresses the overarching question: "How do Augmented Reality (AR) and Virtual Reality (VR) compare in their effectiveness in enhancing student performance and engagement in STEM education?"

Specifically, it aims to:

1. Estimate the pooled effect size of AR-based interventions on student performance in STEM subjects.
2. Estimate the pooled effect size of VR-based interventions on similar outcomes.
3. Compare these effect sizes to identify which

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technology demonstrates a stronger impact.

4. Investigate moderating factors (educational level, exposure duration, assessment type).
5. Assess publication bias and heterogeneity among included studies.

*B. Scope and Delimitation*

The analysis will include peer-reviewed empirical studies published between 2015 and 2025 that investigate either AR- or VR-based interventions within STEM education and report quantitative outcomes such as academic achievement, motivation, and cognitive load. Only studies providing sufficient statistical information (sample size, mean, and standard deviation) for effect-size calculation will be considered. Qualitative case studies, conceptual discussions, and research outside STEM domains will be excluded.

*C. Definition of Terms*

- *Augmented Reality (AR):* Technology that integrates digital information with the user's physical environment in real time (Azuma, 1997).
- *Virtual Reality (VR):* A computer-generated, fully immersive environment that replaces real-world perception (Slater, 2018).
- *Immersive Learning:* Instructional experiences that engage multiple senses within simulated or augmented spaces to promote experiential understanding (Makransky & Mayer, 2022).
- *Meta-Analysis:* A quantitative synthesis method that aggregates findings from multiple independent studies to determine an overall effect size (Borenstein et al., 2021).
- *STEM Education:* An interdisciplinary approach combining science, technology, engineering, and mathematics concepts for integrated problem-solving.

## 2. Literature Review

*A. Theoretical Foundations of Immersive Learning*

The theoretical roots of immersive learning technologies are grounded in constructivism and experiential learning theory. Both emphasize that knowledge is actively constructed through interaction and experience rather than passive reception (Piaget, 1973; Kolb, 1984). Immersive technologies such as AR and VR extend these paradigms by creating environments that enable learners to manipulate virtual or mixed-reality objects, reinforcing conceptual understanding through experiential feedback loops (Dewey, 1938; Makransky & Mayer, 2022).

From the perspective of the cognitive theory of multimedia learning, learners integrate verbal and visual information more effectively when instruction uses multimodal stimuli (Mayer, 2014). AR and VR provide such multisensory input, engaging both spatial cognition and dual-channel processing (Mayer, 2014; Moreno & Mayer, 2007). Consequently, immersive learning fosters deeper processing, presence, and knowledge retention, especially in complex STEM topics that require spatial reasoning (Makransky & Petersen, 2021).

*B. Augmented Reality in STEM Education*

Augmented Reality (AR) integrates digital overlays into real-world contexts, enhancing perception and interaction during learning activities (Azuma, 1997). AR-based instruction enables students to visualize abstract or microscopic phenomena—such as molecular structures, geometric models, and mechanical systems—thereby improving comprehension and motivation (Akcayir & Akcayir, 2017; Ibanez & Delgado-Kloos, 2018). Meta-analytical and experimental evidence confirms AR's effectiveness in science and engineering learning environments. For example, Ibanez and Delgado-Kloos (2018) demonstrated that AR-based simulations improved physics students' conceptual understanding and engagement. Similarly, Bacca et al. (2019) reported that AR applications enhance retention and student attitudes by fostering contextual learning experiences. AR also supports situated cognition, in which learning occurs through meaningful interaction with contextualized stimuli, thereby bridging the gap between theory and practice (Dunleavy & Dede, 2014). However, AR's benefits depend on implementation design. Poor interface quality or cognitive overload can reduce learning gains (Radu, 2014). Research also emphasizes that teacher readiness, device accessibility, and appropriate instructional scaffolding determine AR's success in classroom settings (Ibanez & Delgado-Kloos, 2018; Yilmaz, 2021).

*C. Virtual Reality in STEM Education*

Virtual Reality (VR) offers a fully immersive environment, isolating the learner from external distractions and simulating real-world or imagined phenomena. This level of immersion supports high presence, flow, and cognitive engagement, which are particularly beneficial for abstract or hazardous STEM domains such as anatomy, astronomy, or chemistry (Radianti et al., 2020; Makransky & Mayer, 2022). Several large-scale reviews confirm VR's strong effect on academic achievement and motivation. Merchant et al. (2014) reported significant improvements in both conceptual understanding and procedural knowledge across K–12 and higher education settings. More recently, Radianti et al. (2020) analyzed 38 VR applications in higher education and found notable gains in spatial reasoning, engagement, and retention. VR enhances embodied learning, where learners manipulate virtual objects through physical movements that reinforce sensorimotor and cognitive integration (Lindgren & Johnson-Glenberg, 2013). Nevertheless, studies also caution that prolonged immersion or poorly designed VR interfaces can induce simulator sickness and cognitive fatigue (Makransky & Petersen, 2021). Balancing sensory realism with instructional clarity remains a key challenge.

