

Intelligent Immersive Accessibility: A Systematic Review of AI-Enhanced Virtual Reality Interaction Design for Inclusive and Equitable Education

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ABSTRACT

This study systematically synthesises findings about artificial intelligence (AI)-enhanced virtual reality (VR) and extended reality (XR) systems developed for accessibility and inclusive education. It examines the architectural, implementation, and evaluation principles behind AI-infused immersive learning environments as adaptive systems for educational contexts. We conducted a systematic literature review following the PRISMA 2020 guidelines. We searched Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and ERIC databases for peer-reviewed articles published between 2021 and 2025. Only nine of those studies ultimately met the screening and eligibility criteria. The included studies were assessed through a structured narrative synthesis, which examined AI integration patterns, immersive interaction design, accessibility operationalisation, evaluation maturity, and architectural contributions. The study revealed that AI integration occurs mainly at the perceptual layer, including recognition, classification, and translation, but the system lacks a complete closed-loop adaptive architecture that connects learner modelling with real-time personalisation and longitudinal learning analytics. Interaction design is largely disability-dependent, while evaluation methods often choose between usability and system performance testing, and between system performance testing and educational outcome assessment. Architectural contributions exist as separate modules that fail to integrate accessibility, adaptive intelligence, pedagogy, and governance into a cohesive system. The Intelligent Immersive Accessibility Framework (IIAF), a conceptual, evidence-traceable but not yet empirically validated layered architecture, addresses this fragmentation. The emerging nature of AI-based immersive accessibility research helps explain why only a few studies were included, and why the field needs research that spans multiple contexts and extends over longer periods.



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I. INTRODUCTION

The convergence of artificial intelligence (AI) and immersive technologies, particularly virtual and extended reality (VR/XR), has been increasingly positioned as a catalyst for advancing inclusive and equitable education [1]–[3]. Immersive environments enable embodied interaction, multisensory engagement, and contextual simulation, offering affordances that extend beyond conventional 2D interfaces [4]–[8]. At the same time, AI technologies enable recognition, classification, modelling, and adaptive feedback mechanisms

that personalise learning experiences [9], [10]. Together, these capabilities present a compelling vision of intelligent immersive accessibility: AI-enhanced VR systems designed not merely to provide access, but to support learners with diverse needs in meaningful educational progression in real time.

Though there is considerable promise, most scholarship is characterised by disciplinary splintering. Studies on immersive technology in education often focus on engagement, presence, and experiential learning outcomes, while accessibility issues draw society's attention to assistive

technologies or impairment-specific adaptations [11], [12]. A similar sentiment is shared by [13], which identified the main accessibility challenges affecting people with physical, sensory, and cognitive disabilities through analysis of multiple workshops. The study proposed a research agenda that includes inclusive design, ethical considerations, and equitable user participation to develop accessible solutions for disabled users in immersive technologies. Another review by Yong et al. (2025) demonstrated that VR technology discriminates against users with diverse abilities, gender identities, age groups, and community ties. The review identified fundamental deficiencies in existing accessibility standards and advocated design practices that engage local communities and ensure fair treatment, cultural recognition, and active participation in virtual reality development.

On the other hand, AI technologies in education have primarily focused on predictive analytics, automated assessment, and personalised recommendation systems [14], [15]. Although these technologies are evolving rapidly, the literature remains insufficiently representative of implementation, deep dives into interactivity in immersive environments, AI-driven adaptations, accessibility design, and measurable educational outcomes within a single operational architecture. Recent systematic literature reviews underscore both the potential and the fragmentation across these areas. VR implementation in higher education has been systematically investigated by [16], who report strong motivational and engagement effects but limited standardisation and integration of accessibility in VR implementations, while Pellas et al. (2021) note that research in these areas is gradually diffusing. Methodological differences and inconsistencies in evaluation frameworks impede the building of cumulative knowledge in this space. An umbrella review by [17] indicates variation in learning outcomes across VR applications in education and calls for more integrative synthesis approaches.

AI in education has shown similarly persistent challenges. For instance, after comparing various dimensions associated with 45 AI USEs in educational contexts, [18] concluded that even adaptive and predictive systems are extensive/foundational. They lamented that fairness, transparency, and context alignment remain underdeveloped, largely because AI in educational systems prioritises optimisation metrics over inclusive design considerations. Within accessibility and special education contexts, further SLRs point to domain-specific innovation but limited architectural consolidation. Furthermore, [19] reviewed existing evidence from university students regarding their views on the use of AI, particularly ChatGPT, in their learning and research activities. Results suggest persistent challenges, including questions about academic integrity, information reliability and evaluation, privacy and security concerns, and ethical debates, while also exhibiting creativity, critical thinking, invalid arguments, and instances that demand clarification of references. Based on the review's findings, improving ChatGPT's educational impact would require addressing student concerns by establishing clear institutional

guidelines, ethical frameworks, and appropriate policies for its responsible integration across learning environments. A review by [20] on AI, VR, and large language model applications in special education identified personalised learning and engagement as recurring patterns, while both raised ethical and scalability concerns. For example, [21] suggested that XR applications for visually impaired students offer potential advantages in spatial cognition and freedom, but these applications have not yet been incorporated into transferable accessibility frameworks. Moreover, [22] reported that augmented reality interventions in K-12 special education programmes show increased engagement and immediate learning. Still, evidence of educational progression remains limited, particularly for consistent, integrated system design.

Several structural patterns emerge from these reviews. Immersive technologies are typically considered in isolation, whereas AI-driven adaptive mechanisms play a minimal role in the overall scenario. In many cases, AI systems are deployed explicitly, but accessibility is not properly operationalised. Evaluation techniques often focus on short-term usability or engagement metrics rather than longitudinal learning measures. Furthermore, discussions mostly centre on subsystemal innovations, gesture recognition, translation pipelines, and behavioural models. If considered, words should pay equal attention to layered integration models, in which technical capabilities could be propagated by aligning pedagogical and accessibility goals with new design requirements. These patterns suggest that technological components mature independently, while systems-level architectural integration provides a limited rationale. Immersive accessibility systems frequently demonstrate technical feasibility at the perceptual layer, such as sign-language recognition or adaptive sensory controls [23], [24], yet they provide little detail on the closed-loop architectures that encompass learner modelling, pedagogical adaptation, assessment analytics, and governance mechanisms. In other words, researchers have implemented technological integration without consolidating the architecture.

The accessibility of immersive learning environments expands interfaces' compliance with independence, multimodal interaction, cognitive load monitoring, adaptive modulation of senses, and flexible instructional scaffolding [25]–[28]. The dynamism of these services lies in AI, immersive interaction design, and measurable learning outcomes; without them, the progressive accessibility of immersive environments would remain an interesting collection of prototypes rather than a viable area for educational innovation. Several prior reviews have examined immersive education, AI in education, and XR accessibility separately, but none have synthesised these areas. Furthermore, none of these reviews has explicitly explored what could be built at the intersection of AI performance, deployment in immersive VR/XR, operationally set-up visual and auditory accessibility, and other learning contexts. Although these fields are making breakthroughs in AI, immersive technologies, and accessibility research, the

literature remains structurally fragmented. In fact, studies across these spheres are largely disjointed: immersive learning research advances through asynchronous approaches, engagement, and experiential learning outcomes; AI in education shows steady progress in predictive analytics, adaptive feedback, and recommendation systems; and accessibility follows. Moreover, AI capabilities, immersive design, accessibility, and technology-enabled learning outcomes show virtually no interplay in operational educational environments. Consequently, the field lacks a coherent architectural perspective to underscore how AI-enhanced immersive environments can be systematically and inclusively designed for educational practice. This fragmentation, typical of isolated technological design, obstructs the transition to a scalable, pedagogically informed infrastructure for immersive accessibility.

