

# Deep Learning–Based Augmented Reality for Inclusive Computational Thinking Education: A Systematic Review

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## ABSTRACT

Computational thinking (CT) has emerged as an essential literacy skill for 21st-century learners; however, students with disabilities remain underrepresented in STEM education. While mobile augmented reality (AR) and deep learning (DL) technologies individually hold promise for creating inclusive learning environments, their convergence in CT education remains underexplored. This systematic review examines the integration of deep learning-based mobile augmented reality systems for inclusive computational thinking education. A systematic literature review was conducted according to the PRISMA guidelines. This review revealed three significant findings. First, the integration of deep learning into mobile AR systems for CT education is in its infancy, with only one study providing empirical evidence of a fully functional DL-based augmented reality (AR) system. The vast majority of these employ static AR without adaptive capabilities. Second, a robust foundation of inclusive design principles exists, including scaffolded instruction, multimodal support, and accessible interfaces; however, these design principles have been applied predominantly to learners with cognitive and neurodevelopmental disabilities, while learners with sensory and physical impairments remain significantly underrepresented. Third, technology-mediated interventions improved CT skills and engagement across all 23 studies, but the measurement of self-efficacy was weak and predominantly qualitative, with few studies employing quantitative instruments. The three critical strands of inquiry, intelligent technology, inclusive design, and meaningful outcomes, remain disconnected. No study to date has successfully combined DL-based adaptive AR with inclusive design principles and evaluated its impact on CT skills, engagement, and self-efficacy across a broad spectrum of learners with disabilities. This review identifies gaps in the literature and proposes a roadmap for future research, emphasizing the need for interdisciplinary collaboration, broader disability representation, and the development of validated self-efficacy instruments.

**Keywords:** Deep Learning, Augmented Reality, Mobile AR, Computational Thinking, Inclusive Education, Students with Disabilities, Special Educational Needs

## INTRODUCTION

The 21st century has firmly established computational thinking (CT) as a fundamental literacy for all students, on par with reading, writing, and arithmetic (Wing, 2006). As the demand for skills in problem-solving, logical reasoning, and algorithmic thinking intensifies across every sector, educators and policymakers worldwide are integrating CT into core curricula from early childhood to higher education. However, the global movement towards universal CT proficiency carries an implicit promise: that these opportunities must be accessible to every student, including the millions of students with disabilities who have historically been marginalized in science, technology, engineering, and mathematics (STEM) education (Israel et al., 2015). Fulfilling the promise of inclusive education requires not only pedagogical will but also the strategic deployment of innovative technologies capable of adapting to diverse cognitive, sensory, and physical needs.

In recent years, two technological advancements have emerged as powerful tools for transforming learning experiences: mobile augmented reality (AR) and deep learning (DL), a subset of artificial intelligence (AI).

Mobile AR overlays digital information onto the real world via smartphones and tablets, and has been shown to increase student immersion, concretize abstract concepts, and provide interactive, hands-on learning experiences (Akçayır & Akçayır, 2017). For students who struggle with traditional instructional methods, AR can offer multimodal representations, combining visual, auditory, and haptic feedback, and making complex ideas more tangible (Palada et al., 2024). Simultaneously, deep learning has revolutionised the potential for personalised education. DL algorithms can power adaptive scaffolding, predict student difficulties, and deliver customised content and feedback effectively, by acting as an intelligent tutor and analysing student interaction data in real-time (Holmes et al., 2019).

The convergence of these two technologies, deep learning-based mobile AR, holds immense yet untapped potential for inclusive computational thinking education. Imagine a student with autism using a tablet to visualise and manipulate code blocks in their immediate physical environment, with the system adjusting the complexity and social demands of the task in real-time based on their stress levels. Imagine a deaf learner receiving instant, AI-generated sign language interpretations of complex algorithmic concepts overlaid on a collaborative AR workspace. Such systems could dynamically bridge the gap between a student's unique needs and the cognitive demands of CT, fostering not only skill development but also the self-efficacy necessary for long-term engagement in STEM fields.

Despite the theoretical promise of this convergence, the field faces multifaceted research problems. While there is a growing body of literature on AR for CT education, a separate body of work on AI-driven personalised learning, and an emerging literature on inclusive design for students with disabilities, these three critical strands of inquiry remain largely disconnected. It is currently unknown how and to what extent these strands have been woven together in the existing research. Therefore, this study presents a systematic literature review that seeks to:

- i. examine the integration of DL in mobile AR systems for CT education
- ii. identify inclusive design principles employed in technology-based CT interventions for students with disabilities.
- iii. examine the impact of these interventions on the CT skills, participation, and self-efficacy of students with disabilities.

This review was guided by three primary research questions:

- i. How is deep learning or artificial intelligence currently integrated into mobile augmented reality systems designed to support computational thinking education?
- ii. What evidence-based inclusive design principles are employed in technology-mediated CT interventions for students with disabilities?
- iii. What is the reported impact of these interventions on learners' computational thinking skills, engagement, and self-efficacy?

## Research Methodology

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure a transparent, reproducible, and rigorous review of deep learning-based mobile augmented reality systems for inclusive computational thinking education (Page et al., 2021).

## Research Design

A systematic literature review was conducted to map existing research and analyze findings on deep learning-based mobile augmented reality systems for inclusive computational thinking education. The PRISMA framework was used to structure the identification, screening, eligibility assessment, and synthesis of relevant studies. This approach enabled a focused examination of how deep learning has been integrated into mobile AR systems, the inclusive design principles employed in technology-mediated CT interventions for students with disabilities, and the reported impact of these interventions on CT skills, engagement and self-efficacy.

A review protocol was developed to define the scope, search strategy, inclusion and exclusion criteria, and methods for data extraction and analysis before commencing the search. The protocol was guided by three research questions focusing on (1) the integration of deep learning in AR systems, (2) evidence-based inclusive design principles for students with disabilities, and (3) the impact of these interventions on CT skills, participation, and self-efficacy.

### Search Strategy

A comprehensive and systematic search was performed across major scientific databases to identify relevant peer-reviewed studies. The databases were selected to cover the interdisciplinary nature of the topic, spanning educational technology, computer science, special education, and engineering. The following electronic databases were searched: ACM Digital Library, IEEE Xplore, Scopus, Web of Science and ERIC (Education Resources Information Center). The search was conducted in March 2026 and included studies published between January 2015 and March 2026. The year 2015 was chosen as the starting point because it coincided with the widespread maturation of deep learning technologies and the increased accessibility of mobile AR platforms (e.g., ARKit and ARCore). Search queries combined keywords related to deep learning, augmented reality, computational thinking, and disability using Boolean operators to increase coverage while maintaining conceptual specificity. The representative search string was

("deep learning" OR "artificial intelligence" OR "machine learning" OR "neural networks" OR "adaptive learning") AND ("augmented reality" OR "mixed reality" OR "mobile AR") AND ("computational thinking" OR "coding" OR "programming" OR "algorithmic thinking" OR "problem-solving") AND ("disabilities" OR "special education" OR "inclusive education" OR "special needs" OR "neurodivergent" OR "autism" OR "ASD" OR "ADHD" OR "dyslexia" OR "deaf" OR "hard of hearing" OR "visual impairment" OR "physical disability" OR "learning disability").