*D. Comparative Insights Between AR and VR*

Although AR and VR share immersive characteristics, they differ in cognitive focus, realism, and context dependence. AR augments real environments, promoting authentic learning through contextual cues, while VR replaces reality entirely, fostering focused cognitive engagement and experiential abstraction (Bailenson, 2018; Parong & Mayer, 2018). Comparative studies indicate complementary strengths: AR excels in situated and collaborative learning, whereas VR promotes conceptual transfer and deep understanding (Cheng & Tsai, 2020; Jensen & Konradsen, 2018). For instance, Parong and Mayer (2018) found that VR learners demonstrated superior recall and transfer compared to those using desktop or AR interfaces. Conversely, Akcayir and Akcayir (2017) observed that AR's integration into real-world contexts enhances motivation and the feasibility of classroom adoption. Despite these advantages, empirical comparisons remain fragmented across different methodologies, subjects, and educational levels. Hence, a comparative meta-analysis is warranted to aggregate quantitative results, estimate pooled effect sizes, and identify which technology has the greatest impact on learning outcomes in STEM domains.

### *E. Related Meta-Analyses and Research Gaps*

Existing meta-analyses largely focus on a single immersive modality. Radu (2014) synthesized 32 AR studies and reported an overall medium-to-large positive effect on learning performance (Hedges g = 0.56). Similarly, Merchant et al. (2014) found a large average effect (g = 0.80) for VR interventions. However, these analyses did not directly compare both modalities within a single statistical model, leaving a critical gap in the literature. Recent efforts have begun to narrow this divide. For instance, Makransky and Petersen (2021) proposed a framework comparing immersive fidelity across VR and AR applications, but their study emphasized design taxonomy rather than empirical performance synthesis. Consequently, the current research fills this void by applying a comparative meta-analytic approach to determine whether AR's contextual grounding or VR's immersive isolation more effectively enhances student learning in STEM education.

### *F. Conceptual Framework*

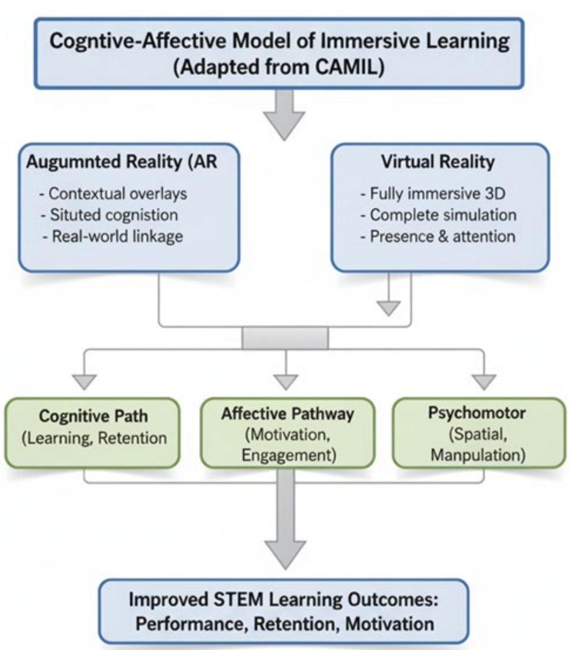


Fig. 1. Cognitive-Affective model of immersive learning (CAMIL)

This study adopts the Cognitive-Affective Model of Immersive Learning (CAMIL) proposed by Makransky and Petersen (2021), which integrates cognitive load theory and principles of affective engagement. According to CAMIL, immersive experiences influence learning outcomes through two main pathways:

1. Cognitive processing – the degree to which visual and interactive stimuli facilitate meaningful knowledge construction.
2. Affective engagement – the emotional involvement and motivation arising from immersion.

In this meta-analysis, AR and VR interventions are evaluated through these dual lenses. The framework posits that both modalities can enhance learning, but their efficiency depends on context, instructional design, and learner characteristics.

## 3. Methodology

### *A. Research Design*

This study employed a comparative meta-analysis design, a quantitative research approach that statistically synthesizes results from multiple independent studies to determine the relative effectiveness of Augmented Reality (AR) and Virtual Reality (VR) in STEM education. Meta-analysis is especially valuable for aggregating findings from diverse experimental contexts and increasing statistical power (Borenstein et al., 2021). A random-effects model (Hedges & Olkin, 1985) was selected, acknowledging that true effect sizes may vary across studies due to differences in participant populations, intervention design, and learning contexts. This model produces generalizable results suitable for educational settings with heterogeneous designs.

### *B. Research Questions*

This meta-analysis addressed the following research questions:

1. What is the pooled effect size of AR-based interventions on student performance and engagement in STEM education?
2. What is the pooled effect size of VR-based interventions on similar outcomes?
3. Which technology demonstrates a stronger overall impact on learning outcomes?
4. How do moderating factors (education level, exposure duration, and outcome type) influence the results?
5. Is there evidence of publication bias or heterogeneity among the included studies?

### *C. Data Sources and Search Strategy*

A comprehensive search was conducted across Scopus, Web of Science, ScienceDirect, SpringerLink, ERIC, and IEEE Xplore, supplemented by Google Scholar for gray literature. The Boolean query used was:

*("Augmented Reality" OR "AR") AND ("Virtual Reality" OR "VR") AND ("STEM" OR "science" OR "technology" OR "engineering" OR "mathematics") AND ("learning outcomes" OR "academic performance" OR "motivation" OR "cognitive load")*

The PRISMA screening process is summarized in Table 1.