The specific gap this review addresses, distinct from the individually focused reviews cited above, is architectural: existing systematic reviews of immersive learning [16], [17], AI in education [18]–[20], and XR accessibility [13], [21], [22] each synthesise one of these domains in depth but stop short of modelling how AI capability, interaction design, pedagogy, evaluation, and governance interact as a single system. Existing accessibility frameworks outside this literature, such as the Web Content Accessibility Guidelines (WCAG), Universal Design for Learning (UDL), and the W3C XR Accessibility User Requirements (XAUR), likewise address interface-level or pedagogical-level accessibility but were not designed to model the AI-mediated adaptive loop specific to immersive environments. The Intelligent Immersive Accessibility Framework (IIAF) proposed in this study is positioned in this gap: it does not replace WCAG, UDL, or XAUR, but extends their interface- and pedagogy-level guidance with an explicit AI capability and governance layer, derived from and traceable to the evidence synthesised in Section III, that these existing frameworks do not specify.

Accordingly, this study conducts a systematic review following PRISMA 2020 principles on all peer-reviewed studies published between 2021 and 2025, meeting four criteria simultaneously: (a) such studies incorporated AI or adaptive mechanisms, (b) immersive VR/XR deployment, (c) explicit considerations for accessibility or disability, and (d) learning context for educational outcomes. This intersectional lens narrows the subset for analysis when seeking possible interpretations of current theoretical notions and practices of intelligent immersive accessibility. The main research question is: *How are AI-enhanced VR systems conceptualised, architected, and operationalised as accessibility design frameworks to advance inclusive and equitable education?* The study identifies structural regularities and constraints shaping this emerging landscape by exploring the scope of AI synergy, interaction design strategies, evaluation maturity, and architectural contributions across the selected studies. The analysis intentionally focuses not on the volume of innovation but on the maturity of architectural integration.

The 2021–2025 window was selected deliberately, not by default. It covers the period after the mainstream commercial availability of standalone VR/XR headsets and the rapid diffusion of transformer-based AI models, both of which materially changed what "AI-enhanced immersive accessibility" could technically mean in practice. Relevant pre-2021 work is still engaged with narratively as background literature earlier in this section to situate the review historically, but such studies were not eligible for inclusion in the synthesis itself, since the review is deliberately bounded to the most recent five-year window in order to characterise the field's current technological configuration rather than its full history.

For this review, accessibility is defined broadly rather than as a single disability-specific construct. It encompasses visual, auditory, motor, cognitive, and neurodiversity-related access; language and communication access; device and infrastructural access (e.g., hardware cost, connectivity, and platform compatibility); and environmental or contextual access (e.g., physical space, supervision, and socio-cultural constraints on use). This multidimensional definition was applied consistently during screening, data extraction, and synthesis, and underpins the coding framework described in Section II.E.

A *closed-loop adaptive architecture* is defined here as a system in which sensing/perception (capturing user behaviour, physiology, or performance), learner modelling (constructing and updating a representation of the individual learner), decision-making (selecting an instructional or interaction adjustment based on that model), adaptation/intervention (enacting the adjustment within the immersive environment), feedback (returning the outcome of the adjustment to the learner and to the system), and longitudinal analytics (aggregating adaptation history over time to refine the learner model and evaluate progression) are all present and functionally connected, such that the output of each stage becomes the input of the next in a continuing cycle. A system performing only one or two of these functions in isolation, for example, perception without a persisting learner model, or feedback without longitudinal analytics, is classified in this review as partially adaptive rather than closed loop. This operational definition is applied consistently in Section III.B and underpins the AI capability layer of the IIAF in Section IV.A.

This research contributes to and extends the current discussion on AI-enhanced immersive accessibility in three ways. First, it provides an integrated overview of the research body, from AI capabilities to the design of accessible immersiveness, VR/XR, and their implementation in educational practice. Second, by identifying implemented systems, the literature highlights AI integration, immersive interaction design, evaluation practices, and architectural contributions. Thirdly, the study presents the IIAF, an architectural work plan grounded in human-computer interaction (HCI) and education, designed to support the emergence of adaptive and accessible immersive learning systems. The rest of the paper is structured as follows: Section

II outlines the systematic review methodology and PRISMA workflow. Section III presents the synthesis results. Section IV situates these findings within the broader context of post-2020 scholarship, introduces the IIAF as an integrative architectural response, traces its layers to the underlying evidence and states its validation status, and discusses the study's theoretical, practical, and policy implications, including equity, governance, and the ethics of AI in immersive environments. Section V covers limitations, future research directions, and concluding reflections.

II. MATERIALS AND METHODS

A. Review design

A Systematic Literature Review (SLR) design was adopted to synthesise the AI-enhanced immersive technology literature on its support for inclusive practices in education. The SLR search was conducted on the 22nd of February 2026 to ensure methodological transparency, replicability, and reporting rigour [29]. The focus was on articles published between 2021 and 2025, as this period has witnessed the rapid integration of AI and immersive technologies.

The review directly addressed the following research questions:

- How is AI integrated with VR/XR immersive systems to bring enhanced accessibility to learners with disabilities?
- Which principles of immersive interaction are integrated for an inclusive learning experience with equity?
- Which design frameworks or system architectures are proposed for AI-enhanced immersive accessibility in aggregated education?
- How are both accessibility and learning outcomes evaluated in AI-enhanced immersive educational systems?

B. Data sources and search strategy

Five interdisciplinary databases were selected to ensure coverage across computer science, human-computer interaction (HCI), educational technology, and accessibility research. These include Scopus, Web of Science, IEEE Xplore, ACM Digital Library and ERIC. Database-specific search strings combined controlled vocabulary and keyword terms relating to:

- Artificial intelligence ("AI", "machine learning", "deep learning", "intelligent system*", "AI-driven", "intelligent agent*").
- Immersive technologies (e.g., "virtual reality", "extended reality", "XR", "immersive environment").
- Accessibility/disability ("accessibility", "assistive technology", "inclusive design", "universal design", "disability", "equitable access", "sensory impairment", "cognitive impairment", "motor impairment", "visual impairment", "hearing impairment").
- Education/learning contexts ("educational technolog*", "learning environment*", "digital learning", "inclusive education").

- Design frameworks or system architecture ("conceptual framework*", "architectural model*", "system architecture", "design model*").

We applied search filters in the databases before export to restrict results to the defined timeframe, language, document type, and publication stage.