### Inclusion and Exclusion Criteria

Studies were included if they met the following criteria:

- i. involved learners formally identified as having disabilities or special educational needs, or explicitly discussed the implications for inclusive education for students with disabilities (including cognitive, sensory, physical, and neurodevelopmental disabilities);
- ii. investigated or discussed the use of technology-mediated interventions for teaching or supporting computational thinking, coding, or related problem-solving skills (including AR, AI/DL systems, games, robotics, or other digital tools);
- iii. were conducted in educational contexts, including K-12, higher education, or specialized learning environments;
- iv. were peer-reviewed journal articles, full-length conference papers, or systematic reviews published in English; and
- v. were published between January 2015 and March 2026.

The following studies were excluded:

- i. focused on typically developing learners without any discussion of the implications for or inclusion of students with disabilities;
- ii. addressed technologies not relevant to the research questions (e.g., virtual reality without an AR component and traditional classroom instruction without technology);
- iii. were non-peer-reviewed publications (e.g., books, book chapters, editorials, opinion pieces, poster abstracts, and grey literature);
- iv. were not published in English; or
- v. were published before 2015.

## Study Selection Procedure

The review followed the four PRISMA stages: identification, screening, eligibility, and inclusion. All retrieved records were exported to a reference management tool, where duplicates were removed. Titles and abstracts were screened independently by two reviewers based on the inclusion and exclusion criteria. Disagreements between the reviewers were resolved through discussion or consultation with a third reviewer. The full texts of potentially relevant studies were then retrieved and assessed for eligibility by two independent reviewers, with reasons for exclusion documented at this stage. Common reasons for exclusion included a lack of focus on disability, no discussion of CT or related skills, and the absence of a relevant technological intervention. The final set of studies was compiled after resolving any ambiguities through a close textual examination. A PRISMA flow diagram (Figure 1) summarizes the selection process and the number of studies retained at each stage.

## Data Extraction

A structured extraction protocol was used to ensure consistency across studies. A standardized data extraction form was developed in Microsoft Excel to systematically capture key information from each included study. The form was piloted on a small subset of studies and refined before its full implementation. Data were extracted by one reviewer and verified by another. The extracted data included:

- i. bibliographic information (author(s), year, title, source);
- ii. study focus and aim (primary objective).
- iii. Methodology (research design, sample size, participant characteristics, including type of disability, and context)
- iv. Intervention details (type of technology used, description of learning activity, and duration)
- v. data related to RQ1 (specific DL algorithms used, purpose of integration, and level of integration with AR);
- vi. data related to RQ2 (specific design principles, accessibility features, and scaffolding strategies employed);
- vii. Data related to RQ3 (findings related to CT skills, participation, and self-efficacy, including both quantitative and qualitative data).
- viii. Key findings and limitations (authors' main conclusions and self-reported limitations).

This schema facilitated a direct comparison of methodological features, integration strategies, and outcomes across diverse interventions.

## Data Analysis

A structured analytical framework was employed to extract, organize and analyze data from each eligible study. Owing to the anticipated heterogeneity in study designs, interventions, and outcome measures, a meta-analysis was not feasible; instead, a thematic analysis approach was adopted. An inductive–deductive analytical strategy was employed deductively, and the coding structure followed predefined domains aligned with the review questions inductively. Emerging patterns and methodological innovations were identified during full-text analysis. This dual approach ensured both theoretical alignment and flexibility in capturing novel contributions.

Data extraction and coding were conducted using Microsoft Excel to ensure consistency and traceability throughout the review. Braun and Clarke's (2006) six-phase thematic analysis guided the synthesis and interpretation of the extracted data. The phases of familiarization, initial coding, theme development, theme review, theme refinement, and narrative reporting were systematically applied to derive overarching thematic categories related to each of the three research questions. The thematic analysis enabled the identification of recurrent methodological trends, unresolved challenges, and opportunities for advancing deep learning-based mobile augmented reality in inclusive computational thinking education.