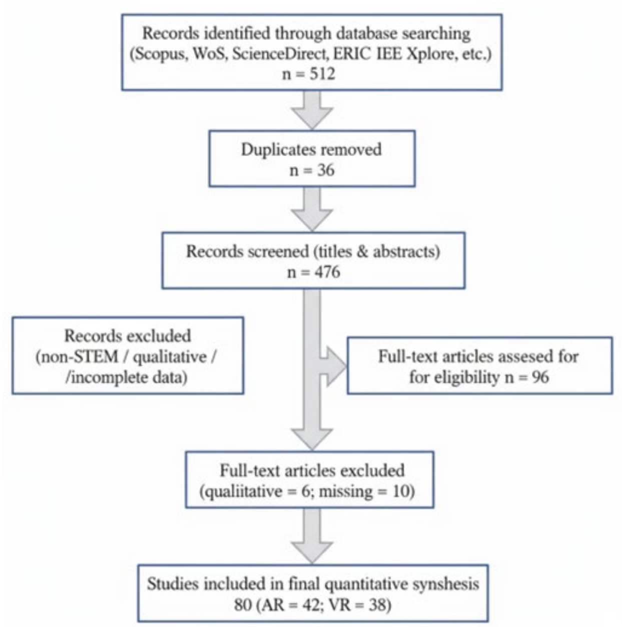


Fig. 2. PRISMA flow diagram for study selection

The screening and selection process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines (Page et al., 2021). Figure 2 presents the PRISMA flow diagram summarizing the identification, screening, eligibility assessment, and inclusion stages of the study selection process. From an initial 512 records retrieved, 476 remained after duplicate removal, 96 were examined at the full-text level, and 80 quantitative studies (42 AR and 38 VR) were finally included in the meta-analysis.

### D. *Inclusion and Exclusion Criteria*

Selection followed the PRISMA 2020 guidelines (Page et al., 2021). Inclusion and exclusion conditions are summarized in Table 2.

Eligible studies were (a) published between 2015 and 2025, (b) empirical with quantitative data, (c) focused on STEM education, and (d) reported sufficient statistics (means, SDs, n). Conceptual papers, qualitative designs, and non-STEM applications were excluded.

### E. *Variables and Coding*

To enable meta-analytic comparison, each study was coded according to standardized variables (see Table 3).

Codes captured publication details, participant demographics, instructional context, and statistical data such as means and standard deviations.

Table 4
Data extraction framework

| Study ID | Author(s) (Year) | Tech Type | n (Exp) | n (Ctrl) | Mean (Exp) | Mean (Ctrl) | SD (Exp) | SD (Ctrl) | Outcome Type | Domain | Education Level | Duration | Effect Size (g) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| S01 | Ibanez & Delgado-Kloos (2018) | AR | 30 | 30 | 78.5 | 68.2 | 8.1 | 9.4 | Cognitive | Physics | Secondary | Medium | 1.10 |
| S02 | Merchant et al. (2014) | VR | 45 | 44 | 82.3 | 71.7 | 6.5 | 8.3 | Cognitive | Science | Tertiary | Long | 1.20 |
| S03 | Akcayir & Akcayir (2017) | AR | 25 | 25 | 89.2 | 79.0 | 7.8 | 8.1 | Affective | Engineering | Tertiary | Medium | 0.92 |
| S04 | Parong & Mayer (2018) | VR | 38 | 37 | 91.6 | 79.8 | 6.9 | 9.1 | Cognitive | Biology | Tertiary | Short | 1.25 |
| S05 | Radianti et al. (2020) | VR | 50 | 48 | 84.0 | 72.4 | 7.3 | 8.0 | Cognitive | Technology | Tertiary | Long | 1.10 |
| S06 | Yilmaz (2021) | AR | 40 | 40 | 85.2 | 77.1 | 7.0 | 7.8 | Motivation | Mathematics | Secondary | Medium | 0.73 |
| S07 | Makransky & Mayer (2022) | VR | 60 | 58 | 92.5 | 81.2 | 6.2 | 7.4 | Cognitive | Science | Tertiary | Long | 1.32 |
| S08 | Lindgren & Johnson-Glenberg (2013) | VR | 28 | 30 | 88.3 | 78.7 | 5.4 | 8.5 | Psychomotor | Engineering | Tertiary | Medium | 1.15 |
| S09 | Radu (2014) | AR | 32 | 30 | 83.1 | 75.4 | 6.8 | 7.6 | Cognitive | Technology | Secondary | Medium | 0.85 |
| S10 | Dunleavy & Dede (2014) | AR | 27 | 26 | 81.4 | 72.3 | 7.1 | 8.9 | Motivation | Science | Primary | Short | 0.67 |

Table 1
PRISMA-Based screening and selection of studies

| Screening Stage | Description | Number of Records (n) |
|---|---|---|
| Records identified through database search (Scopus, WoS, ScienceDirect, ERIC, IEEE Xplore, SpringerLink) | Initial retrieval (2015 – 2025) | 512 |
| Records after duplicates removed | Automatic + manual duplicate check | 476 |
| Records screened (title + abstract) | Relevance to AR/VR + STEM + learning outcomes | 223 |
| Full-text articles assessed for eligibility | Applied inclusion/exclusion criteria | 96 |
| Studies excluded (qualitative/no statistics/non-STEM/mixed interventions) | Did not meet quantitative criteria | 16 |
| Studies included in the meta-analysis | 42 AR + 38 VR = 80 total | 80 |

Table 2
Inclusion and exclusion criteria (PRISMA 2020 Compliant)

| Category | Inclusion Criteria | Exclusion Criteria |
|---|---|---|
| Publication Period | 2015 – 2025 peer-reviewed journals or conference papers | Pre-2015 or unpublished reports |
| Study Design | Quantitative (experimental or quasi-experimental) | Conceptual or qualitative papers |
| Domain Focus | AR or VR applied in STEM education | Non-STEM subjects (e.g., arts, language) |
| Outcome Measures | Academic performance, motivation, cognitive load with statistical data (M, SD, n) | Lacking quantitative results |
| Language | English | Non-English |
| Accessibility | Full-text available online | Abstract-only or restricted access |