To ensure reproducibility, the core Boolean search string, adapted to each database's syntax and controlled vocabulary, was: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "intelligent system*" OR "AI-driven" OR "intelligent agent*") AND ("virtual reality" OR "extended reality" OR "XR" OR "immersive environment") AND ("accessibility" OR "assistive technology" OR "inclusive design" OR "universal design" OR "disability" OR "equitable access" OR "sensory impairment" OR "cognitive impairment" OR "motor impairment" OR "visual impairment" OR "hearing impairment") AND ("educational technolog*" OR "learning environment*" OR "digital learning" OR "inclusive education"). This base string was combined, where a database supported it, with an optional fourth block on design frameworks ("conceptual framework*" OR "architectural model*" OR "system architecture" OR "design model*") to aid precision without being applied as a hard filter, since architectural contributions were extracted rather than used for exclusion. Scopus and Web of Science title/abstract/keyword fields were searched using their native proximity and wildcard operators; IEEE Xplore and the ACM Digital Library used full-text and metadata search with the same Boolean logic; ERIC used its thesaurus-mapped descriptor search combined with free-text terms. All five searches were executed on 22 February 2026, the date reported in Section II.A, with database-specific filters applied for the 2021-2025 publication window, English language, and peer-reviewed article/conference-paper document types. Scopus, Web of Science, IEEE Xplore, the ACM Digital Library, and ERIC were selected because, together, they provide cross-disciplinary coverage of computer science and engineering (Scopus, IEEE Xplore, ACM Digital Library), multidisciplinary citation indexing (Web of Science), and education-specific literature (ERIC); no single database indexes all four intersecting fields of this review (AI, immersive technology, HCI, and educational research) with adequate depth, so the five were combined to reduce field-specific indexing bias.

C. Study selection process

The study selection process followed PRISMA 2020 procedures, summarised in Figure 1. The initial database search identified 6,678 records (Scopus = 3,102; Web of Science = 88; IEEE Xplore = 19; ACM Digital Library = 3,297; ERIC = 172). After applying automated database filters (publication years 2021–2025; English-language only; document type (peer-reviewed articles and conference papers); final publication stage) and removing duplicates across databases, 3,403 records were removed before screening, leaving 3,275 records for title and abstract

screening. The authors conducted title, abstract, and full-text screening independently and resolved disagreements through discussion to ensure consistent inclusion decisions. During screening, 2,655 records were excluded due to:

- Absence of an immersive VR/XR component
- No implemented AI or adaptive decision mechanism
- No explicit accessibility or disability operationalisation
- Non-educational context
- Ineligible publication type

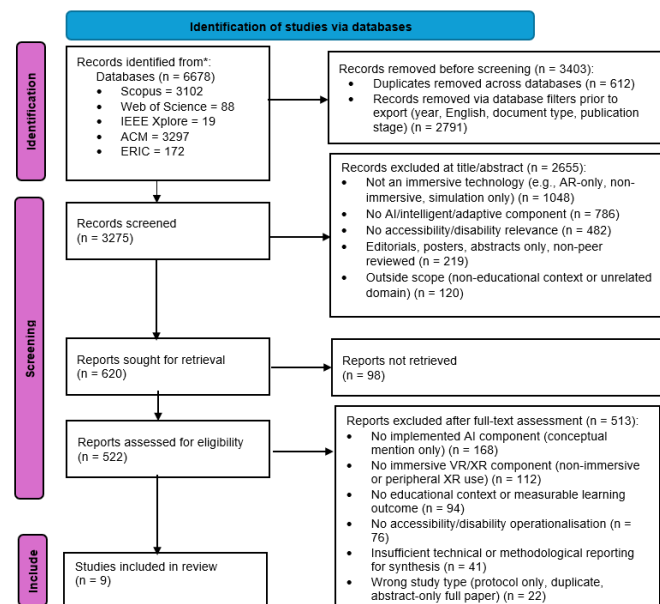


Fig 1. The PRISMA workflow diagram

We sought 620 reports for retrieval; 98 were not accessible in full text. Most non-retrieved reports corresponded to conference abstracts or restricted-access proceedings unavailable through institutional subscriptions at the time of review. We assessed the remaining 522 full-text articles for eligibility. At full-text review, 513 reports were excluded because they did not simultaneously meet all four core inclusion criteria:

- Operational AI integration (beyond conceptual mention)
- Immersive VR/XR implementation
- Educational learning context with identifiable outcomes
- Explicit accessibility or disability-targeted design

Consistent with PRISMA 2020 reporting requirements, the specific reasons for the 513 full-text exclusions, as detailed in the Figure 1 flow diagram, were: no implemented AI component beyond conceptual mention ($n = 168$); no immersive VR/XR component, i.e., non-immersive or peripheral XR use ($n = 112$); no educational context or measurable learning outcome ($n = 94$); no explicit accessibility or disability operationalisation ($n = 76$); insufficient technical or methodological reporting to support synthesis ($n = 41$); and wrong study type, such as a protocol only, duplicate, or abstract-only full paper ($n = 22$).

Nine studies met all eligibility requirements and were included in the qualitative synthesis. The marked reduction at each screening stage reflects the stringent intersection of the inclusion criteria. While innovative technologies such as AI applications and XR are well researched on their own, few integrate them under a unified operating system architecture. The resulting entity served as a focused evidence base at the juncture of AI, immersiveness, accessibility design, and educational use.

The fact that only nine studies met the inclusion criteria should not be construed as a limitation of the review process but rather as a reflection of the stringent intersectional criteria applied. While significant literature exists on AI in education, immersive VR/XR learning, and accessibility research independently, few studies integrate all four dimensions concurrently: operational AI functionality, immersive VR/XR environments, explicit accessibility or disability-centred design, and measurable educational learning contexts. By prioritising this intersection, the review deliberately focuses on implemented intelligent immersive accessibility systems rather than conceptual discussions. The observed reduction across screening stages reflects a structural gap in the literature rather than a methodological limitation of the review itself. Similar intersection-focused reviews in emerging interdisciplinary fields often report few implementations, as systems that simultaneously satisfy multiple technological and contextual criteria remain scarce. The resulting identified studies thus represent a highly focused subset of the literature in which AI functionality, immersive VR/XR deployment, accessibility operationalisation, and measurable educational outcomes are simultaneously implemented within a single system context.

D. Eligibility criteria

Studies were considered and included, provided:

- Testified to deployed AI or adaptive mechanisms within the system architecture.
- Employed immersive VR or XR technologies as a central component.
- Were situated within formal or informal educational contexts.
- Explicitly operationalised accessibility or disability-targeted design.

Studies were excluded on the condition that they:

- Were purely conceptual without implemented systems.
- Used non-immersive technologies.
- Focused solely on clinical rehabilitation without educational learning outcomes.
- Did not operationalise accessibility or disability considerations.
- Were editorials, abstracts, posters, or non-peer-reviewed outputs.

