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Integration of Augmented Reality, Virtual Reality, and Artificial Intelligence for Adaptive Human–Machine Interaction: A Structured Review of Architectures, Adaptation Mechanisms, and Application Domains

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ABSTRACT

Augmented reality (AR), virtual reality (VR), and artificial intelligence (AI) have matured as separate technology families, yet their convergence is only beginning to redefine how humans and machines exchange information, intent, and control. Conventional immersive interfaces remain largely static: content layout, interaction modality, and task guidance are fixed at design time and ignore the user's changing cognitive state, skill, and surroundings. This review examines how AI-driven perception, user modelling, and decision-making can be integrated with AR and VR to deliver adaptive human–machine interaction (HMI). A structured narrative review, guided by established systematic-review principles, was used to synthesise foundational and representative studies on sensing, context inference, adaptation policies, rendering, and evaluation. A five-layer reference architecture and a closed-loop adaptation cycle are proposed, and the literature is mapped across adaptation targets, AI techniques, and application domains. The synthesis indicates that gaze, physiological, and interaction-log signals combined with learning-based policies can lower cognitive load and task errors in training, maintenance, and clinical settings, while latency, data scarcity, privacy, and trust remain the principal barriers. Education, industrial maintenance, and healthcare rehabilitation emerge as the most mature domains. The paper closes with a research agenda covering edge-native pipelines, federated personalisation, explainable adaptation, and standardised evaluation protocols.

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KEYWORDS: *Augmented reality, Virtual reality, Artificial intelligence, Adaptive interfaces, Human–machine interaction, Mixed reality, Reinforcement learning, Cognitive load, Edge computing, Explainable AI*

INTRODUCTION

Human–machine interaction (HMI) has progressed from command-line text, through graphical windows and touch screens, towards interfaces that exploit natural human perception and movement. Immersive technologies are central to this progression. Milgram and Kishino described a reality–virtuality continuum spanning the real environment, augmented reality, augmented virtuality, and fully virtual environments [1]. Azuma defined AR by three properties: the combination of real and virtual content, real-time interactivity, and registration in three dimensions [2]. VR, in contrast, replaces the physical surroundings with a synthetic world whose value depends on immersion and the resulting sense of presence [3, 4]. Advances in standalone head-mounted displays, on-device accelerators, and large-scale machine learning have placed these capabilities within reach of industrial and consumer users alike.

Despite rapid hardware progress, most AR and VR applications remain static. Information density, guidance style, and interaction modality are chosen by designers in advance and applied uniformly to every user. This mismatch has measurable consequences. Excessive or poorly timed overlays raise extraneous cognitive load and degrade task performance [5, 6], while inappropriate locomotion, latency, or scene complexity can provoke visual discomfort and simulator sickness [7]. Artificial intelligence offers a remedy: deep learning enables robust perception of gestures, gaze, and scenes [8], whereas reinforcement learning allows an agent to learn adaptation policies from interaction feedback [9, 10]. Adaptive user interfaces that tailor presentation to the individual have already shown benefits on conventional screens [11], but their extension to spatial, multimodal immersive environments is far less mature.

The central problem addressed here is the absence of a unified, evidence-based view of how AR, VR, and AI should be combined to produce interaction that adapts reliably, safely, and transparently to the user. This paper contributes (i) a five-layer reference architecture, (ii) a closed-loop adaptation cycle, (iii) a cross-domain synthesis of adaptation mechanisms and evaluation practice, and (iv) a research agenda. The remainder of the paper reviews the literature, identifies the research gap, states the objectives, describes the review methodology,

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presents results, and discusses engineering significance, limitations, and future scope. Throughout, adaptive HMI is taken to mean interaction in which the system modifies content, modality, or difficulty in response to inferred user state without requiring explicit commands.

LITERATURE REVIEW

Foundations of AR, VR, And Mixed Reality

Billinghurst et al. surveyed more than four decades of AR research and identified tracking, display, interaction, and authoring as the enduring technical pillars, noting that usability rather than registration accuracy increasingly limits adoption [12]. Foundational VR texts emphasise that perceived presence depends on sensory fidelity, low latency, and consistent sensorimotor contingencies [3, 4]. Bowman et al. consolidated three-dimensional interaction techniques for selection, manipulation, and navigation, providing the design vocabulary on which adaptive layers are now built [13]. Bibliometric analysis by Cipresso et al. shows that the AR/VR literature has expanded rapidly across psychology, medicine, engineering, and education, but with limited integration between communities [14].