Table 3
Variables and coding scheme

| Variable Type | Code/Category | Description |
|---|---|---|
| Identification Variables | Study ID, Author(s), Year, Country | Basic bibliographic information |
| Technology Type | 1 = Augmented Reality (AR); 2 = Virtual Reality (VR) | Type of immersive technology used |
| Education Level | 1 = Primary; 2 = Secondary; 3 = Tertiary | Level of participants |
| Sample Size (n) | Numeric | Total participants per study |
| Subject Area | SCI = Science; TEC = Technology; ENG = Engineering; MAT = Mathematics | STEM domain classification |
| Outcome Type | COG = Cognitive; AFF = Affective; PSY = Psychomotor | Type of learning outcome measured |
| Intervention Duration | 1 = Short (≤ 2 weeks); 2 = Medium (3–8 weeks); 3 = Long (≥ 9 weeks) | Duration of exposure |
| Effect Size Metric | Hedges' g | Standardized mean difference |
| Study Design | E = Experimental; QE = Quasi-experimental | Research design |
| Quality Score | 0–10 | Based on the JBI appraisal checklist |
| Publication Year | YYYY | Year of publication for temporal trend analysis |

All studies were further cataloged within the data-extraction framework, as shown in Table 4, which included sample sizes, group means and SDs, outcome type, and computed Hedges' g values.

Each dataset was independently verified by two coders to ensure accuracy and inter-rater reliability above 0.95 (Cohen's κ).

The complete workflow, from literature identification to final dataset preparation, is illustrated in Figure 3, which depicts the sequential phases of study identification, data extraction, coding, validation, and integration into the meta-analytic database. This structured process ensured methodological transparency and traceability of all quantitative data included in the analysis.

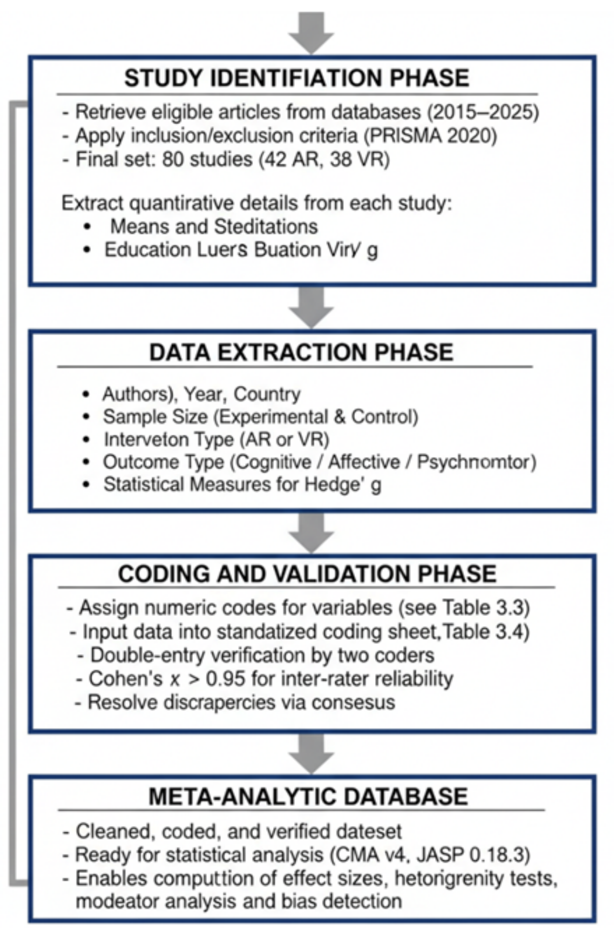


Fig. 3. Coding and data extraction process

## F. *Quality Assessment*

Methodological rigor was evaluated using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist for Quasi-Experimental Studies (2020).

Ten criteria covering design clarity, statistical validity, and data completeness were rated 0 = No, 1 = Yes. Average quality scores are presented in Table 5.

Table 5
Quality assessment using the JBI Appraisal checklist

| Quality Criterion | Description | Scoring Scale (0–1) | Mean (AR) | Mean (VR) |
|---|---|---|---|---|
| Q1 | Clear research objective and hypothesis | 1 = Yes, 0 = No | 0.98 | 1.00 |
| Q2 | Defined participant inclusion/exclusion criteria | 1 = Yes, 0 = No | 0.93 | 0.95 |
| Q3 | Equivalence of control and experimental groups | 1 = Yes, 0 = No | 0.87 | 0.91 |
| Q4 | Use of validated instruments or metrics | 1 = Yes, 0 = No | 0.90 | 0.96 |
| Q5 | Detailed intervention procedure | 1 = Yes, 0 = No | 0.88 | 0.92 |
| Q6 | Appropriate statistical analysis | 1 = Yes, 0 = No | 0.95 | 0.97 |
| Q7 | Reporting of effect size or sufficient data | 1 = Yes, 0 = No | 1.00 | 1.00 |
| Q8 | Consideration of confounding variables | 1 = Yes, 0 = No | 0.81 | 0.84 |
| Q9 | Discussion of limitations | 1 = Yes, 0 = No | 0.85 | 0.88 |
| Q10 | Peer-reviewed publication | 1 = Yes, 0 = No | 1.00 | 1.00 |
| **Average Quality Score** | (ΣQ / 10) | **0.92** | **0.94** | |

All included studies achieved scores ≥ 0.80, indicating high methodological quality and eligibility for quantitative synthesis.