To make screening reproducible, the four core constructs above were operationally defined prior to full-text review. *AI-enhanced* required documented evidence of a computational mechanism (rule-based, statistical, or machine-learning) that processed user input and produced a system response, as

distinct from AI mentioned only as future work or motivation. VR/XR required a head-mounted display, CAVE system, or comparably immersive stereoscopic environment as the primary interaction medium, excluding desktop-only 3D or 360° video without stereoscopic immersion. *Accessibility* required an explicit, named accommodation for a disability, sensory, cognitive, motor, or neurodiversity-related need (per the multidimensional definition given in Section I), rather than incidental usability discussion. *Inclusive education* required deployment or evaluation within a formal or informal teaching/learning setting with an identifiable learner population, rather than purely clinical or entertainment settings. These four operational definitions, rather than title keywords alone, governed full-text inclusion decisions and reduced subjectivity in the screening process.

Regarding document type, automated database filters at the initial search stage restricted results to peer-reviewed journal articles and peer-reviewed conference papers, consistent with standard SLR practice for controlling source quality. Conference papers were therefore eligible throughout, and two of the nine included studies were disseminated as peer-reviewed book chapters within edited, peer-reviewed conference or Springer proceedings volumes; these were retained because their peer-review status and methodological content were equivalent to the conference papers and journal articles otherwise included. Workshop papers without formal peer review, dissertations, and preprints were excluded at the eligibility stage, since their review status could not be consistently verified across the five databases; this is acknowledged in Section V as a source of potential coverage bias, given that VR/XR research frequently disseminates early findings through workshops and preprint servers.

E. Data extraction and synthesis

A structured data extraction mechanism was designed to capture:

- AI integration patterns (perception, modelling, adaptation).
- Immersive interaction design strategies.
- Educational context and outcome measures.
- Evaluation maturity (short-term, validated instruments, longitudinal evidence).
- Architectural or framework contributions.

Structured narrative analysis was used to identify patterns that cut across studies and serve as convergence points, with an emphasis on structural fragmentation. Coding followed a framework synthesis approach: the five extraction categories above were used as an initial deductive coding frame, applied independently by two authors to each of the nine included studies; a third author reconciled disagreements. Within each deductive category, sub-codes (e.g., “recognition-only”, “partial adaptation”, “closed-loop” under AI integration) were then developed inductively from the study content and iteratively refined until stable, consistent with common practice in framework synthesis for heterogeneous evidence bases. Codes were tabulated per study (Tables I–VI) before cross-study patterns were narratively synthesised.

F. Quality appraisal

We assessed methodological robustness using an adapted version of the Mixed Methods Appraisal Tool (MMAT), selected because the included studies spanned systematic reviews, an ML-based quantitative study, and qualitative/mixed design-oriented studies that a single-design tool (e.g., a randomised-trial checklist) could not accommodate. The MMAT’s generic screening questions were retained, and its criteria were operationalised for immersive AI-accessibility systems across five domains:

- Conceptual clarity
- Technical transparency
- Immersive design validity
- Accessibility integration
- Evaluation rigour

We classified the studies as high-methodology, moderate-consensus, or exploratory/prototype. Quality appraisal informed the ratings during synthesis but was not an inclusion criterion.

G. Risk of bias assessment

We assessed risk of bias using an adapted appraisal framework commonly applied in systematic reviews of digital learning technologies and human-computer interaction systems. Because immersive AI systems often involve prototype environments and experimental deployments, the framework emphasised architectural transparency and evaluation validity over reliance on clinical trial criteria. The appraisal framework evaluated five dimensions: selection bias, reporting transparency, measurement validity, evaluation duration, and architectural completeness.

III. RESULTS

A. Overview of included studies

Nine studies met the full eligibility criteria for inclusion in the qualitative synthesis. The structural compression observed in the existing literature tends to reflect tools within the emerging prime zone rather than the methodological outlook. Of these, three were systematic reviews [30]–[32]; one was a machine-learning-driven assessment study [33], and five were empirical or design-oriented system studies [34]–[38].

The inclusion of three systematic reviews reflects the limited number of implemented AI-XR accessibility systems reported in primary empirical studies. The reviews remained in the collection because they provided architectural insights by synthesising the implementation of immersive accessibility systems. In terms of disability focus, three studies addressed Deaf/Hard-of-Hearing contexts [30], [32], [36]; three focused explicitly on autism spectrum conditions [31], [33], [37]; two addressed broader, inclusive, or neurodiverse learning contexts [34], [35] and one addressed inclusive creative/skills-based immersive interaction without a single disability category focus [38]. No included study explicitly targeted physical impairment or multi-disability contexts. This is summarised in Figure 2.

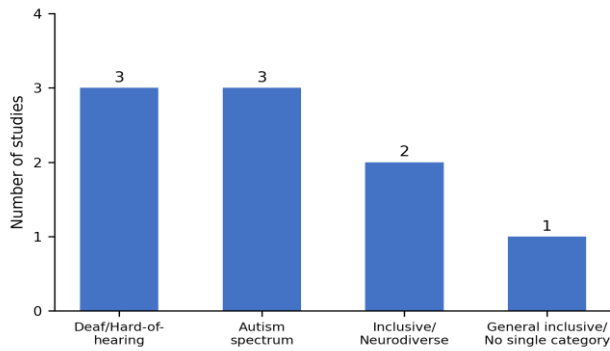


Fig 2. Distribution of disability focus across included studies

B. AI integration patterns in accessible immersive learning systems

Addressing RQ1, the synthesis reveals that AI capabilities are primarily deployed at the perceptual layer rather than as fully integrated adaptive instructional systems. Across the nine included studies, AI integration is most consistently deployed at the perceptual layer rather than as a fully adaptive pedagogical engine. This is summarised in Table 1. Four of the nine studies (44%) operationalise AI primarily for recognition, translation, or behavioural classification. In Deaf/Hard-of-Hearing contexts, AI-driven sign-language recognition and translation pipelines mediate immersive communication [30], [36]. In autism-focused systems, machine learning supports behavioural modelling and assessment classification [33], while [31] synthesise AI-assisted monitoring and adaptive response mechanisms across immersive serious-game implementations. Two studies (22%) demonstrate partial adaptive or personalised features within immersive environments [37], [38]. However, adaptation remains session-bound and context-specific; neither study presents a continuously updated learner model or longitudinal validation of AI-driven instructional progression. The remaining three studies (33%) foreground immersive design constructs or inclusive pedagogical approaches in which AI plays a limited or non-central role [32], [34], [35].

TABLE I
DISTRIBUTION OF AI INTEGRATION PATTERNS

AI integration category	Included studies	Primary AI function
Recognition/classification	Berrezueta-Guzman et al., 2025; Caruso et al., 2023; Leser & Islam, 2025; Minissi et al., 2024	Sign recognition, translation, behavioural classification, and AI-assisted monitoring.
Partial adaptive/personalised	Wongwan et al., 2025; Zaccagnino et al., 2025	Context-bound adaptive scaffolding and feedback mechanisms
Fully closed-loop architecture	None	Real-time learner modelling with validated longitudinal adaptation (not observed)
Limited/peripheral AI integration	Abdul Rahim et al., 2024; Glaser et al., 2025; Jadán-Guerrero et al., 2023	Conceptual AI reference or non-central AI components

This distribution reflects a deliberate distinction, applied during coding, between AI that performs perception or recognition (interpreting sensor input, such as gesture or speech, into a symbolic output) and AI that provides genuine adaptive intelligence, defined per the closed-loop criteria in Section I as requiring a persisting learner model that feeds forward into subsequent instructional decisions. Computer vision, speech recognition, classification, and translation, on their own, satisfy only the perception stage of that definition; they were coded as "recognition/classification" (Table I) unless the study also demonstrated a learner model and a feedback-driven adjustment mechanism, in which case they were coded as "partial adaptive/personalised" instead. Applying this distinction, none of the nine studies presents a fully articulated closed-loop architecture integrating real-time sensing, learner modelling, dynamic adaptation, and measured long-term learning progression. The distribution (4 recognition-focused; 2 partially adaptive; 0 closed-loop; 3 limited integration) suggests that AI within immersive accessibility research is currently strongest as an enabling perception mechanism rather than as a comprehensive adaptive learning system.