AI Techniques for Perception and User Modelling

Vision-based hand-gesture recognition has progressed from hand-crafted features to deep networks that operate in real time on head-mounted hardware [15]. Eye tracking supplies a rich implicit signal of attention, intent, and workload [16], and gaze-contingent foveated rendering exploits it to reduce rendering cost without perceptible quality loss [17]. Affective computing extends sensing to physiological and facial cues of emotion and stress [18]. Sequence models based on self-attention have improved multimodal fusion and intent prediction [19]. Context, defined as any information characterising the situation of a user or application, remains the organising concept for deciding what to adapt [20].

Adaptive Interfaces and Human–AI Interaction

Gajos et al. showed that interfaces generated by optimisation against a model of the user's abilities outperformed static designs, particularly for users with motor impairments [11]. In mixed reality, Lindlbauer et al. proposed an optimisation-based system that adjusts the placement and level of detail of virtual content according to estimated cognitive load and task context, reducing perceived load in user studies [21]. Grubert et al. framed this direction as pervasive AR, in which context awareness governs when and where information appears [22].

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Human-centred principles are equally important: Amershi et al. published guidelines that stress predictability, correctability, and clear communication of system behaviour [23], and Lee and See demonstrated that user reliance depends on calibrated trust [24]. Holzinger argued that keeping the human in the learning loop improves both accuracy and acceptance [25].

Evaluation and Design Standards

Evaluation practice in immersive HMI relies on a small set of validated instruments. NASA-TLX quantifies multidimensional workload [6], the System Usability Scale provides a brief global usability score [26], presence questionnaires capture subjective immersion [27], and the Simulator Sickness Questionnaire records discomfort [7]. Technology acceptance models explain adoption intentions [28]. Although each instrument is well established, adaptive systems add new requirements, such as measuring the stability of adaptation, the accuracy of inferred state, and the user's perceived control, for which no consensus protocol exists.

Application-Domain Evidence

Radianti et al. reviewed immersive VR in higher education and found positive effects on engagement, although learning gains depended heavily on instructional design [29]. Makransky et al. reported that added immersion increased presence yet reduced learning when it overloaded learners, a finding that supports adaptive control of immersion [30]. Palmarini et al. found that AR maintenance support is concentrated on assembly and inspection tasks, with limited use of intelligent personalisation [31]. Dwivedi et al. outlined opportunities and risks of persistent shared virtual worlds, including privacy, safety, and governance concerns [32].

RESEARCH GAP

The reviewed work reveals four gaps. First, perception, adaptation, and rendering are usually studied in isolation, and no widely accepted reference architecture links them end to end. Second, adaptation policies are mostly rule-based or evaluated in short laboratory sessions with small samples, leaving long-term personalisation and generalisation unproven. Third, evaluation is fragmented: studies employ different workload, usability, presence, and comfort instruments, preventing quantitative comparison [6, 26, 27]. Fourth, privacy, trust, and latency constraints, which are decisive for deployment, are rarely treated as first-class design requirements. This review addresses these gaps through a unifying architecture, a comparative synthesis, and an explicit agenda.

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OBJECTIVES

- To propose a layered reference architecture integrating AR, VR, and AI for adaptive HMI.
- To classify adaptation targets, input signals, and AI techniques reported in the literature.
- To synthesise evidence on performance, workload, usability, and comfort outcomes across application domains.
- To identify technical, ethical, and organisational barriers to deployment.
- To formulate a prioritised research agenda for adaptive immersive systems.

METHODOLOGY

Review Design and Scope

This is a review-based study employing a structured narrative synthesis. The design follows the planning, conduct, and reporting stages recommended for software-engineering reviews [33] and adopts the transparency principles of the PRISMA 2020 statement [34]. The review question was: how can AI-driven perception and decision-making be integrated with AR and VR so that interaction adapts to the user, and what evidence supports its effectiveness? Scope covers head-mounted and handheld AR, tethered and standalone VR, and AI methods used for sensing, inference, and adaptation. Purely non-immersive adaptive interfaces were considered only as conceptual precedents.