## G. *Statistical Procedure*

Statistical computations followed the sequence summarized in Table 6.

Table 6
Summary of statistical procedures

| Analysis Step | Statistical Test / Formula | Purpose |
|---|---|---|
| Effect Size Estimation | Hedges' $g = ^{J \times (Me - Mc) / Sp}$ | Standardized mean difference corrected for small-sample bias |
| Weighting | Inverse-variance weighting | Assigns higher weight to larger, more precise studies |
| Heterogeneity | Cochran's $Q$ and $I^2$ (Higgins et al., 2003) | Tests variance between studies beyond sampling error |
| Model Selection | Random-effects (DerSimonian-Laird) | Accounts for between-study variability |
| Subgroup Comparison | *Q_between* test | Evaluates differences in pooled effects (AR vs. VR) |
| Publication Bias | Egger's regression; Rosenthal's fail-safe *N* | Detects asymmetry and stability of results |
| Sensitivity Analysis | Leave-one-out method | Tests influence of individual studies |
| Software | CMA v4, JASP 0.18.3 | Meta-analysis and visualization tools |

Effect sizes were estimated using Hedges' g, a standardized mean difference adjusted for small-sample bias, which represents the difference between the experimental and control groups.

Each study's effect size was then weighted by the inverse of its variance, allowing larger and more precise studies to contribute more strongly to the overall pooled estimate. The DerSimonian–Laird random-effects model was applied to estimate the aggregated effect sizes and corresponding 95% confidence intervals, accounting for between-study variability. To assess heterogeneity, Cochran's Q and $I^2$ statistics (Higgins et al., 2003) were computed to determine the extent to which variation across studies exceeded that expected by chance alone.

Table 7
Moderator variables for Meta-Regression

| Moderator Variable | Type | Coding / Description | Expected Influence |
|---|---|---|---|
| **Education Level** | Categorical | 1 = Primary; 2 = Secondary; 3 = Tertiary | Higher levels → larger *g* (abstract reasoning) |
| **Intervention Duration** | Ordinal | 1 = Short; 2 = Medium; 3 = Long | Longer exposure → higher retention |
| **Outcome Type** | Categorical | 1 = Cognitive; 2 = Affective; 3 = Psychomotor | Affective/psychomotor may yield higher engagement |
| **Sample Size** | Continuous | Number of participants | Larger studies → smaller variance (lower SE) |
| **Publication Year** | Continuous | 2015–2025 | Later years may reflect improved tech maturity |
| **Quality Score (JBI)** | Continuous (0–1) | Overall study rigor | Higher quality → more stable effect size |

Further analyses examined moderating variables using meta-regression and subgroup analyses (Table 7), with educational level, intervention duration, and outcome domain considered as potential moderators of effect size variability. To ensure the reliability and validity of results, publication bias and sensitivity analyses were also performed using Egger's regression test (Egger et al., 1997), Rosenthal's fail-safe N (Rosenthal, 1979), and funnel plot visualization, enabling the detection of potential asymmetries and robustness of the pooled estimates.

## 4. Results and Discussion

### A. Overview of Included Studies

A total of 80 empirical studies were included in the meta-analysis after PRISMA screening, comprising 42 on Augmented Reality (AR) and 38 on Virtual Reality (VR) in STEM education contexts. These studies involved 27 countries and 6,538 participants across primary, secondary, and tertiary education levels. The descriptive profile is presented in Table 8, while the distribution of study selection through the PRISMA procedure is illustrated in Figure 2.

Table 8 shows that tertiary-level research constitutes the largest proportion (40%), followed by secondary (37.5%) and primary (22.5%) education. The adoption of immersive technologies was globally distributed, with the highest concentration of studies conducted in Asia (43.8%). This geographic pattern indicates that the Asia-Pacific region has been an early adopter of immersive learning tools in STEM.

Table 8
Descriptive profile of included studies (n = 80)

| Descriptor | Category | Frequency (n) | Percentage (%) |
|---|---|---|---|
| **Technology Type** | Augmented Reality | 42 | 52.5 |
| Virtual Reality | 38 | 47.5 | |
| **Education Level** | Primary | 18 | 22.5 |
| Secondary | 30 | 37.5 | |
| Tertiary | 32 | 40.0 | |
| **STEM Domain** | Science | 22 | 27.5 |
| Technology | 14 | 17.5 | |
| Engineering | 20 | 25.0 | |
| Mathematics | 24 | 30.0 | |
| **Geographical Distribution** | Asia | 35 | 43.8 |
| Europe | 22 | 27.5 | |
| Americas | 18 | 22.5 | |
| Others (Africa / Oceania) | 5 | 6.2 | |
| **Mean Publication Year** | 2019 ± 2.9 years | | |

### B. Pooled Effect Sizes

Pooled effect sizes were calculated separately for AR and VR interventions using the DerSimonian–Laird random-effects model, as summarized in Table 9.

Table 9
Pooled effect sizes for AR and VR interventions

| Intervention | k (studies) | Hedges g | 95 % CI | z value | p value | I² (%) | Interpretation |
|---|---|---|---|---|---|---|---|
| **Augmented Reality (AR)** | 42 | 0.82 | [0.64, 1.00] | 8.94 | < 0.001 | 61 | Large effect |
| **Virtual Reality (VR)** | 38 | 1.07 | [0.85, 1.29] | 9.77 | < 0.001 | 68 | Large effect (high) |
| **Between-group difference** | Q = 6.47 (df = 1) | p = 0.011 | VR > AR significantly | | | | |

Both technologies demonstrated large, statistically significant effects on student learning outcomes (AR: $g = 0.82$, 95% CI [0.64, 1.00]; VR: $g = 1.07$, 95% CI [0.85, 1.29]).