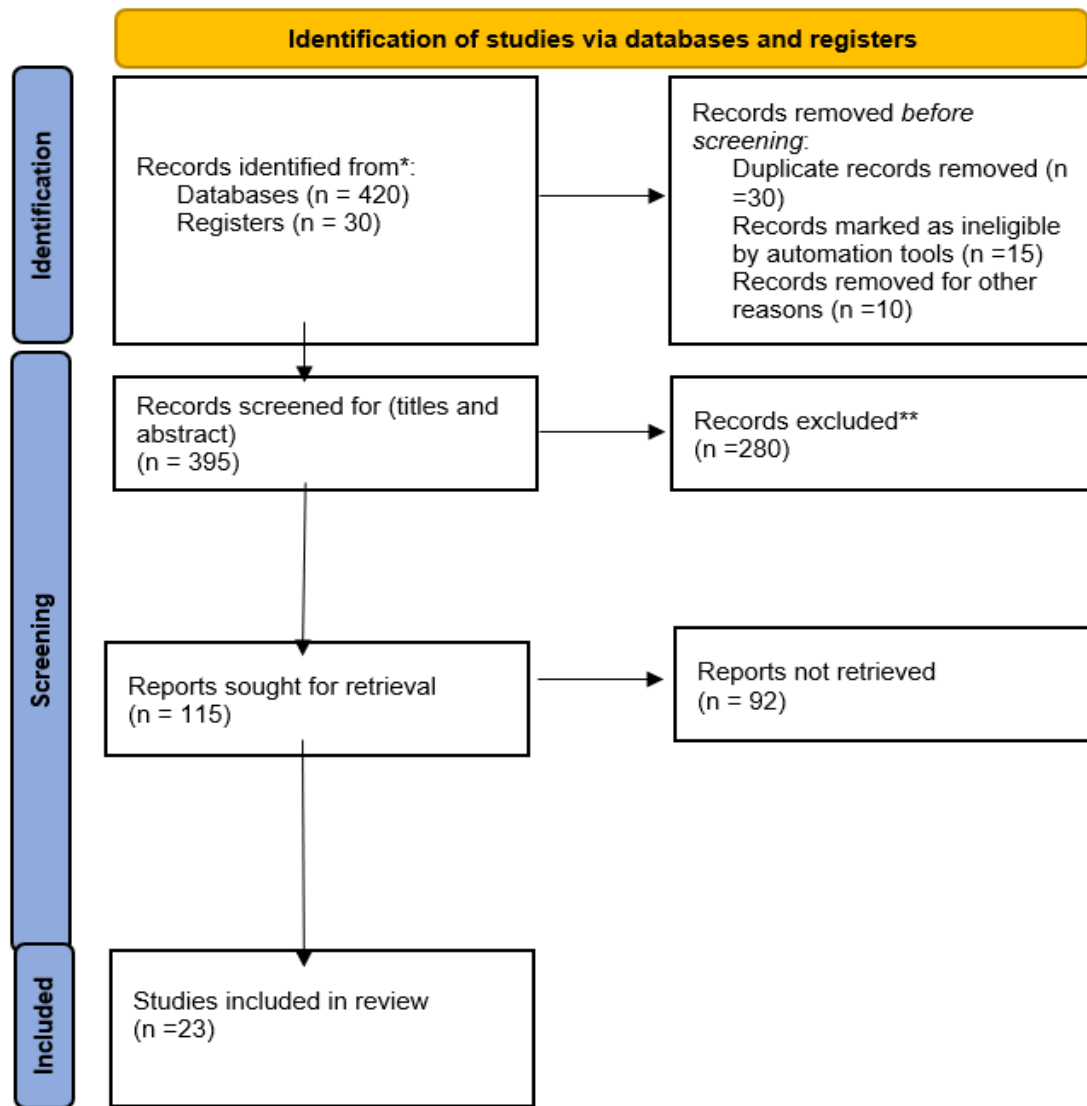


Figure 1: PRISMA Flow Diagram

## RESULTS

The 23 studies included in this review were published between 2015 and 2026. The studies covered a range of methodologies, including experimental designs (n=17), mixed-methods studies (n=2), and systematic or scoping reviews (n=4). The target populations varied, with the majority focusing on students with cognitive or neurodevelopmental disabilities (e.g., autism spectrum disorder, ADHD, learning disabilities), while a smaller number addressed sensory or physical disabilities. Geographically, the studies originated from diverse regions, including Asia, Europe, and North America, indicating global interest in inclusive technology-enhanced learning. However, studies from Africa were absent from this review.

### Research Question 1: Integration of Deep Learning in AR Systems

The first research question examined how deep learning or artificial intelligence has been integrated into mobile augmented reality systems for computational thinking education. The review shows a significant gap in the convergence of DL and AR in CT education, in the contexts of students with disabilities.

As shown in Table 1, the vast majority of empirical studies (e.g., Seo et al., 2025; Veiga et al., 2025; Işık Arslanoğlu et al., 2024; Lee & Hsu, 2024) have employed AR as a standalone technology. In these studies, AR was used to create immersive, interactive learning environments that enhanced visualization and participation; however, the experiences were static and non-adaptive. None of these studies incorporated any form of DL to personalise the learning experience in real-time.

A small subset of studies acknowledged the potential of AI and made theoretical suggestions for its integration. For instance, Angraini et al. (2024) suggested that machine learning could be used for adaptive learning in AR contexts but did not implement it. Similarly, Zhan et al. (2025) noted that machine learning could be applied to dynamically adjust difficulty in their AR game, but this remained a suggestion for future work. Systematic reviews by Weng et al. (2024) and Wu et al. (2025) identified that some game-based interventions have begun to integrate DL for personalization; however, they noted that AR is rarely combined with these approaches.

Only one study (Lin & Chen, 2020) provided empirical evidence of a fully functional DL-based AR system. Their system used deep learning algorithms to provide adaptive scaffolding to learners during CT activity. However, as the authors noted, the study's sample was not extensively diverse, and its applicability to students with a wide range of disabilities remains unknown.

Table 1: Integration of Deep Learning in AR Systems

| Source                   | Study Focus   | Methodology                              | RQ1: DL/AI Integration in AR                             | RQ2: Inclusive Design Principles  | RQ3: Impact on CT, Engagement & Self-Efficacy                                 | Findings   | Limitations  |
|--------------------------|---|--|--|---|---|--|--|
| Lin & Chen (2020)        | DL-based AR system for CT for non-majors & diverse learners | Experimental AR system and DL algorithms | Deep learning used to provide adaptive scaffolding in AR | Scaffolded learning; differentiated instruction for cognitive, sensory, motor needs | CT skills improved; engagement higher; self-efficacy enhanced                 | DL-enabled AR supports adaptive, personalized learning                 | Limited empirical evaluation; sample diversity not extensive |
| Seo et al. (2025)        | AR and collaborative activities for CT in K-12              | Mixed-methods                            | No DL integration; focus on collaborative AR             | Collaborative scaffolding, accessible interface                                     | CT concept understanding improved; engagement high; self-efficacy qualitative | AR and collaborative tasks enhance learning                            | No AI adaptation; small sample                               |
| Veiga et al. (2025)      | Systematic review: CT & learning disabilities               | Literature review                        | No DL in AR; mostly teaching strategies                  | lack of disability-specific CT strategies   | Teaching strategies varied; engagement & CT gains noted                       | Highlights gaps in CT instruction for dyscalculia & other disabilities | Scarcity of experimental data; limited disability focus      |
| Arslanoğlu et al. (2024) | Child-designed AR activities for CT                         | Experimental with children               | No DL integration  | Child-centered design; scaffolded AR activities                                     | CT skills improved; engagement high   | Learner-designed AR fosters deeper CT understanding                    | Age range limited; AI adaptation absent                      |
| Kert et al. (2022)       | CT skills in students with disabilities                     | Experimental                             | No DL in AR; suggestions for ML                          | Algorithmic & mental rotation scaffolds   | CT skill improvement noted; engagement enhanced                               | Robotics & CT support inclusion  | AI/AR adaptation not applied; self-efficacy not quantified   |
| Lee & Hsu (2024)         | AR and social stories &                                     | Experimental                             | No DL integration  | Social story scaffolding;   | Social skills & CT improved; engagement high                                  | AR and CT games  | Small sample; AI not applied                                 |