C. Immersive interaction design for accessibility

Regarding RQ2, the evaluation examined how immersive interaction principles are translated into practice to enable accessibility for people with diverse disability backgrounds. Interaction design strategies across the reviewed studies closely align with disability-specific requirements, as shown in Table 2.

TABLE II
IMMERSIVE INTERACTION DESIGN PATTERNS

Disability context	Included studies	Core interaction design focus	Accessibility strategy emphasised
Deaf / hard-of-hearing	Abdul Rahim et al., 2024; Berrezueta-Guzman et al., 2025; Leser & Islam, 2025	Gesture-mediated communication; avatar-based interaction; visual fidelity	Sign-language translation; visual clarity; interaction accuracy
Autism/neurodiversity	Caruso et al., 2023; Minissi et al., 2024; Wongwan et al., 2025	Structured tasks; controlled immersive environments	Sensory regulation; predictable sequencing; behavioural scaffolding
Inclusive/general disability contexts	Glaser et al., 2025; Jadán-Guerrero et al., 2023; Zaccagnino et al., 2025	Gamification; empathy-driven design; creative immersive interaction	Co-design principles; engagement scaffolding; accessible interaction feedback

Three studies addressing Deaf/Hard-of-Hearing learners prioritise visual fidelity, gesture-mediated interaction, and avatar intelligibility [30], [32], [36]. Accessibility is operationalised through the clarity of visual rendering and the accuracy of translation within immersive communication

spaces. Three autism-focused studies emphasise structured interaction and sensory regulation within immersive environments [31], [33], [37]. Immersive serious games and controlled task sequencing scaffold social and behavioural learning while mitigating overstimulation. Two studies foreground inclusive gamification and empathy-driven co-design approaches [34], [35], and one study situates adaptive immersive interaction within creative skills development [38].

This disability-contingent characterisation is not an impression but the direct output of the coding scheme summarised in Table II: each study's primary interaction-design decisions (e.g., avatar/gesture fidelity, sensory pacing, task scaffolding) were coded first by disability context and only secondarily by interaction modality. Under this coding, eight of the nine studies [30]–[34], [36], [37] justify their principal design choice by reference to a single disability category (Deaf/Hard-of-Hearing or autism) rather than to a modality-based accessibility requirement that could generalise across categories (e.g., "provide a visual alternative to audio" as a standalone design rule, independent of which disability motivates it). Only [38] frames its design decisions in modality-general terms applicable beyond one diagnostic group. Across the nine studies, immersive design is therefore disability-contingent rather than grounded in a unified multimodal accessibility architecture.

D. Educational contexts and evaluation practices

RQ4 examined accessibility evaluation and learning outcomes within an immersive AI-driven learning environment. The educational contexts represented in the current research landscape reflect communication learning (3 studies), social and behavioural development (3 studies), inclusive gamified learning (2 studies), and immersive creative skills training (1 study). However, evaluation depth varies substantially. Three studies employ validated or named instruments, including ADOS-2 and machine-learning performance metrics [33], the Social Responsiveness Scale [37] and UEQ and POMS-SF [38]. Three systematic reviews synthesise outcome domains across primary studies [30]–[32]. The remaining three empirical studies rely primarily on usability indicators, system performance measures, or qualitative feedback [34]–[36]. This is summarised in Table 3.

TABLE III
EDUCATIONAL CONTEXTS AND EVALUATION APPROACHES

Educational focus	Included studies	Evaluation approach	Evaluation maturity
Sign-language/communication learning	(Abdul Rahim et al., 2024; Berrezueta-Guzman et al., 2025; Leser & Islam, 2025)	Recognition accuracy, system performance, review-level outcome synthesis	Prototype-level / synthesised evidence
Social/behavioural skill development (ASD)	Caruso et al., 2023; Minissi et al., 2024;	ADOS-2; SRS; ML metrics; review-based	Moderate methodological robustness

	Wongwan et al., 2025	outcome domains	
Inclusive/gamified learning contexts	Glaser et al., 2025; Jadán-Guerrero et al., 2023	Usability metrics; qualitative feedback	Exploratory evidence
Creative / skill-based immersive training	Zaccagnino et al., 2025	UEQ; POMS-SF; task performance metrics	Moderate robustness

None of the nine studies reports longitudinal, multi-site validation of learning progression. Educational effectiveness is thus inconsistently operationalised, with learning outcomes frequently inferred from engagement or interaction performance rather than from independently validated measures of pedagogical gains.

To substantiate the claim that studies prioritise either usability/system performance or educational outcomes, but rarely both, each study was additionally coded against eight indicators used consistently across the accessible-immersive-learning literature: usability, accessibility, task performance, learning outcomes, engagement, cognitive load, presence, and system performance. Usability and system performance were reported by seven of the nine studies [30]–[33], [35], [36], [38]; task performance or recognition accuracy by five [30], [33], [36], [37], [38]; engagement by six [31], [32], [34], [35], [37], [38]; and named learning-outcome instruments by only three [33], [37], [38]. Cognitive load was reported explicitly by a single study [37], and presence was reported explicitly by a single study [38]; neither construct was measured consistently enough across the evidence base to support cross-study comparison. No study reported all eight indicators concurrently, and only [38] combined a validated experience measure (UEQ), an affect measure (POMS-SF), and task performance within a single evaluation design. This uneven coverage substantiates, rather than merely asserts, the claim that the literature tends to prioritise either system-level usability/performance or educational outcomes, seldom evaluating both alongside cognitive load and presence, which are arguably central to immersive accessibility specifically.

E. Design framework contributions and fragmentation

To address RQ3, the synthesis examined whether the reviewed literature includes proposals for adaptable software frameworks. The current body of knowledge largely lacks explicit, transferable architectural frameworks, as summarised in Table 4. Three systematic reviews synthesise immersive accessibility constructs and design considerations [30]–[32] yet do not merge them into operational models. Among the six empirical or system-oriented studies, contributions remain modular. [36] contribute a translation pipeline architecture; [33] develop a machine-learning behavioural assessment framework; [37] and [35] extend gamified scaffolding structures; [34] foreground empathy-driven co-design; and [38] integrate adaptive immersive interaction within creative training. However, no study has examined how to integrate accessibility, AI capability layers, immersive pedagogies, evaluation mechanisms, and

governance considerations into a layered, interoperable framework. Architectural innovation exists at the component level but is spread across domains. However, none of the nine studies combines accessibility requirements, AI capability layers, immersive learning, and evaluation mechanisms into a single evaluative model, nor do they address governance issues. The existing literature reflects architectural fragmentation to some extent: innovation is present at the component level, but integration across layers is lacking. Thus, the fragmentation supports the need for a consolidated framework.