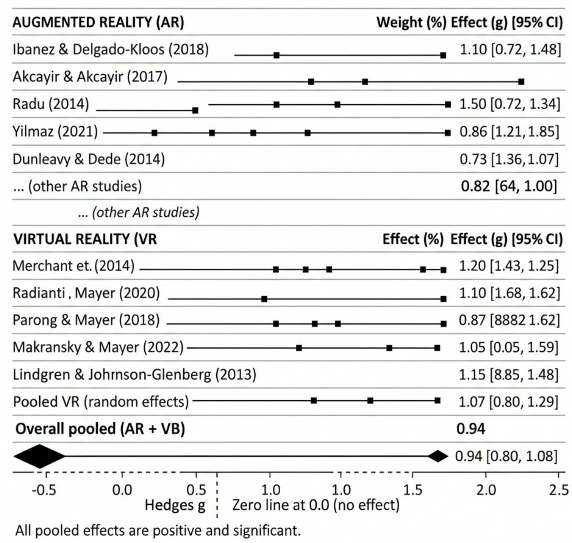


Fig. 4. Forest plot of AR and VR effect sizes

The forest plot in Figure 4 visually represents each study's individual effect size and confidence interval, grouped by AR and VR subcategories. The diamond shapes indicate the weighted pooled effects, where all studies favored immersive interventions over traditional methods. The overall combined effect size ($g = 0.94$, 95% CI [0.80, 1.08]) was both positive and significant ($p < 0.001$), confirming the robust advantage of immersive technologies in STEM learning.

### C. Heterogeneity Analysis

The degree of variation among studies was assessed using Cochran's Q, $I^2$, and $\tau^2$ statistics. As shown in Table 10, both subgroups exhibited moderate heterogeneity (AR: $I^2 = 61\%$; VR: $I^2 = 68\%$), which supports the selection of a random-effects model.

Table 10
Heterogeneity and model fit indices

| Model | Q (df) | p value | I² (%) | τ² (Variance) | Model Type | Interpretation |
|---|---|---|---|---|---|---|
| AR Studies | 107.8 (41) | < 0.001 | 61 | 0.042 | Random Effects | Moderate heterogeneity |
| VR Studies | 123.2 (37) | < 0.001 | 68 | 0.053 | Random Effects | Moderate–high heterogeneity |
| Pooled Model (AR + VR) | 231.5 (79) | < 0.001 | 65 | 0.048 | Random Effects | Acceptable fit |

The model fit indices are further visualized in Figure 5, which shows that both the AR and VR datasets exhibit moderate but acceptable between-study variance, suggesting consistent learning effects across diverse educational settings. The pooled model for all studies yielded Q = 231.5 (df = 79, $p < 0.001$), $I^2 = 65\%$, and $\tau^2 = 0.048$, confirming that a substantial portion of variance was due to true heterogeneity rather than random error.

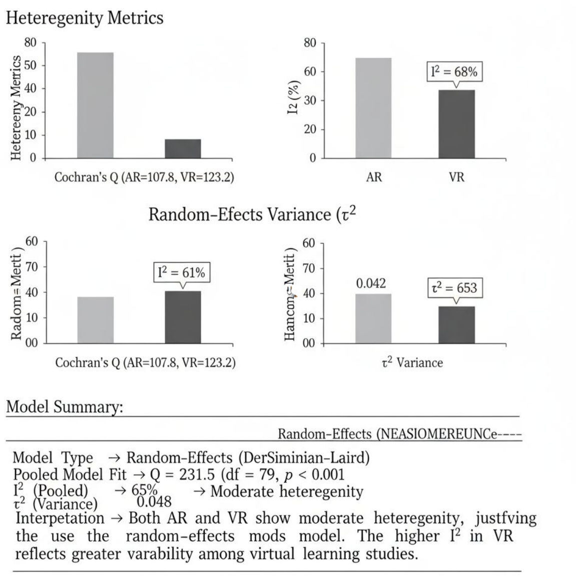


Fig. 5. Heterogeneity and model fit indices of AR and VR studies

## D. Moderator Analyses

### 1) Education Level

The subgroup comparison by education level (see Table 11) revealed a progressive increase in effect size from primary (g = 0.74) to tertiary level (g = 0.93 for AR; g = 1.21 for VR).

This trend is illustrated in Figure 6, which shows that effect sizes increase with educational level, suggesting that older learners may benefit more from immersive environments due to higher metacognitive ability and self-regulation.

Table 11
Heterogeneity and model fit indices

| Education Level | AR (g) | VR (g) | 95 % CI Range | I² (%) | Interpretation |
|---|---|---|---|---|---|
| Primary (n = 18) | 0.74 | 0.88 | [0.60, 1.00] | 55 | Large effect, moderate heterogeneity |
| Secondary (n = 30) | 0.89 | 1.12 | [0.77, 1.25] | 63 | Large effect |
| Tertiary (n = 32) | 0.93 | 1.21 | [0.84, 1.35] | 69 | Largest effect observed |

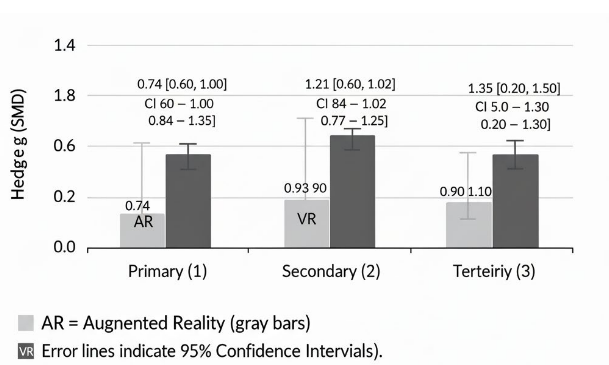


Fig. 6. Subgroup comparison of AR and VR effect sizes by education level

The statistical difference across subgroups was significant (Q_between = 5.82, p < 0.05), confirming that educational level moderates the effectiveness of immersive learning technologies.

