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Designing a Human-Centric Immersive AI Classroom for Adaptive Personalised Learning

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Abstract. This position paper presents an adaptive XR work environment as a human–AI collaborative system for cognitive task execution within emerging human-centred socio-technical paradigms (e.g., Education 5.0 and Industry 5.0). The platform integrates AI-driven adaptive dialogue and personalised task structuring, supported by real-time neurofeedback, to enable dynamic task performance in immersive settings. The system also explores the integration of portable XR devices, brain–computer interface (BCI) concepts, and multimodal AI systems as a forward-looking form-factor for next-generation "smart glasses" technologies, aiming to investigate how such systems may reshape future education and industrial work environments. Rather than assuming adaptive support is inherently beneficial, the system is framed as a socio-technical intervention that may enhance performance while also reshaping autonomy, coordination, transparency, and user well-being within human–AI work systems. From a Human Work Interaction Design (HWID) perspective, cognitive work is distributed between humans and AI, with XR acting as an embodied interaction layer. Adaptation is examined not only as a workload-reduction mechanism, but also as a force that redistributes control and reorganises work relations, influencing trust and human agency. Educational settings are used as a controlled testbed for observing work-like behaviour in structured cognitive tasks, enabling ecologically valid capture of multimodal data (e.g., interaction behaviour, task performance, and neurofeedback signals) to analyse human–system workload and adaptive interaction dynamics under authentic learning conditions.

Keywords: Adaptive XR Systems, Human–AI Collaboration, Industry 5.0, Human Work Interaction Design, Socio-Technical Systems, Cognitive Work, Work Augmentation, Immersive Learning, Immersive AI, AI Tutors, Neurofeedback, Human–Computer Interaction

1 Introduction

Immersive technologies, including Virtual, Augmented, and Mixed Reality (XR), enable interactive, spatially rich environments that extend beyond the limitations of traditional 2D systems. By supporting embodied interaction and dynamic manipulation of scale, XR allows users to explore complex three-dimensional information and perform cognitive tasks that are difficult to achieve with conventional interfaces [1,2]. XR is particularly important for simulating future smart glasses experiences, maintaining continuous connection between digital content and the physical environment in everyday contexts.

In this paper, work is defined as structured cognitive problem-solving within an immersive XR environment, involving perception, reasoning, and decision-making in response to spatial and conceptual tasks. This includes interpreting 3D structures, identifying relationships between entities, and completing goal-directed knowledge tasks within a controlled XR system. In emerging Industry 5.0 contexts, such cognitive work is increasingly performed within human–AI collaborative systems. In this study, the work system consists of a human user and a conversational AI embedded within the XR environment. The AI acts as an adaptive cognitive partner that provides guidance, feedback, and instructional scaffolding, while the user remains the primary decision-maker and executor of task actions. Within this configuration, work is dynamically distributed between the human and the AI. The AI structures information, generates explanations, offers recommendations, and adapts support based on user state. The human performs perception, interpretation, spatial reasoning, and final decision-making, including the acceptance or rejection of AI-generated input, forming a continuous interaction loop of co-adaptation. In addition, personalisation is a necessary factor in developing inclusive and adaptive e-learning systems and pedagogical models. This includes the need for longitudinal studies on their efficacy, exploring sensory overload and accessibility barriers, and evaluating the effectiveness of generative AI and immersive technologies [3].

From a HWID perspective, the system represents a socio-technical work environment in which cognition is distributed across human–AI interaction [4]. Interaction design therefore functions as a mechanism for task allocation, coordination, and cognitive regulation within an embodied workspace. This arrangement reshapes responsibility, control, autonomy, and coordination. Responsibility remains primarily with the human user, while control is partially mediated by the AI through adaptive feedback. Autonomy becomes dynamically negotiated, as AI interventions shape the decision space while users retain final authority. Coordination emerges through continuous bidirectional adaptation between user behaviour and AI responses. This research reframes educational XR environments as controlled testbeds for studying human–AI collaboration. While implemented in learning contexts, the approach is intended as a transferable framework for Industry 5.0 environments, where collaboration involves dynamic task allocation, shared decision-making, and continuous co-adaptation. Rather than assuming adaptive support is inherently beneficial, this work examines adaptation as a socio-technical intervention that may both enhance performance and reshape autonomy, control, and transparency in human–AI work systems.