Selection Criteria and Analytical Framework

Representative sources were drawn from peer-reviewed journals, conference proceedings, and authoritative textbooks indexed in major engineering and computing databases. Works were retained when they addressed at least one of the following: immersive display or interaction fundamentals, AI-based perception or user modelling, adaptation of immersive content or behaviour, or empirical evaluation with human participants. Each retained work was coded against five analytical dimensions: sensing modality, inference method, adaptation target, evaluation instrument, and application domain. Table 1 summarises the technical components that formed the coding scheme.

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Table 1. Technical Components of an Adaptive AR/VR–AI System

Component	Function	Typical Techniques	Key Challenge
Sensing	Capture user and scene state	Eye/hand tracking, EEG, HRV, depth SLAM [16]	Noise, calibration drift
Perception	Recognise gestures, gaze, intent	CNNs, transformers [8, 19]	Real-time inference on-device
User model	Store skill, preference, workload	Bayesian, learned embeddings [11]	Cold start, data scarcity
Adaptation policy	Select content and modality	Rules, optimisation, RL [9, 21]	Stability, explainability
Rendering	Present AR/VR output	Foveated, multimodal [17]	Latency, thermal limits

Evaluation Constructs

Outcomes were organised under five constructs: task performance (time and errors), cognitive workload measured by NASA-TLX [6], usability measured by the System Usability Scale [26], presence measured by presence questionnaires [27], and comfort measured by the Simulator Sickness Questionnaire [7]. Technology acceptance [28] and trust [24] were recorded where reported. Findings were compared narratively because heterogeneity of designs precluded statistical meta-analysis.

RESULTS AND FINDINGS

Proposed Reference Architecture

Figure 1 presents the five-layer architecture derived from the coding exercise. The sensing layer gathers eye, head, hand, physiological, voice, and environmental data. The perception layer converts raw streams into estimates of attention, workload, and intent. The adaptation engine combines a persistent user model with a policy that may be rule-based, optimisation-based, or learned. The rendering layer realises the decision as AR overlays, VR scene changes, or multimodal feedback, and the application layer defines task goals. Cross-cutting services for edge–cloud computation, privacy, latency, trust, and evaluation span all layers, and user response flows back as feedback.

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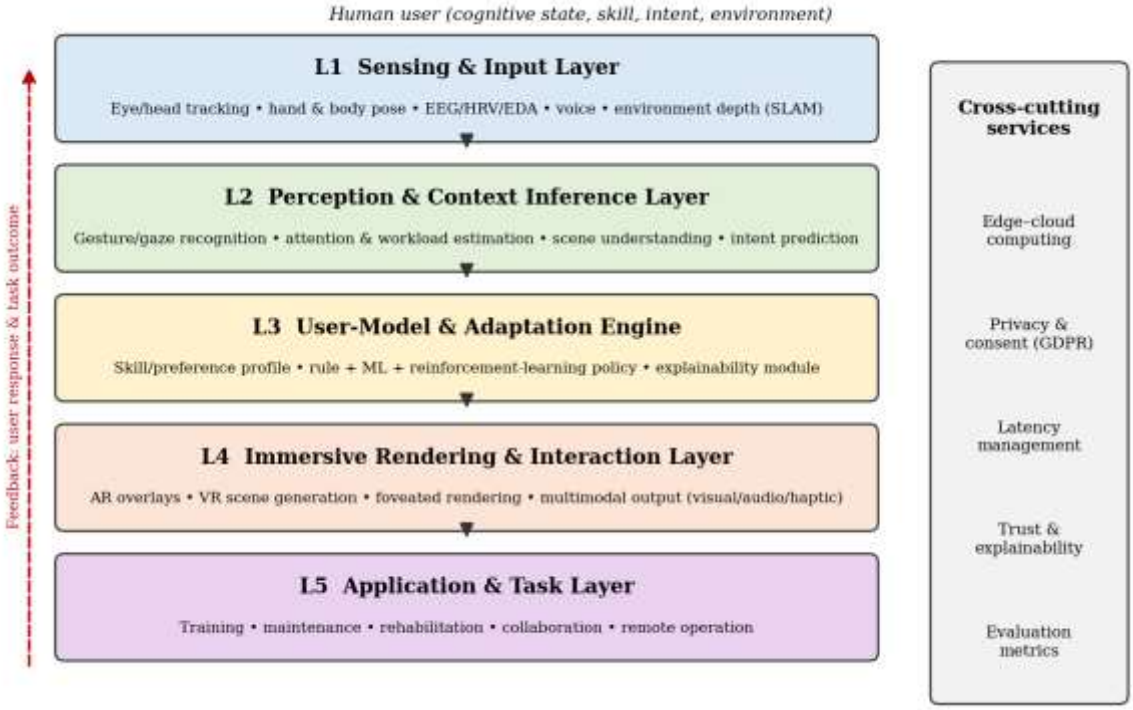