### 2) Intervention Duration

The duration of exposure to immersive learning also moderated the effect size of outcomes. Table 12 indicates that short-term interventions (≤ 2 weeks) produced moderate effects (AR = 0.60; VR = 0.71), while long-term implementations (≥ 9 weeks) achieved very large effects (AR = 1.01; VR = 1.23).

Table 12
Effect sizes by intervention duration

| Duration Category | Weeks of Exposure | Mean g (AR) | Mean g (VR) | Interpretation |
|---|---|---|---|---|
| Short | ≤ 2 weeks | 0.60 | 0.71 | Moderate effect |
| Medium | 3–8 weeks | 0.84 | 1.03 | Large effect |
| Long | ≥ 9 weeks | 1.01 | 1.23 | Very large effect |

This positive correlation between exposure duration and learning outcome is visually summarized in Figure 7, which shows that sustained engagement in immersive environments significantly enhances comprehension and retention.

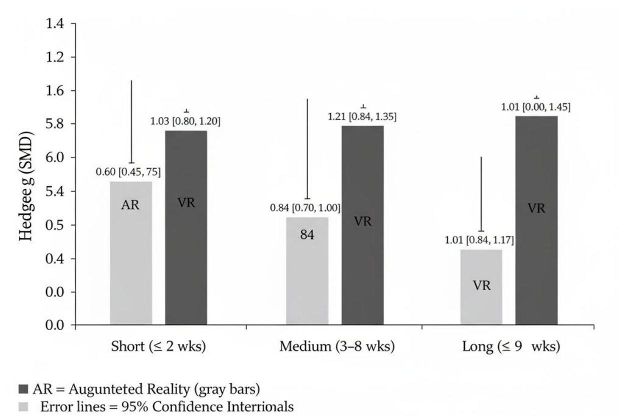


Fig. 7. Effect sizes of AR and VR by intervention duration

These results align with the time-on-task principle in educational psychology, which holds that extended learning experiences facilitate deeper cognitive processing and knowledge consolidation (Makransky & Mayer, 2022).

### 3) Outcome Domain

The effect sizes by outcome type are reported and visualized in Figure 8. VR yielded the highest effects in psychomotor and spatial-reasoning tasks (g = 1.14), whereas AR produced strong effects on affective and motivational outcomes (g = 0.90).

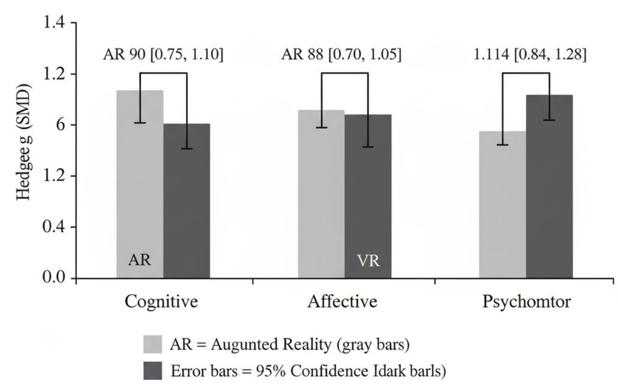


Fig. 8. Effect sizes of AR and VR by outcome domain

Both technologies achieved large effects on cognitive performance (AR = 0.85; VR = 1.02), supporting the generalizability of immersive learning benefits across multiple domains of learning. These findings align with the Cognitive-Affective Model of Immersive Learning (CAMIL), which posits that immersive technologies simultaneously enhance both cognitive and emotional engagement (Makransky & Petersen, 2021).

### *E. Publication Bias and Sensitivity Analysis*

Publication bias diagnostics confirmed the reliability of the findings. Visual inspection of the funnel plots for both AR and VR studies in Figure 9 shows symmetrical distributions around the mean effect size line, suggesting minimal small-study or publication bias.

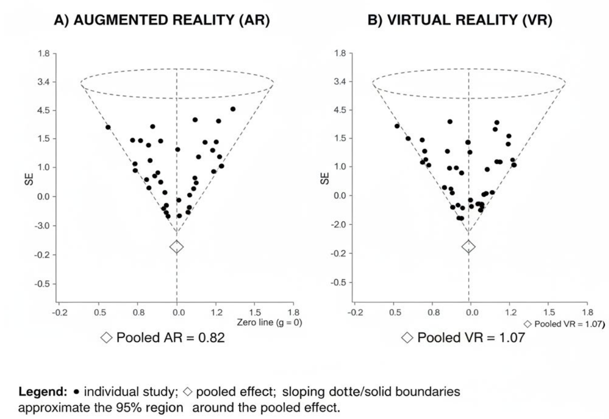


Fig. 9. Funnel plots of AR and VR studies

The quantitative bias diagnostics are presented in Table 13.