|                              |   |              |  |   |  |                                     |  |
|------------------------------|---|--------------|--|---|--|-------------------------------------|--|
|                              | CT games for ASD                                      |              |  | tailored game instructions                                    |  | effective for ASD learners          |  |
| Hanid et al. (2022)          | AR in geometry CT                                     | Experimental | No DL; AR application enhances visualization           | Scaffolding for middle school students                        | CT skills improved; engagement increased                                     | AR supports CT acquisition          | Limited adaptive personalization; self-efficacy not measured |
| Alivia et al. (2025)         | Programming algorithms for CT in ASD                  | Experimental | DL not applied; AR discussed conceptually              | Personalized instruction for ASD learners                     | CT skill improvement observed  | Algorithmic exercises and AR useful | AI/DL absent; small sample; self-efficacy qualitative        |
| Wu (2023)                    | Video modeling and AR for math problem-solving        | Experimental | DL not applied   | Visual and AR scaffolding for developmental disabilities      | CT & math problem-solving improved; engagement high                          | AR enhances understanding           | Self-efficacy mostly qualitative; AI absent                  |
| Iatraki & Mikropoulos (2025) | Immersive AR for physics in intellectual disabilities | Experimental | DL not applied   | Accessible AR experiences; supports intellectual disabilities | Engagement & comprehension improved  | AR enhances STEM inclusion          | AI/DL absent; self-efficacy not measured                     |
| Angraini et al. (2024)       | AR for CT in mathematics                              | Mixed-method | Suggested ML for adaptive learning; DL not implemented | Scaffolded AR tasks; multisensory support                     | CT skills improved; engagement increased                                     | AR promotes deeper learning         | DL not implemented; self-efficacy qualitative                |
| Rakhimzhanova et al. (2025)  | AR for digital literacy in special needs              | Experimental | No DL applied  | Accessible interfaces; scaffolded instruction                 | CT engagement & self-efficacy improved; self-efficacy reported qualitatively | AR supports CT development          | AI/DL not applied; small sample                              |
| Lilis et al. (2024)          | AR-based learning for mathematical CT                 | Experimental | No DL integration                                      | Scaffolded AR learning; accessibility considerations          | CT skills improved; engagement enhanced                                      | AR enhances mathematics CT          | Self-efficacy rarely measured; AI absent                     |
| Adhe et al. (2025)           | AR app for critical thinking in early childhood       | Experimental | No DL; multisensory AR                                 | Inclusive features for special needs children                 | Critical thinking & engagement improved                                      | AR supports early CT learning       | Self-efficacy mostly qualitative; AI absent                  |
| Karagianni & Drigas (2022)   | STEM education for Down syndrome                      | Experimental | DL/AI not applied                                      | Algorithmic scaffolding for intellectual disabilities         | CT skill improvement observed  | Tailored STEM supports inclusion    | AI/DL absent; self-efficacy not measured                     |

|                                 |   |                   |   |  |  |  |  |
|---------------------------------|---|-------------------|---|--|--|--|--|
| Bertacchini et al. (2022)       | Project-based learning for CT                     | Experimental      | Some AI/ML tools applied for adaptive tasks                                 | PBL with scaffolded collaboration; inclusion limited                   | CT skills, engagement improved   | PBL effective for inclusive CT                       | Limited AR integration; disability focus narrow                            |
| Zhan et al. (2025)              | Immersive AR game with competing mechanisms       | Experimental      | ML suggested for adaptive difficulty  | Scaffolded AR for special needs  | CT engagement enhanced   | Competition-based AR motivates learners              | Small sample; AI/DL underdeveloped   |
| Al Omoush & Mehigan (2024)      | AR, VR & robotics for dyslexic learners           | Experimental      | DL suggested for adaptive feedback; not implemented                         | Accessible robotics/AR/VR interfaces                                   | CT & math skills improved; engagement high   | Multi-tech integration benefits dyslexic learners    | AI/DL mostly theoretical; small sample                                     |
| Rao & Bhagat (2024)             | Systematic review: CT tools, pedagogy, assessment | Literature review | DL suggested; AR games recommended  | Scaffolding, visual/audio support                                      | CT skills, mental rotation improved; engagement increased                            | Highlights gaps in AI/AR inclusion                   | Limited empirical implementation; self-efficacy inconsistently measured    |
| Weng et al. (2024)              | AI and CT instructional design review             | Systematic review | DL/neural networks applied in some interventions; AR mentioned conceptually | Scaffolded instruction, adaptive feedback                              | CT skills, problem-solving improved; engagement increased; self-efficacy qualitative | AI/DL enhances CT learning; AR promising             | Few AR+DL+inclusive implementations; self-efficacy qualitative             |
| Gundersen & Lampropoulos (2025) | Serious & digital games for CT                    | Systematic review | AR integrated in some games; DL/AI rare                                     | Visual/audio scaffolds; simplified interfaces; cognitive accessibility | CT programming & skills improved; engagement increased; self-efficacy qualitative    | Game-based & AR interventions effective              | DL integration limited; self-efficacy inconsistently measured              |
| Wu et al. (2025)                | CT, game design, design thinking scoping review   | Scoping review    | Some games integrate DL to personalize learning; AR rarely combined         | Scaffolded tasks; Micro:bit tools; adaptive difficulty                 | CT skills improved; engagement high; self-efficacy qualitative                       | DL-enhanced games scaffold learning for disabilities | Limited AR and DL empirical studies; self-efficacy mostly qualitative      |
| Costa Junior et al. (2024)      | Educational robotics for CT                       | Experimental      | AR/VR experiments included; no DL applied                                   | Mobility support; scaffolded robotics tasks; adjustable difficulty     | CT skills improved; engagement increased; self-efficacy anecdotal                    | Robotics and AR/VR supports inclusive CT             | DL not applied; disability diversity limited; self-efficacy not quantified |

## Research Question 2: Inclusive Design Principles and Strategies used

The second research question examined the inclusive design principles and strategies employed in technology-mediated CT interventions for students with disabilities. In contrast to the technological gap identified in RQ1, the literature provides a richer, though still evolving, set of design principles. Table 2 shows the inclusive strategies used in the included studies.

The most frequently employed design principle was scaffolded instruction. Nearly all experimental studies (e.g., Seo et al., 2025; Kert et al., 2022; Abdul Hanid et al., 2022; Wu, 2023) broke down complex CT tasks into smaller, manageable steps, providing structured support that could be gradually removed as students gained proficiency in using the tool. This principle is often operationalized through visual prompts, step-by-step guides, or progressive task difficulty.

Multimodal and visual supports are another basis for inclusive design. Studies have also incorporated visual aids, audio cues, and simplified interfaces to accommodate diverse learning needs. For example, Gundersen and Lampropoulos (2025) highlighted the importance of visual and audio scaffolds in serious games for CT, while Angraini et al. (2024) emphasised multisensory support in their AR mathematics intervention. This approach aligns with the principles of Universal Design for Learning (UDL) by providing multiple means of representation.

Accessible interface design has been addressed in several studies, particularly those involving learners with physical or mobility impairments. Costa Junior et al. (2024) used mobility support and adjustable difficulty in their robotics intervention, while Al Omoush and Mehigan (2024) designed accessible interfaces across AR, VR, and robotics platforms for dyslexic learners.