Figure 1. Five-layer reference architecture for adaptive AR/VR–AI human–machine interaction with cross-cutting services and a feedback path

Adaptation Mechanisms

Figure 2 shows the closed-loop cycle that underlies the reviewed systems: sense, infer, decide, adapt, and evaluate. Table 2 classifies the principal adaptation targets. Content adaptation, such as repositioning or decluttering annotations according to estimated load, is the most frequently reported interface-level adaptation and has moderate supporting evidence [21, 22]. Difficulty and pacing adaptation, usually implemented with reinforcement learning, dominates training and rehabilitation [9, 10]. Modality adaptation, which switches among visual, auditory, and haptic channels, and comfort adaptation, which modifies locomotion or field of view, are comparatively under-explored.

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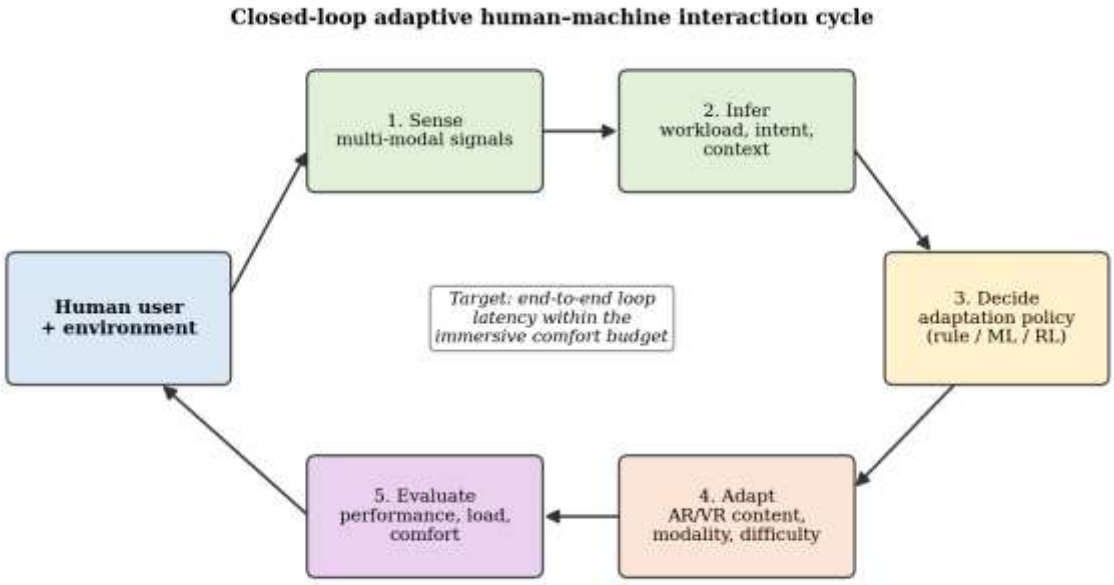


Figure 2. Closed-loop adaptation cycle linking sensing, inference, decision, adaptation, and evaluation

Table 2. Classification of Adaptation Targets in the Reviewed Literature

Adaptation Target	AI Technique	Input Signals	Evidence Strength	Typical Benefit
Content layout and detail	Optimisation, rules [21]	Gaze, task state	Moderate	Lower load
Difficulty and pacing	Reinforcement learning [9]	Performance logs	Moderate	Better learning
Modality and guidance	Classifiers [15]	Gesture, voice	Limited	Fewer errors
Comfort and locomotion	Threshold or learned models [7]	Head motion, HRV	Limited	Less sickness
Rendering resources	Gaze prediction [17]	Eye tracking	Strong	Lower compute