TABLE IV
DESIGN FRAMEWORK CONTRIBUTIONS

Included studies	Contribution type	Nature of contribution	Framework integration level
Abdul Rahim et al., 2024; Berrezueta-Guzman et al., 2025; Caruso et al., 2023	Conceptual / review-level design synthesis	Thematic synthesis of immersive accessibility and learning constructs	Conceptual (non-operational)
Leser & Islam, 2025; Minissi et al., 2024	AI architectural components	Translation pipelines; ML-based behavioural modelling	Modular / domain-specific
Jadán-Guerrero et al., 2023; Wongwan et al., 2025; Zaccagnino et al., 2025	Immersive pedagogical structures	Gamified scaffolding; adaptive creative interaction	Context-bound
Glaser et al., 2025	Design methodology /	Empathy-driven inclusive	Process-oriented

TABLE V
EVIDENCE ARCHITECTURE MATRIX SYNTHESISING AI CAPABILITY, INTERACTION DESIGN, EVALUATION MATURITY, AND ARCHITECTURAL INTEGRATION ACROSS INCLUDED IMMERSIVE ACCESSIBILITY SYSTEMS.

Study	AI capability layer	Immersive interaction design	Accessibility operationalisation	Evaluation depth	Architectural integration
Berrezueta-Guzman et al. (2025)	Recognition/translation	Avatar-mediated sign interaction	Sign-language mediation	Review-level outcome synthesis	Conceptual synthesis
Leser & Islam (2025)	Recognition/translation	Gesture-based avatar communication	Sign-language translation pipeline	System performance metrics	Modular architecture
Minissi et al. (2024)	Behavioural classification (ML)	Structured behavioural VR interaction	Autism behavioural monitoring	Validated instruments (ADOS-2)	Domain-specific ML framework
Caruso et al. (2023)	Recognition/monitoring	Immersive serious-game interaction	Autism-oriented task scaffolding	Review the synthesis of outcomes	Conceptual aggregation
Wongwan et al. (2025)	Partial adaptive personalisation	Gamified mixed-reality interaction	Sensory-regulated immersive tasks	SRS + usability metrics	Early adaptive prototype
Zaccagnino et al. (2025)	Partial adaptive mechanisms	Creative immersive skill interaction	Accessible digital musical interfaces	UEQ, POMS-SF, performance metrics	Context-bound adaptive interaction
Abdul Rahim et al. (2024)	Peripheral AI integration	Immersive TVET learning constructs	Deaf learner accessibility principles	Review-level evaluation synthesis	Conceptual design taxonomy
Glaser et al. (2025)	Peripheral AI reference	Empathy-driven immersive co-design	Neurodiverse inclusive interaction	Qualitative usability feedback	Process-oriented methodology
Jadán-Guerrero et al. (2023)	Peripheral AI reference	Inclusive gamified interaction	Disability-inclusive gamification	Usability and engagement metrics	Context-specific pedagogical structure

	co-design orientation	design principles	(non-architectural)
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F. Cross-cutting constraints in the evidence base

The evidence architecture matrix shows consistent structural fragmentation across all reviewed works. As a rule, AI resides in the sensory layer, at least in the initial stage of perception-based UI responses, where it performs tasks in sight, gesture, and voice/pattern recognition. Indeed, some systems incorporate partial adaptation mechanisms, but none truly demonstrate full loop closure across sensor-learner modelling, pedagogical adaptation, and long-term evaluation. The interaction design is disconnected from other contexts, disability-specific, and focuses on deafness/hard-of-hearing or autism contexts rather than implementing a unified, multimodal, accessible architecture. Regarding the level of evaluation, it is either deep or shallow, and researchers use it in various ways: some use validated instruments, while others focus only on usability or performance metrics. Collectively, these patterns indicate a research landscape characterised by technological experimentation and component innovation but limited system-level architectural integration. This is summarised in Table 5.

The matrix reveals a continuing structural imbalance which impacts all evidence elements. AI capabilities, confined primarily to perceptual functions, are far from adaptive learning systems and governance mechanisms. Interaction design strategies mainly depend on disability needs, but they do not include multiple communication modes. These patterns indicate that the field is generating technological innovation but has not yet achieved system-level architectural integration.

G. Risk of bias results

We assessed risk of bias across multiple methodological dimensions, including sample representativeness, reporting transparency, measurement validity, evaluation duration, and overall study quality. In the reviewed literature, transparency in reporting and measurement approaches was, for the most part, adequate; however, evaluation duration emerged as the most consistent likely source of bias, and most systems warrant full-term testing and longitudinal validation. This pattern is linked to the emergent status of AI-driven immersive access providers, in which the technology's feasibility is often demonstrated before extended educational deployment, as summarised in Table 6.

TABLE VI
RISK OF BIAS ASSESSMENT ACROSS INCLUDED STUDIES

Study	Selecti on bias	Reporti ng transpa rency	Measure ment validity	Evaluati on duration	Overall risk
Berrezue ta- Guzman et al. (2025)	Moder ate	Low	Moderate	High	Moder ate
Abdul Rahim et al. (2024)	Moder ate	Moderate	Moderate	High	Moder ate
Leser & Islam (2025)	Moder ate	Low	Moderate	High	Moder ate
Caruso et al. (2023)	Moder ate	Moderate	Moderate	High	Moder ate
Minissi et al. (2024)	Moder ate	Moderate	Moderate	High	Moder ate
Wongwa n et al. (2025)	Moder ate	Moderate	Moderate	High	Moder ate
Glaser et al. (2025)	Moder ate	Moderate	Moderate	High	Moder ate
Jadán- Guerrero et al. (2023)	Moder ate	Moderate	Moderate	High	Moder ate
Zaccagni no et al. (2025)	Moder ate	Moderate	Moderate	High	Moder ate

The bias pattern in the reviewed studies suggests the infancy of the research development lifecycle of AI-based immersive accessibility systems, constrained by short evaluation times and small sample sizes, and exposing a probable inability to understand the metadata due to inter-architectural separation across the body of evidence. An emerging pattern of moderate risk across most constructs indicates that the domain is exploratory rather than methodological. The synthesis should be viewed as revealing a new architectural domain rather than as representative of a fully-fledged empirical evidence base.

IV. DISCUSSION

The synthesis above identified a constructive pattern across AI infusion, immersive interaction design, evaluation maturity, and architectural contributions in the nine studies selected for the review. Rather than treating them as isolated findings, this section argues for an interpretation that reflects the overall development of research on AI-assisted immersive accessibility. By placing the recognised structural patterns against the backdrop of post-2020 research on AI in education, XR accessibility, and HCI, the discussion offers a field-level account of both improvements and limitations.