A smaller but notable group of studies showed the value of contextualised and personalised scaffolding. Lee and Hsu (2024) used social stories within an AR game to provide personalised social and cognitive support for learners with autism spectrum disorder. Similarly, Alivia et al. (2025) emphasized personalized instruction for ASD learners in programming algorithms, although their intervention did not use AI to deliver this personalisation.

Finally, learner-centered and co-design approaches emerged as powerful, though less common, principles. İşik Arslanoğlu et al. (2024) showed that allowing children to design their own AR activities fostered deeper participation and understanding, suggesting that inclusive design is not only about removing barriers but also about empowering learners as active participants in the design process.

However, a critical limitation of the literature is the narrow scope of disability types addressed. As shown in Table 2, the vast majority of design strategies target cognitive or neurodevelopmental disabilities (e.g., autism, ADHD, learning disabilities). Students with sensory disabilities, such as deaf or hard-of-hearing students and those with visual impairments, are underrepresented. Only Alivia et al. (2025) explicitly focused on deaf learners, highlighting a major gap in the inclusivity of "inclusive design" research.

Table 2: Inclusive Design Principles for RQ2

| Design Principle             | Description  | Frequency   | Representative Studies  |
|------------------------------|--|-------------|---|
| Scaffolded Instruction       | Breaking down complex tasks into manageable steps and providing structured support that fades over time. | High (n=18) | Seo et al. (2025); Kert et al. (2022); Abdul Hanid et al. (2022); Wu (2023); Rakhimzhanova et al. (2025); Lilis et al. (2024); et al. |
| Multimodal & Visual Supports | Visual aids, audio cues, haptic feedback, and simplified interfaces can be used to present               | High (n=15) | Angraini et al. (2024); Gundersen & Lampropoulos (2025);  |

|  |   |                |   |
|--|---|----------------|---|
|  | information in multiple formats.  |                | Rao & Bhagat (2024); Adhe et al. (2025); et al.   |
| Accessible Interface Design              | Designing interfaces that are usable by learners with physical or mobility impairments (e.g., alternative input and adjustable controls). | Moderate (n=6) | Costa Junior et al. (2024), Al Omoush and Mehigan (2024), Seo et al. (2025), et al.             |
| Contextualised/ Personalised Scaffolding | Tailoring support to the specific needs of individual learners or disability types (e.g., social stories for ASD).                        | Moderate (n=5) | Lee & Hsu (2024); Alivia et al. (2025); Lin & Chen (2020); Weng et al. (2024); Wu et al. (2025) |
| Learner-Centered/Co-Design               | Involving learners in the design of their learning activities or tools.   | Low (n=2)      | Işık Arslanoğlu et al. (2024); Bertacchini et al. (2022)  |
| <b>Disability Types Addressed</b>        |   |                |   |
| Cognitive/Neurodevelopmental             | Autism, ADHD, dyslexia, dyscalculia, intellectual disabilities, learning disabilities   | High (n=20)    | Majority of studies   |
| Physical/Mobility                        | Physical disabilities, mobility impairments   | Low (n=3)      | Costa Junior et al. (2024); Seo et al. (2025); Lin & Chen (2020)                                |
| Sensory (Hearing/Visual)                 | Deaf, hard of hearing, visual impairments   | Very Low (n=1) | Alivia et al. (2025)  |

### Research Question 3: Impact on CT Skills, Engagement, and Self-Efficacy

The third research question examined the reported impact of technology-mediated interventions on three key outcomes: computational thinking skills, engagement, and self-efficacy. The findings, summarized in Table 3, show a pattern of strong positive effects for CT skills and engagement, coupled with a significant gap in the rigorous measurement of self-efficacy.

#### Computational Thinking Skills

Improvements in CT skills were consistently reported across all 23 studies. Whether the intervention employed AR (e.g., Abdul Hanid et al., 2022; Angraini et al., 2024; Lilis et al., 2024), robotics (Kert et al., 2022; Costa Junior et al., 2024), games (Gundersen & Lampropoulos, 2025), or a combination of technologies (Al Omoush & Mehigan, 2024), students with disabilities demonstrated gains in core CT skills. These include algorithmic thinking, problem-solving, sequencing, pattern recognition, and debugging. The consistency of this finding across diverse interventions and disability types provides strong evidence that technology-mediated instruction can effectively foster CT skills in learners with special educational needs when appropriately designed.

#### Participation

Improved participation was the second most consistently reported positive outcome of the studies. Studies employing AR and game-based approaches have noted significant increases in learner motivation, interest, and participation. Seo et al. (2025) reported high participation levels in their collaborative AR activities, while Zhan et al. (2025) found that competition-based AR games enhanced motivation. Lee and Hsu (2024) observed that the combination of AR and social stories not only improved CT skills but also sustained the attention and participation of learners with ASD. The immersive and interactive nature of these technologies appears to be a key factor in capturing and maintaining the interest of diverse learners.

## Self-Efficacy

In contrast to the robust findings for CT skills and participation, the evidence for self-efficacy is limited and methodologically weak. As shown in Table 3, most studies either did not measure self-efficacy at all or relied on qualitative, anecdotal reports. For example, Rakhimzhanova et al. (2025) reported that self-efficacy was qualitatively reported, whereas Adhe et al. (2025) noted that self-efficacy findings were mostly qualitative. Only a handful of studies, such as Lin and Chen (2020), provide quantitative evidence of enhanced self-efficacy. The systematic reviews by Weng et al. (2024), Gundersen and Lampropoulos (2025), and Wu et al. (2025) all noted that self-efficacy was inconsistently measured and rarely quantified across the studies they analysed.

This gap is significant because self-efficacy, a learner's belief in their ability to succeed, is a known predictor of long-term persistence and achievement in STEM fields. The lack of rigorous measurement means that while we know these interventions can teach skills and engage students, we do not know whether they build the confidence necessary for learners with disabilities to continue pursuing CT and related disciplines in the long term.