Domain-Wise Synthesis

Table 3 and Figure 3 summarise the domains. Education and industrial maintenance show the most mature evidence, driven by structured tasks that permit measurable outcomes [29, 31]. Healthcare rehabilitation benefits from adaptive difficulty and gamification, although regulatory validation lags [35]. Collaborative metaverse applications exhibit the lowest

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adaptation maturity because social context is difficult to model and carries heightened privacy risk [32]. The ratings in Figure 3 are ordinal judgements assigned by the authors from the coded literature and are not measured quantities.

Table 3. Domain-Wise Assessment of Adaptive AR/VR–AI Interaction

Domain	AR Role	VR Role	AI Role	Maturity	Main Barrier
Education	Visual annotation	Immersive labs [36]	Learner modelling	High	Instructional design
Maintenance	Step guidance	Remote rehearsal	Task recognition	High	Tracking robustness
Healthcare	Image overlay	Rehabilitation	Adaptive difficulty	Medium	Clinical validation
Collaboration	Shared overlays	Virtual spaces	Avatar and intent	Low	Privacy, trust
Automotive	Head-up display	Simulation	Driver state	Medium	Safety certification

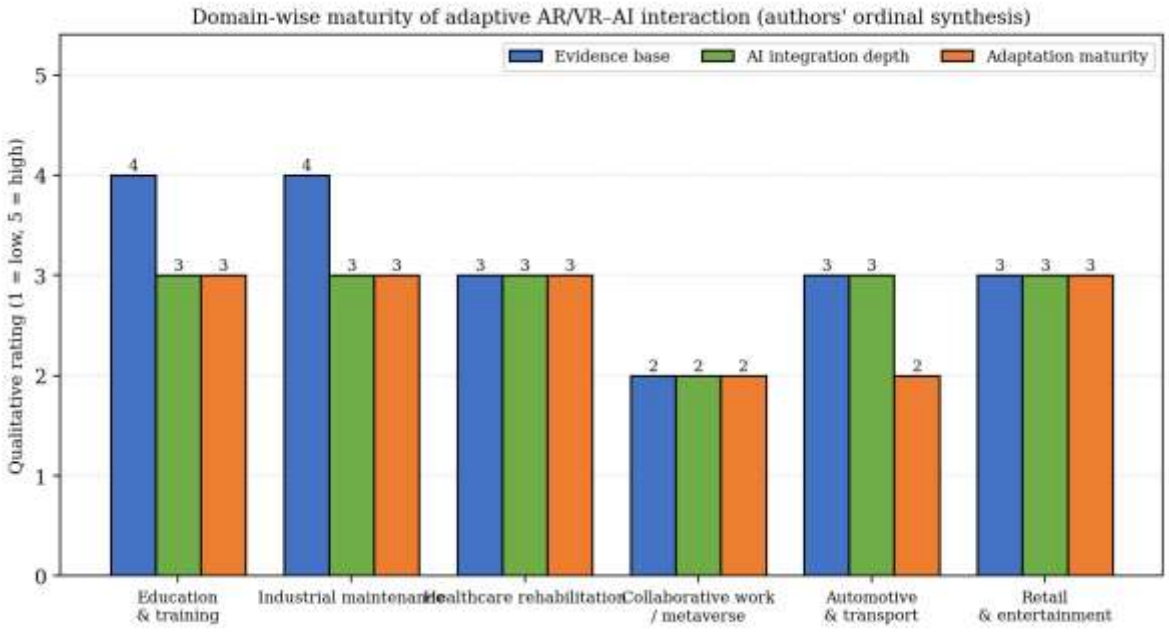


Figure 3. Qualitative maturity ratings (1–5) of adaptive AR/VR–AI interaction by application domain

Evaluation Findings

Reported studies most often measure task time, error rate, NASA-TLX, and SUS, while presence and comfort are less consistently recorded [6, 26, 27]. Adaptive conditions are

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generally reported to reduce perceived workload and improve usability relative to static baselines, but sample sizes are small, sessions are short, and effect sizes are seldom reported. Two cautions recur. Immersion that exceeds the learner's capacity can impair learning [30], and increased immersion does not always improve outcomes [36]. Adaptive control of immersion therefore appears more valuable than maximal immersion.