AI functionality tends to focus on the perceptual level, implying that, by contrast, immersive accessibility research has clearly prioritised sensing and recognition mechanisms over pedagogically grounded adaptive mechanisms. In some operationalisation cases, AI was observed in tasks such as translating sign language and conducting behavioural assessments, with some showing partially adaptive mechanisms that can transcend certain contexts. AI-XR reviews point to an emergent, context-specific, performance-based adaptive system, in contrast to the lack of generalised, multimodal, continuous-learning adaptation [39]. General focus on instant successes and overall prototype feasibility yields comments that are highly relevant to the youth of this field, developmentally, given that perceptual AI capabilities have evolved more quickly than their integration into powerful adaptive learning systems. This issue resonates with critics of AI in education research more broadly, who argue against possible but not always sensible, coherent pedagogical uses [40].

Interaction design in all reviewed papers is influenced by disability-related requirements. For instance, in Deaf/Hard-of-Hearing contexts, there is an emphasis on visual and gestural favouritism, while in autism settings, sensory integration is crucial. Some studies epitomise inclusive, gamified, or empathetic design approaches; one study on the contextual creative-skills landscape demonstrates the potential for a wide range of interactive scaffolding. Emphatically, the disability-centeredness of these designs aligns with a long-standing trend in the XR accessibility space: that work from a disability perspective is often masochistic rather than intersectional or applied to construction itself [41]. This is also in line with HCI criticism, which views access to virtual space primarily as the removal of specific barriers, often at the expense of the holistic design of a VR experience, according to [42] and [43]. This enhances inclusivity by leveraging AI-powered assistive technologies, as advocated for by [2].

Evaluative methods vary in complexity across the nine reports. Some use rigorous frameworks and validated assessment instruments. Others rely on system or performance metrics. All research lacks longitudinal data or multiple data collection sites for validation. This finding corroborates the interdisciplinary XR education literature, which identifies inconsistent evaluation metrics and a scarcity

of longitudinal evidence as key challenges to achieving educational effectiveness [44], [45].

The study also elucidated an unresolved gap in any architectural framework capable of integrating, within a single model, AI capabilities, immersive interaction design, accessibility operationalisation, and evaluation mechanisms. While each study may probe module insights such as machine-learning components, adaptive interaction mechanisms, or gamified pedagogical structures, these remain functionally isolated at the architectural level. Consequently, immersive accessibility research currently advances through component innovation rather than through integrated system architectures that support scalable inclusive learning environments. The layered architecture illustrates how the evidence synthesis in Table 5 translates into a complete system model. This is depicted in Figure 3.

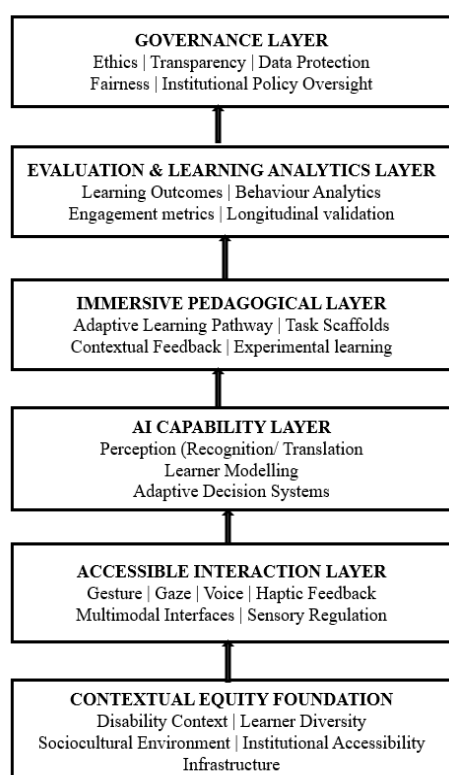


Fig 3. Evidence-informed layered architecture synthesising AI capability, immersive interaction design, accessibility operationalisation, and governance within AI-enhanced immersive educational systems.

A. Intelligent Immersive Accessibility Framework (IIAF)

The preceding synthesis revealed four recurrent structural deficits across the reviewed studies: (1) perceptual-level AI integration without adaptive pedagogical architectures, (2) disability-contingent interaction design needing multimodal accessibility generalisation, (3) inconsistent evaluation maturity across educational implementations, and (4) modular rather than integrated architectural contributions. These structural patterns directly describe the development of the IIAF, depicted in Figure 4. The IIAF functions more

conceptually than prescriptively, primarily serving as an architectural reference system that developers use to create AI-based immersive accessibility environments.

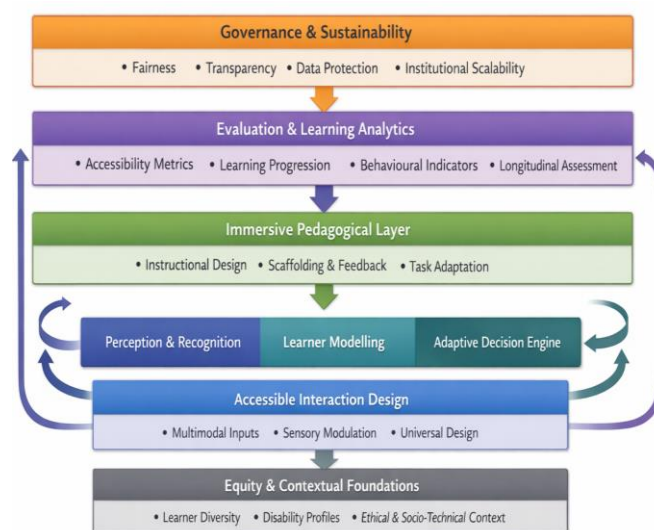


Fig 4. The Intelligent Immersive Accessibility Framework: A layered integrative architecture for AI-enhanced inclusive immersive education.

The IIAF is conceptualised as a tiered architecture that links the underpinnings of contextual equity to governance oversight through interconnected system components. Rather than operating as isolated modules, the framework's subsystems interact through feedback mechanisms, enabling continuous adaptation within immersive learning environments.

- The framework locates immersive accessibility within the wider context of learner diversity, disability profile, sociocultural environments, and institutional limitations. Accessibility is therefore treated as context-sensitive rather than as a fixed set of technical features. By anchoring design in equity-oriented principles, accessibility becomes a systemic property of the learning environment rather than reactive accommodation.
- Building on this base, the Accessible Interaction Interface provides multimodal access utilising gestures, gaze, voice, haptic feedback and adaptive sensory interfaces, with the aim of using Universal Design principles. Instead of relying on interaction solutions designed for people with disabilities, the model generalises these insights into a flexible interaction mechanism that accommodates the needs of diverse learners.
- AI capabilities form an operative layer integrating perception, learner modelling and adaptive decision-making. Perception involves interpreting user behaviour through gesture recognition, behaviour classification, and translation pipelines. Learner modelling captures patterns of engagement, accessibility preferences, and trajectory progression, which together give the system an understanding of an

individual's learning context. The adaptive decision mechanism transforms some of these understandings into instructional adjustments. While current research often stabilises at the perceptual level of AI capability, the IIAF integrates modelling and adaptation much more uniformly into a single operational layer.