Table 3: RQ3: Impact on CT Skills, Engagement, and Self-Efficacy

| Outcome                       | Reported Impact       | Evidence Base  | Representative Studies   |
|-------------------------------|-----------------------|--|--|
| Computational Thinking Skills | Consistently Positive | Strong empirical evidence was found across all 23 studies. Improvements in algorithmic thinking, problem-solving, sequencing and debugging.        | Abdul Hanid et al. (2022); Angraini et al. (2024); Kert et al. (2022); Gundersen & Lampropoulos (2025); Costa Junior et al. (2024).  |
| Participation                 | Consistently Positive | Strong empirical evidence, particularly for AR and game-based interventions. High levels of motivation, interest, and participation were reported. | Seo et al. (2025); Lee & Hsu (2024); Zhan et al. (2025); Işık Arslanoğlu et al. (2024); Adhe et al. (2025).  |
| Self-Efficacy                 | Inconclusive / Weak   | Limited and methodologically weak evidence was found. Most reports were qualitative or anecdotal. Few quantitative measurements were performed.    | Qualitative Studies: Rakhimzhanova et al. (2025); Adhe et al. (2025); Alivia et al. (2025); Weng et al. (2024); Gundersen & Lampropoulos (2025); Wu et al. (2025). Quantitative Studies: Lin & Chen (2020). Not measured: Karagianni & Drigas (2022), Iatraki & Mikropoulos (2025), Lilis et al. (2024). |

## DISCUSSION

The analysis of 23 studies reveals a field characterized by promising foundations and significant, well-defined gaps. This discussion interprets the findings in relation to each research question, explores the implications of the disconnected strands of inquiry, and proposes a forward-looking agenda for research, development, and practice in the field.

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## The Technological Disconnect: DL and AR as Parallel Universes

The first major finding of this review is the near-total absence of integrated deep learning and augmented reality systems in computational thinking education for students with disabilities. As shown in Table 1, most empirical studies employed AR as a static, non-adaptive tool. While these interventions successfully used AR's capacity for visualization, immersion, and participation (e.g., Seo et al., 2025; Abdul Hanid et al., 2022; Iatraki & Mikropoulos, 2025), they failed to harness the transformative potential of AI-driven personalization. The learning experience, however rich, remained identical for every learner, regardless of their individual progress, difficulties or unique needs.

Conversely, in the few studies where AI or deep learning was used (e.g., Bertacchini et al., 2022; Weng et al., 2024), it was typically applied in non-AR contexts, such as game-based learning environments or intelligent tutoring systems. This creates a paradoxical situation in which the two technologies, each powerful in its own right, operate in parallel universes, and their potential synergy remains largely unexplored.

The lone exception, Lin and Chen (2020), provides a crucial proof of concept. Their demonstration that deep learning algorithms can successfully power adaptive scaffolding within an AR environment confirms the technical feasibility of integration. However, the study's limited sample diversity, as noted in its limitations, means that its applicability to learners with a wide range of disabilities remains an open question. This single study serves not as a solution but as a beacon, illuminating a path that future research has yet to travel.

Students with disabilities are not a monolithic group; they present a spectrum of cognitive, sensory, physical, and neurodevelopmental profiles, each with unique strengths and challenges. A static AR experience, no matter how well-designed, cannot possibly meet the diverse and often fluctuating needs of these learners. Deep learning offers the missing piece, the ability to sense, interpret, and adapt. A DL-based AR system could, in theory, analyse a learner's gaze patterns, response times, problem-solving strategies, and even emotional state to infer, and then dynamically adjust the level of scaffolding, the mode of representation, or the complexity of the task. This is the difference between a ramp that provides access and an intelligent exoskeleton that actively supports and extends a learner's capabilities. The current literature provides ample evidence of the ramp; it offers almost no evidence of the exoskeleton.

### Inclusive Design Principles

In contrast to the technological gap, the review identified a relatively robust foundation of inclusive design principles (see Table 2). The consistent use of scaffolded instruction, multimodal supports, and accessible interfaces across numerous studies (e.g., Kert et al., 2022; Angraini et al., 2024; Gundersen & Lampropoulos, 2025) shows that the field has developed a shared understanding of how to make technology-mediated learning more accessible. These principles align closely with the Universal Design for Learning (UDL) framework, which advocates for multiple means of engagement, representation, and action and expression (CAST, 2018). The fact that these strategies are being applied across diverse technological contexts, AR, robotics, games, suggests they represent a transferable core of inclusive practice.

However, this foundation rests on significant faulty lines. The most glaring is the narrow scope of disability types addressed. As the analysis revealed, the vast majority of design strategies target cognitive or neurodevelopmental disabilities, such as autism, ADHD, dyslexia, and general learning disabilities. Learners with sensory disabilities, deaf, hard of hearing, blind, or low-vision students, are dramatically underrepresented. The study by Alivia et al. (2025), which focused on deaf learners, stands as a rare exception that underscores the rule. Similarly, learners with physical or mobility impairments receive only passing attention (e.g., Costa Junior et al., 2024).

This narrow focus is problematic for several reasons. First, it perpetuates a form of inclusivity that is not truly inclusive, addressing only the most researched or most visible disability categories while neglecting others. Second, it means that the design principles we have identified may not be generalizable. A visual scaffold that supports a learner with dyslexia may be entirely inaccessible to a learner with a visual impairment. An engaging

AR interaction that relies on gesture-based control may exclude a learner with limited mobility. The field has built a house on a foundation that only covers part of the ground.

Furthermore, these design principles have been developed and validated primarily within the context of static technologies. We do not yet know how these principles translate to adaptive, DL-based systems. For example, how should a deep learning algorithm be trained to recognize when a deaf learner needs a different mode of sign language interpretation? How should an adaptive system balance the need for cognitive scaffolding with the sensory preferences of a learner with autism? The existing design principles provide a starting point, but they must be re-examined, extended, and re-validated in the context of intelligent, adaptive environments.

### **Engagement as a Proxy for Self-Efficacy**

The findings related to learner outcomes (RQ3) present a mixed picture of success and oversight. On one hand, the evidence for improved computational thinking skills is robust and consistent. Across all 23 studies, learners with disabilities demonstrated gains in core CT competencies when provided with technology-mediated instruction. This is a non-trivial finding. It refutes any residual assumptions that computational thinking is a domain reserved for a narrow subset of learners and provides empirical support for the "CT for all" movement. The effectiveness of AR in particular for visualizing abstract concepts (Abdul Hanid et al., 2022; Angraini et al., 2024) suggests that immersive technologies can play a vital role in making CT accessible.

Similarly, the consistent finding of increased engagement is both valuable and intuitive. Interactive, game-like, and immersive experiences are inherently more motivating than traditional instruction for many learners. For students with disabilities, who may have experienced repeated failure or disengagement in traditional academic settings, this motivational boost is not merely a nice-to-have; it is a prerequisite for learning. Engagement is the gateway through which all other learning must pass.

However, the field's near-exclusive focus on engagement as the primary affective outcome, to the neglect of rigorous self-efficacy measurement, represents a significant blind spot. As Bandura's (1997) social cognitive theory makes clear, self-efficacy, the belief in one's capability to succeed, is a critical mediator between ability and action. A student may acquire CT skills (ability) and enjoy the learning process (engagement), but if they do not believe they are capable programmers or problem-solvers, they are unlikely to persist in CT-related fields. Self-efficacy is the internal compass that guides learners toward future challenges.