2 Background

Industry 5.0 and Education 5.0 both emphasise close collaboration between humans and advanced technologies, such as spatial computing and adaptive AI systems, to enhance cognitive performance, productivity, and decision-making processes. Within educational contexts, these paradigms describe the integration of such technologies into teaching and learning activities to support more adaptive, personalised, and human-centred experiences [5]. In this framing, educational environments increasingly serve as experimental spaces where human–AI collaborative systems and pedagogical approaches can be explored and refined before potential transfer to Industry 5.0 applications. Consequently, digital and intelligent technologies are becoming central to contemporary education, making the identification of fundamental requirements for effective learning an increasingly important research focus. Foundational learning theories, particularly Experiential Learning Theory (ELT), conceptualise learning as a cyclical process involving concrete experience, reflective observation, abstract conceptualisation, and active experimentation. Kolb and Kolb [6] further introduced the concept of learning spaces, highlighting that learning is shaped not only by individual cognitive processes but also by social, institutional, and psychological contexts. These environments can either support or constrain experiential learning depending on how they are structured and enacted. This section systematically examines existing literature to identify key factors that support effective learning, with particular emphasis on presence, immersion, and enabling technologies. It aims to identify current research gaps and inform the formulation of the study's research questions. In addition, it considers learning from a human-centred perspective in traditional educational settings, focusing on how learners engage with and process information in non-immersive environments. By integrating findings from traditional learning research and technology-enhanced learning, the review supports a more comprehensive understanding of learning processes and clarifies the role of immersive and adaptive technologies in future educational systems. In this context, educational environments are increasingly viewed as validation environments for human–AI collaboration approaches prior to their deployment in Industry 5.0 settings.

2.1 Human Nature of Learning

Learning can be defined as a change in cognitive structures that occurs as a result of experience. Learners who possess greater prior knowledge are often better equipped to acquire new information, as existing knowledge provides a foundation for integrating new concepts [7]. Importantly, learning is not a passive process but an active one in which learners interact with and adapt to their environment. Research has shown that learners actively construct understanding through experience, emphasising the dynamic and constructive nature of learning [8].

Motivation also plays a critical role in effective learning. Prior studies highlight that motivation and existing knowledge significantly influence cognitive engagement and deeper learning processes [9]. From this viewpoint, learning is not simply the accumulation of information but a continuous process of reorganising and integrating knowledge into increasingly complex cognitive structures. Educational technologies have the potential to support this process by providing interactive and adaptive learning environments. Cognitive load theory further explains how the limited capacity of working memory affects learning efficiency [10]. When instructional materials impose excessive cognitive demands, learning can be impaired; however, well-designed instructional strategies can reduce unnecessary cognitive load and improve learning outcomes. These factors are even more important in immersive environments, where instructions and tasks can be presented in three-dimensional space. Feedback and reinforcement are also essential components of learning. A large-scale meta-analysis demonstrated that effective feedback is one of the most powerful influences on student achievement [11]. Feedback is most effective when it is timely, specific, and focused on task performance, learning processes, or self-regulation rather than on the individual. Based on these findings, the present research aims to investigate how an AI tutor can provide real-time, adaptive feedback aligned with learners' cognitive states and spatial interaction to enhance learning outcomes in XR environments. While learning theories traditionally focus on cognitive change, motivation, and feedback processes [9, 10, 11], HWID extends this perspective by framing learning as situated cognitive work embedded within sociotechnical systems [12]. From this perspective, the XR classroom can be analysed as a work domain in which learners, AI tutors, immersive tools, and neurofeedback mechanisms form an integrated work system. Rather than treating adaptive functionality as a feature of user interface optimisation, real-time adaptivity becomes a work interaction problem: how cognitive tasks, responsibilities, feedback loops, and decision-making authority are dynamically distributed between human actors and intelligent systems. This shift in framing foregrounds issues of agency, transparency, trust, and role reconfiguration, which are central to sociotechnical design. Consequently, the proposed adaptive XR classroom is conceptualised not merely as a performance-enhancing technology but as a reconfiguration of educational work practices in which cognition is distributed across human and artificial agents.

2.2 Technological Foundations of Immersive Adaptive Learning

Understanding XR-based adaptive learning systems requires clarifying the underlying technological concepts, trends, and limitations of their individual components. Spatial computing, as one of the foundational core technologies of the future Metaverse, represents a broad class of immersive technologies and can be defined as an emerging three-dimensional computing paradigm that integrates artificial intelligence, computer vision, extended reality, and sensor-based perception to merge digital content with the physical world. Under this umbrella (see Fig. 1), XR includes VR, which provides a fully immersive and closed virtual environment; MR, which overlays digital content onto the physical environment and is primarily designed for head-mounted displays; and AR, which similarly overlays digital information onto the real world, typically via mobile devices such as smartphones or tablets. Recent research suggests that the integration of spatial computing and artificial intelligence can enhance educational experiences. For example, Thanyadit et al. demonstrated that AI-driven XR avatars can improve student engagement and attention during learning tasks by guiding focus and enabling more responsive instructional feedback [14]. These findings highlight the potential of XR–AI systems to support more personalised and adaptive learning environments.