- Above this, the immersive pedagogical layer connects AI-generated insights with instructional design through scaffolded task sequencing, contextual feedback, and adaptive pathways for learning. An associated evaluation and learning analytics layer supports performance data, learning progress, behavioural analytics, and long-term validation measures, ensuring the system responds effectively.
- Finally, governance is transitioned across the architecture to maintain fairness, transparency, accountability, and data protection levels; the IIAF matures accessibility through a cohesive system model. Its integration of contextual foundations, interaction design, AI, pedagogy, evaluation, and governance thus moves immersive environments from isolated prototypes toward equitable, scalable learning infrastructures.

B. Traceability to the evidence base and validation status

Each layer of the IIAF traces to specific evidence in Section III rather than standing as an independent conceptual proposal. The Accessible Interaction Interface layer is derived from the disability-contingent design patterns in Table II, generalised from single-disability solutions (e.g., sign-language avatars in [30], [32], [36]; sensory-regulated tasks in [31], [33], [37]) into modality-general requirements. The AI capability layer's three sub-components (perception, learner modelling, adaptive decision-making) map directly onto the AI integration categories in Table I: perception is evidenced by the recognition/classification cluster [30], [33], [36]; the absence of a persisting learner-model component across all nine studies motivates its explicit inclusion as a required, currently unmet, layer; and adaptive decision-making is evidenced only partially by [37] and [38], which is why the framework specifies it as an integration target rather than a demonstrated capability. The Evaluation and Learning Analytics layer responds directly to the inconsistent indicator coverage documented in Section III.D (only [38] combined more than two of the eight evaluation indicators). The Governance layer, which none of the nine studies addresses as a system component, was developed from the accessibility-equity and AI-ethics literature outside the primary evidence base [40], [42], [43] rather than from the included studies themselves, precisely because governance was found to be absent from the evidence base; this asymmetry is intentional and is flagged as such in Table 5's architectural-integration column.

The governance layer specifically operationalises privacy protection for behavioural and physiological data captured by VR/XR sensors (eye-tracking, motion, and biometric signals),

informed consent procedures appropriate to learners who may be minors or have cognitive disabilities, algorithmic bias auditing for perception and classification models trained on non-representative samples, explainability of adaptive decisions to learners, educators, and caregivers, accessibility equity in procurement and deployment (avoiding a two-tier system in which adaptive features are available only on premium hardware), and defined data-retention and security requirements for sensitive learner data. These six governance dimensions are proposed as the layer's minimum content; their empirical prioritisation is left to the validation work below.

Consistent with this traceability exercise, the IIAF should be read as a conceptual, evidence-derived framework mapped against, but not yet empirically validated against, real-world deployment. It has not been tested through expert evaluation, a Delphi study, or design-science evaluation cycles, and it should not be described or cited as a framework demonstrated to be effective. Section V identifies expert panel review and Delphi-based consensus validation, followed by a design-science evaluation in at least one deployed AI-enhanced immersive learning system, as necessary next steps before claims of demonstrated effectiveness are warranted.

C. Implications

Theoretical implications

The findings thus underscore an urgent need to theorise AI+XR access not as an issue related to HCI alone but as a systems-wide problem, whereby accessibility should not be confined to interface compliance but be understood in relation to adaptive interaction, pedagogical alignment, and outcomes equity. This resonates with critical AI-education perspectives that consider the governance of deployment, risks of discrimination, and the socio-technical character thereof [40]. At the same time, it aligns well with responsible AI/human-centred AI in education, which highlights fairness, privacy, agency, and transparency as the core principles of ethical educational AI systems.

Practical implications

Design teams should prioritise (i) multiple interaction styles (eye/ gaze, gesture options, adjustable load), (ii) accessibility requirements tracing across XR components and (iii) evaluation frameworks that align (separating usability/presence metrics from the learning outcome measures and making both results transparently available). To align the presentation of design requirements with the testing of immersive technologies, this paper clearly elaborates the W3C XR Accessibility User Requirements.

Policy implications

To foster an inclusive educational environment, policymakers must adopt a policy that treats AI+XR deployment as learning infrastructure. It should be auxiliary, not secondary, and not just a classroom tool. It will require fairer procurement standards, essentially AI+XR with

disabilities in mind, and enforceable transparency and accountability mechanisms, as well as the enactment of what should be transparent. A global policy race on AI ethics would focus on fairness and the equitable distribution of benefits, without discrimination, while considering disability, biometric sensing, and educational decision-making.

V. CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

This systematic review synthesised nine peer-reviewed studies examining AI-enhanced immersive technologies in accessible education and revealed a field characterised by technical innovation but architectural fragmentation. AI integration is predominantly concentrated at the perceptual layer, with recognition and classification functions more mature than sustained adaptive pedagogical systems. Immersive interaction design is strongly disability-contingent yet lacks a transferable multimodal accessibility architecture. Evaluation practices vary in rigour and rarely include longitudinal validation of learning progression. Overall, these patterns point to a distribution agency in the absence of systemic consolidation. Consequently, this study presented the IIAF, a layered integration model that connects the foundational domains of contextual equity, accessible interaction design, AI capabilities, pedagogical structuring, evaluation mechanisms, and governance oversight within a coherent architectural schema. By synthesising the fragmented contributions into a definitive systems-level design model, this framework moves from modular intervention prototypes, with a technical interventionist view, towards scalable, adaptive, and equity-oriented learning infrastructures. Given the ongoing, enforced convergence of immersive technologies and AI in educational applications, accessibility must also evolve beyond mere interaction mediation to encompass sustained pedagogical intelligence and reflexive design. This study's essential contribution is to consolidate the requisite structural conditions for AI-imbued immersive education.

This study faced several limitations inherent to systematic review methodology and the emerging nature of AI-enhanced immersive accessibility research. Although we applied PRISMA 2020 guidelines and predefined inclusion criteria, the search was limited to peer-reviewed English-language publications indexed in the selected databases; we excluded workshop papers, dissertations, and preprints (Section II.D), which may have omitted early-stage VR/XR work disseminated outside indexed venues. Database selection may introduce indexing bias, as relevant XR accessibility studies published in emerging interdisciplinary venues may not yet be indexed within the selected databases. Most importantly, the inclusion of only nine studies, while a direct consequence of the review's deliberately strict four-criterion intersection (Section II.C), constitutes a genuine limitation on generalisability and carries a risk of selection bias: with so few eligible studies, the synthesis may be disproportionately shaped by the specific disability contexts (Deaf/Hard-of-Hearing and autism) that happened to meet all four criteria,

rather than by the full range of accessibility needs relevant to AI-enhanced immersive education. No included study addressed physical or motor impairment, multi-disability, or intersectional accessibility contexts, and the findings and the IIAF should accordingly be read as characterising the current, narrow evidence base rather than as generalisable claims about AI-enhanced immersive accessibility as a whole. Future investigations are expected to expand adaptive immersive architectures to other impairments and intersectional accessibility contexts, and to revisit this synthesis as the evidence base grows beyond nine studies. Furthermore, evaluation of these systems remains immature: most studies are limited to prototype systems or short-term interventions, and longitudinal, multi-site validation of adaptive immersive learning systems remains scant. Finally, as noted in Section IV.B, the IIAF itself has not yet been empirically validated; future work should prioritise expert-panel or Delphi-based validation of its layers, followed by design-science evaluation within at least one deployed system, before treating its architectural claims as demonstrated rather than proposed.

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