The finding shows that self-efficacy is "mostly qualitative" or "not measured" in the vast majority of studies (see Table 3) is therefore deeply concerning. It suggests that the field is prioritising short-term, observable outcomes (skills, engagement) over the deeper, longer-term psychological constructs that determine educational trajectories. We are teaching students to code, and we are keeping them happy while they learn, but we are not measuring whether we are building the confidence they need to continue coding once the supportive intervention is removed. This gap is particularly acute for students with disabilities, who may enter learning contexts with lower academic self-efficacy due to a history of struggle or marginalization. If our interventions fail to address this, we risk creating a new generation of skilled but under-confident learners who do not see themselves as belonging in STEM.

### **Bridging the Three Strands**

Taken together, the findings of this review point to a single challenge: the three strands of inquiry, intelligent technology (DL), inclusive design (principles for disability), and impactful outcomes (CT, engagement, self-efficacy), remain almost entirely disconnected. We have studies that excel at one or two of these strands, but none that successfully weave all three together into a coherent whole.

This disconnect is visually represented in the Table 1), where columns for RQ1, RQ2, and RQ3 reveal a pattern of fragmentation. A study may show strong inclusive design (RQ2) and positive CT outcomes (RQ3) but lack any AI integration (e.g., Lee & Hsu, 2024). Another may explore AI-driven personalization (RQ1) and measure CT skills (RQ3) but fail to address inclusive design for a broad range of disabilities (e.g., Lin & Chen, 2020). The pieces of the puzzle exist, but no one has yet assembled them.

The consequence of this fragmentation is that the field lacks a model for what a truly intelligent, inclusive, and effective CT learning environment looks like. We have theories and isolated examples, but no empirically validated blueprint. This leaves teachers with piecemeal guidance, developers without a clear set of requirements, and researchers without a coherent agenda. The findings of this review carry significant implications for multiple stakeholders. The most urgent need is for design-based research that deliberately integrates DL-based AR with evidence-based inclusive design principles. Researchers should move beyond asking whether AR or AI works in isolation and instead ask how they can work together to serve diverse learners. Future studies must intentionally recruit and design for learners across the full spectrum of disabilities, including those with sensory and physical impairments. This will require collaboration with special education experts and, crucially, with disabled learners themselves through co-design processes (as exemplified by Işık Arslanoğlu et al., 2024). There is an urgent need to develop and validate quantitative instruments for measuring CT-specific self-efficacy in learners with disabilities. These measures should be designed to be accessible (e.g., offering visual or auditory administration options) and should be routinely included in intervention studies. The inclusive design principles identified in this review, scaffolding, multimodality, accessibility, should be seen as non-negotiable starting points for any CT intervention targeting diverse learners.

## CONCLUSION

This systematic literature set out to examine the state of research at the intersection of deep learning-based mobile augmented reality, inclusive design, and computational thinking education for students with disabilities. Through the systematic analysis of 23 studies, this review has shown both the promising foundations and the well-defined gaps that characterise this emerging field.

The findings reveal a landscape of disconnected innovation. On one hand, the literature provides robust evidence that augmented reality and game-based technologies can effectively enhance computational thinking skills and engagement for learners with diverse cognitive and neurodevelopmental disabilities. A foundational set of inclusive design principles, scaffolded instruction, multimodal supports, and accessible interfaces, has been established and validated across multiple studies. These achievements demonstrate that the goal of "CT for all" is not merely aspirational but demonstrably achievable when learning environments are thoughtfully designed.

On the other hand, the review exposes critical gaps that must be addressed if the full potential of these technologies is to be realized. The integration of deep learning into mobile augmented reality systems remains in its infancy, with only a single study providing empirical evidence of a fully functional adaptive AR system. The scope of inclusive design remains narrow, focusing predominantly on cognitive disabilities while neglecting learners with sensory and physical impairments. Most concerning, the measurement of self-efficacy, a construct central to long-term persistence in STEM, is almost entirely absent or methodologically weak, leaving us with an incomplete understanding of how these interventions shape learners' identities and trajectories.

The overarching conclusion of this review is that the three critical strands of inquiry, intelligent technology, inclusive design, and meaningful outcomes, remain largely disconnected. The field possesses the pieces of the puzzle but has yet to assemble them into a coherent whole. No study to date has successfully combined DL-based adaptive AR with evidence-based inclusive design principles and rigorously evaluated its impact on CT skills, engagement, and self-efficacy across a broad spectrum of learners with disabilities.

This gap is not merely an academic oversight; it is a missed opportunity with real-world consequences. For the millions of students with disabilities worldwide, the promise of computational thinking as a gateway to 21st-century opportunity will remain unfulfilled if the technologies designed to support them are not truly adaptive, truly inclusive, and truly effective. The ramp without the exoskeleton provides access but not empowerment.

The path forward requires a deliberate and coordinated effort. Researchers must move beyond siloed inquiry to embrace interdisciplinary collaboration, bringing together computer scientists, special educators, learning scientists, and accessibility experts. Designers must broaden their conception of inclusivity to encompass the full diversity of disabled learners and must engage those learners as co-designers, not merely as subjects. Practitioners must demand evidence that goes beyond engagement to demonstrate impact on both skills and self-

efficacy. Policymakers and funders must prioritize large-scale, longitudinal, and interdisciplinary initiatives that can address the grand challenge this review has identified.

In conclusion, this systematic review serves as both a map of the current landscape and a call to action. The foundation has been laid. The technologies are within reach. The need is urgent and undeniable. What remains is the collective will to bridge the gaps, connect the strands, and build the intelligent, inclusive learning environments that students with disabilities deserve. The question is no longer whether deep learning-based mobile augmented reality could transform computational thinking education for diverse learners. The question is whether we have the vision and the commitment to make it a reality.