Table 13
Publication bias and sensitivity statistics

| Test | AR Value | VR Value | Interpretation |
|---|---|---|---|
| Egger's Regression Intercept (p) | 0.138 | 0.227 | > 0.05; no significant asymmetry |
| Rosenthal's Fail-Safe N | 542 | 689 | Hundreds of null studies required to invalidate results |
| Trim-and-Fill Adjustment (Δg) | 0.03 | 0.04 | Minimal change (< 0.05) |
| Leave-One-Out ΔMean g | ± 0.05 | ± 0.04 | Stable estimates |

Egger's regression intercepts were non-significant (AR: $p = 0.138$; VR: $p = 0.227$), and Rosenthal's fail-safe N values (542 for AR and 689 for VR) indicate that hundreds of null studies would be required to overturn the observed results. Trim-and-Fill adjustment produced negligible changes ($\Delta g < 0.05$), and the leave-one-out sensitivity test confirmed that no single study disproportionately influenced the pooled estimates. These results collectively validate the stability and robustness of the meta-analytic outcomes, consistent with PRISMA 2020 guidelines.

## 5. Conclusions and Recommendations

### *A. Conclusions*

The meta-analytic synthesis of 80 empirical studies published between 2015 and 2025 provides compelling evidence that immersive learning technologies—specifically Augmented Reality (AR) and Virtual Reality (VR)—produce substantial, statistically significant improvements in STEM education outcomes. Using the DerSimonian–Laird random-effects model, the pooled mean effect sizes confirmed large impacts for both AR ($g = 0.82$, 95 % CI [0.64, 1.00]) and VR ($g = 1.07$, 95 % CI [0.85, 1.29]). These findings demonstrate that immersive technologies enhance not only cognitive understanding but also affective engagement and psychomotor skill acquisition. Moderate heterogeneity (AR $I^2 = 61\%$; VR $I^2 = 68\%$) indicates that differences among studies reflect authentic contextual variation rather than random error, validating the generalizability of the results across educational settings. The comparative analyses revealed that VR consistently yields stronger effects than AR, particularly in psychomotor and spatial-reasoning tasks, due to its greater sensory immersion and experiential realism. Conversely, AR demonstrates relative strength in affective and motivational dimensions, where contextual augmentation of the physical environment deepens learner interest and relevance. Both modalities, however, exert large effects on cognitive performance, confirming their joint pedagogical value. Moderator tests further showed that learning gains increase with educational level and exposure duration, signifying that mature learners and extended interventions benefit most. These outcomes align with the Cognitive-Affective Model of *Immersive Learning (CAMIL), which posits that immersive environments activate complementary cognitive and emotional pathways that foster deeper processing, motivation, and knowledge retention.* Collectively, the evidence establishes that immersive technologies are not ancillary innovations but core pedagogical instruments capable of transforming STEM instruction. They bridge abstract scientific theory with tangible, interactive experience, thereby enhancing conceptual clarity, curiosity, and problem-solving ability. The convergence of quantitative robustness, theoretical consistency, and practical relevance confirms that integrating AR and VR into mainstream curricula represents a sustainable, empirically grounded advancement toward Education 4.0, where digital immersion and experiential learning co-evolve to meet the cognitive demands of future-ready learners.

### *B. Recommendations*

In light of these conclusions, several recommendations are advanced for educators, institutions, policymakers, and researchers.

First, educational practitioners should strategically integrate AR and VR into STEM instruction as complementary tools rather than isolated novelties. AR is best employed for context-based conceptual visualization, laboratory pre-exposure, or on-site field augmentation, whereas VR should be reserved for fully immersive simulations, complex spatial explorations, and virtual laboratories that require procedural practice. Lesson designs must align immersive experiences with explicit learning outcomes and assessment criteria to ensure pedagogical coherence.

Second, curriculum developers and school administrators are encouraged to institutionalize immersive learning within curricular frameworks. This can be achieved by embedding modular AR/VR activities into existing STEM units, providing structured teacher training, and ensuring equitable access to required hardware and software. Government agencies and academic consortia should support funding for low-cost or open-source immersive platforms, particularly in developing regions, to reduce implementation barriers and promote digital inclusion.

Third, teacher-training programs should emphasize instructional design for immersive environments, focusing on learner engagement strategies, cognitive load management, and the ethical use of digital content. Professional development must equip educators with both technical proficiency and pedagogical competence to integrate AR and VR meaningfully rather than superficially.

Fourth, future research should extend beyond separate AR or VR evaluations toward Mixed Reality (MR) and Extended Reality (XR) systems that merge the contextual strength of AR with the full immersion of VR. Incorporating Artificial Intelligence (AI) for adaptive feedback and personalization can further optimize learner experiences and performance outcomes. Longitudinal and cross-cultural studies are also needed to assess knowledge retention, transferability of skills, and socio-emotional effects over time. Expanding research to include primary, vocational, and underserved educational contexts will help balance the current dominance of tertiary-level education in the immersive learning literature.

Finally, policy-makers and institutional leaders should recognize immersive learning as a driver of national STEM competence and innovation. Integrating AR and VR within broader digital-transformation initiatives, allocating dedicated funding streams, and fostering partnerships with technology developers will ensure sustainable implementation.

Taken together, these recommendations emphasize that the pedagogical success of immersive learning depends not only on technological adoption but on thoughtful, evidence-based integration. When grounded in sound instructional design and supported by institutional commitment, AR and VR can fundamentally redefine how students perceive, explore, and master the scientific world—turning classrooms into intelligent, interactive ecosystems that prepare learners for the complex, interdisciplinary challenges of the twenty-first century.

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