Barriers to Deployment

Four barriers recur across the reviewed domains. Latency and thermal limits on standalone headsets constrain on-device inference, which favours compact models and aggressive quantisation [17, 37]. Training data for individual users are scarce, producing cold-start problems for user models and motivating transfer learning and population priors [11]. Privacy exposure is acute because eye movements and physiological traces can reveal health status, attention, and identity [38]. Finally, opaque adaptation erodes trust and may induce over-reliance or rejection [24]. These barriers are interdependent: stronger privacy protection through local processing increases on-device computational demand, while richer personalisation increases data sensitivity.

DISCUSSION

The synthesis supports the view that adaptivity should be treated as a system property rather than a feature. A policy cannot outperform the signals that feed it, and signals cannot help if rendering latency breaks the sensorimotor loop. Recommended motion-to-photon delays for comfortable VR are commonly cited at around 20 ms [39], so the sense–infer–decide–adapt cycle must be partitioned carefully. Latency-critical steps such as tracking and foveation belong on-device, while heavier user-model updates can run at the edge or in the cloud [37]. This partitioning is the principal engineering significance of the proposed architecture.

Practical applications follow directly. In industrial maintenance, an adaptive AR assistant can shorten guidance for experienced technicians and expand it for novices. In surgical and rehabilitation training, difficulty can track performance to keep learners within an effective challenge zone. In education, adaptive immersion can protect working memory by limiting extraneous detail [5, 30]. In collaborative work, intent-aware avatars and context-sensitive notifications can reduce interruption. Each scenario depends on trustworthy behaviour: users must understand why the interface changed and be able to override it [23, 24].

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From a scientific perspective, adaptive immersive HMI sits at the intersection of cognitive psychology, control theory, and machine learning. The closed-loop cycle resembles a feedback controller whose plant is the human operator; stability, response time, and disturbance rejection therefore become meaningful design criteria. Oscillating adaptation, in which the interface changes faster than the user can follow, is a failure mode analogous to controller instability, and policies should include hysteresis and minimum dwell times. Responsible deployment adds further requirements. Gaze, physiological, and movement traces are sensitive personal data, so purpose limitation, minimisation, and consent obligations of data-protection law apply [38]. Federated learning, which trains shared models without centralising raw data, offers a promising route to personalisation under such constraints [40]. Finally, standardised reporting of workload, usability, presence, and comfort would allow results from different laboratories to be pooled, converting a fragmented literature into cumulative evidence.

LIMITATIONS

- The review is narrative and purposive; it does not claim exhaustive coverage, and selection bias toward widely cited works is possible.
- Heterogeneous designs, populations, and instruments precluded meta-analysis, so effect directions rather than pooled magnitudes are reported.
- Domain maturity ratings in Figure 3 are ordinal judgements by the authors and have not been validated by independent raters.
- Rapid hardware and model progress means recent developments, including generative scene synthesis, may be under-represented.

FUTURE SCOPE

- Longitudinal field studies with diverse participants to test whether learned adaptation policies generalise beyond laboratory sessions.
- Edge-native and on-device inference pipelines that keep the full adaptation loop within comfort-level latency budgets.
- Federated and privacy-preserving personalisation of user models using gaze and physiological data [40].
- Explainable and user-overridable adaptation with calibrated trust measures [23, 24].
- Generative scene synthesis, such as neural radiance fields, for on-demand adaptive virtual content [41], together with shared open benchmarks and reporting standards.

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CONCLUSION

Integrating AR, VR, and AI can transform immersive interfaces from fixed presentations into closed-loop systems that respond to the user. This review proposed a five-layer reference architecture and an adaptation cycle, classified adaptation targets, and synthesised evidence across six domains. Adaptive content, pacing, and rendering show the most consistent support, and education and industrial maintenance are the most mature domains. Realising the potential at scale requires low-latency edge–device partitioning, privacy-preserving personalisation, transparent and controllable behaviour, and standardised evaluation. Addressing these priorities will move adaptive human–machine interaction from promising prototypes to dependable engineering practice.

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