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## REFERENCES

1. Abdul Hanid, M. F., Mohamad Said, M. N. H., Yahaya, N., & Abdullah, Z. (2022). Effects of augmented reality application integration with computational thinking in geometry topics. *Education and Information Technologies*, 27(7), 9485-9521.
2. Adhe, K. R., Safitri, D. G. L., Malaikosa, Y. M. L., Simatupang, N. D., & Fauziddin, M. (2025). Enhancing Children's Critical Thinking through an Augmented Reality Application: A Digital Solution for Early Childhood Education. *Golden Age: Jurnal Ilmiah Tumbuh Kembang Anak Usia Dini*, 10(2), 389-411.
3. Akçayır, M., & Akçayır, G. (2017). Advantages and challenges associated with augmented reality for education: A systematic review of the literature. *Educational research review*, 20, 1-11.
4. Al Omoush, M. H., & Mehigan, T. (2024). Exploring AR, VR, and educational robotics for inclusive mathematics education for dyslexic students. In: *International Conference on Computers Helping People with Special Needs - ICCHP 24, 8-12 July 2024, Linz, Austria*. ISBN 978-3-903480-07-0
5. Alivia, Z. P., Kustija, J., Riza, L. S., Hafina, A., Munir, M., & Wahyudin, W. (2025). Application of Programming Algorithms to Support Computational Thinking in Children with Autism Spectrum Disorder. *AL-ISHLAH: Jurnal Pendidikan*, 17(4).
6. Angraini, L. M., Susilawati, A., Noto, M. S., Wahyuni, R., & Andria, D. (2024). Augmented reality for cultivating computational thinking skills in mathematics completed with literature review, bibliometrics, and experiments to students. *Indonesian Journal of Science & Technology*, 9(01).
7. Bertacchini, F., Scuro, C., Pantano, P., & Bilotta, E. (2022). A project based learning approach for improving students' computational thinking skills. *Frontiers in Robotics and AI*, 9, 720448.
8. Costa Junior, A. D. O., Guedes, E. B., Lima e Silva, J. P. F., & Rivera, J. A. (2024). Developing computational thinking in middle school with an educational robotics resource. *Journal of Intelligent & Robotic Systems*, 110(2), 49.
9. Downs, S. H., & Black, N. (1998). The feasibility of creating a checklist for the assessment of the methodological quality both of randomised and non-randomised studies of health care interventions. *Journal of epidemiology & community health*, 52(6), 377-384.
10. Gundersen, S. W., & Lampropoulos, G. (2025). Using serious games and digital games to improve students' computational thinking and programming skills in K-12 education: a systematic literature review. *Technologies*, 13(3), 113.
11. Hong, Q. N., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., Dagenais, P., ... & Pluye, P. (2018). The Mixed Methods Appraisal Tool (MMAT) version 2018 for information professionals and researchers. *Education for information*, 34(4), 285-291.
12. Iatraki, G., & Mikropoulos, T. A. (2025). Using immersive augmented reality to teach physics to students with intellectual disabilities. *Journal of Computer Assisted Learning*, 41(3), e70040.
13. Işık Arslanoğlu, İ., Kert, S. B., & Tonbuloğlu, İ. (2024). Think together, design together, code together: the effect of augmented reality activity designed by children on the computational thinking skills. *Education and Information Technologies*, 29(7), 8493-8522.

14. Israel, M., Pearson, J. N., Tapia, T., Wherfel, Q. M., & Reese, G. (2015). Supporting all learners in school-wide computational thinking: A cross-case qualitative analysis. *Computers & Education*, 82, 263-279.
15. Karagianni, E., & Drigas, A. (2022). The STEM education of Down syndrome children in algorithmic and computation thinking for a sustainable life. *Technium Sustainability*, 2(5), 58-78.
16. Kert, S. B., Yeni, S., & Fatih Erkoç, M. (2022). Enhancing computational thinking skills of students with disabilities. *Instructional Science*, 50(4), 625-651.
17. Lee, I. J., & Hsu, H. T. (2024). Applied the augmented reality technology combined with social stories strategies and computational thinking games to improve the social skills of children with ASD. *Interactive Learning Environments*, 32(10), 6346-6374.
18. Lilis, M. A., Noto, M. S., & Muhammad, I. (2024). Augmented Reality-Based Learning Media on Mathematical Computational Thinking Ability. *The International Journal of Science, Mathematics and Technology Learning*, 31(2), 89.
19. Lin, P. H., & Chen, S. Y. (2020). Design and evaluation of a deep learning recommendation based augmented reality system for teaching programming and computational thinking. *IEEE Access*, 8, 45689–45699. <https://doi.org/10.1109/ACCESS.2020.2977679>
20. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *bmj*, 372.
21. Palada, B., Chandan, V. S., Gowda, C. P., & Nikitha, P. (2024). The role of Augmented Reality (AR) in education. *International Journal for Research in Applied Science and Engineering Technology*, 12(3), 1400-1408.
22. Rakhimzhanova, L., Issabayeva, D., Kultan, J., Baimuldina, N., Issabayeva, Z., & Aituganova, Z. (2025). Using augmented reality to teach digital literacy course to primary school children with special educational needs. *European Journal of Educational Research*, 14(1), 55-71.
23. Rao, K., Gravel, J. W., Rose, D. H., & Tucker-Smith, T. N. (2023). Universal Design for Learning in its 3rd decade: A focus on equity, inclusion, and design. *International encyclopedia of education*, 6, 712-720.
24. Rao, T. S. S., & Bhagat, K. K. (2024). Computational thinking for the digital age: a systematic review of tools, pedagogical strategies, and assessment practices. *Educational technology research and development*, 72(4), 1893-1924.
25. Seo, M., Kwon, K., Thomas, B., Kim, H., & Kim, K. (2025). Integrating Augmented Reality and Collaborative Activities to Enhance Computational Thinking in K-12 Classrooms. *The Journal of Applied Instructional Design*, 14(2).
26. Shea, B. J., Reeves, B. C., Wells, G., Thuku, M., Hamel, C., Moran, J., ... & Henry, D. A. (2017). AMSTAR 2: a critical appraisal tool for systematic reviews that include randomised or non-randomised studies of healthcare interventions, or both. *bmj*, 358.
27. Veiga, J., Aquini, L., Pereira, K., Cavalheiro, S., Foss, L., da Rosa Junior, L., & Pernas, A. (2025, July). Computational Thinking and Learning Disabilities: A Systematic Review. In *Workshop sobre Educação em Computação (WEI)* (pp. 1126-1138). SBC.
28. Weng, X., Ye, H., Dai, Y., & Ng, O. L. (2024). Integrating artificial intelligence and computational thinking in educational contexts: A systematic review of instructional design and student learning outcomes. *Journal of Educational Computing Research*, 62(6), 1420-1450.
29. Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, 49(3), 33-35.
30. Wu, C. H., Chien, Y. C., Chou, M. T., & Huang, Y. M. (2025). Integrating computational thinking, game design, and design thinking: a scoping review on trends, applications, and implications for education. *Humanities and Social Sciences Communications*, 12(1), 163.
31. Wu, C. L. (2023). Using video modeling with augmented reality to teach students with developmental disabilities to solve mathematical word problems. *Journal of Developmental and Physical Disabilities*, 35(3), 487-507.
32. Zhan, Z., Zhou, X., Cai, S., & Lan, X. (2025). Exploring the effect of competing mechanism in an immersive learning game based on augmented reality. *Journal of Computers in Education*, 12(2), 449-475.