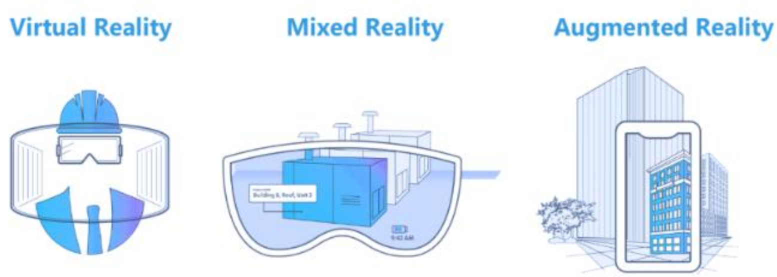

Fig. 1. Extended Reality and its sub-technologies, Source: Adapted from [15]

As a subdomain of spatial computing, VR applications have been widely adopted in the gaming industry. More recently, this landscape has begun to shift towards industrial training and higher education contexts. Universities and companies that adopt XR technologies at an early stage may gain strategic advantages by enhancing learning effectiveness, skill development, and experiential training capabilities [16]. Prior research has shown that VR can positively influence student engagement in higher education. For example, İbrahim and Murat reported that the integration of VR-based learning environments led to significantly higher levels of student engagement compared to traditional instructional methods [17]. Conventional lecture-based approaches often struggle to sustain attention, which can result in disengagement and reduced learning outcomes. In contrast, VR's immersive and interactive characteristics enable experiential learning by situating students within virtual environments that support active exploration and sustained focus.

A recent systematic review by Huang and Tseng further highlights the potential of MR for highly interactive learning scenarios, such as mechanical assembly simulations in engineering education, where learners manipulate virtual models to explore real-world processes [2]. However, the authors note that such applications remain relatively underexplored in educational research. They also argue that integrating artificial intelligence into XR systems could address current limitations, including restricted feedback mechanisms and scalability, by enabling more collaborative, personalised, and data-driven learning experiences. These findings provide a strong foundation for the present research.

2.3 Learning as Coordinated Work in Adaptive XR Environments

Emerging research highlights that immersive technologies reshape how collaboration and cognitive work unfold in learning environments. The Theory of Immersive Collaborative Learning (TICOL) proposes that XR-mediated interactions support unique psychological and social processes such as social presence, physical embodiment, and agency that significantly influence cognitive and socio-emotional interaction patterns during collaborative tasks in immersive settings [18]. In the adaptive XR classroom, the work domain involves learners, teachers, AI tutors, and immersive artefacts, interacting within a shared simulated space. Learning tasks such as knowledge construction, problem-solving, reflection, and attention regulation are distributed across actors and technology, forming a socio-technical work system rather than isolated cognitive processes. This aligns with collaborative learning frameworks that emphasise shared activity and coordinated meaning-making in technology-enhanced environments [18]. Roles within this system are dynamically reconfigured: learners act as primary epistemic agents, teachers guide and scaffold learning, and AI tutors provide adaptive real-time support. Coordination is achieved through feedback loops that link cognitive states with pedagogical interventions, conversational scaffolding, and environmental modulation (e.g., visual complexity, task pacing). These mechanisms support collaboration without undermining learner agency, directly reflecting the collaborative and embodied affordances identified by TICOL.

2.4 Human–AI Collaboration as Work

In the proposed adaptive XR classroom, Human–AI collaboration is conceptualised as participation in a shared work practice rather than as a functional interface interaction. Teaching and learning are treated as situated work activities embedded within social, institutional, and technological contexts, rather than isolated cognitive tasks [9, 10, 11]. From this viewpoint, learners and AI tutors operate as co-participants in a socio-technical work system, in which tasks, responsibilities, and decision-making processes are dynamically distributed.

The AI tutor augments human practice through real-time adaptive feedback, multimodal interaction, and context-sensitive task orchestration, supporting cognitive work rather than merely optimising interface performance. Adaptivity becomes a mechanism for regulating workload, attention allocation, and task sequencing in collaboration with human learners [25]. As such, the system mediates the distribution of cognitive and pedagogical work, influencing how learners construct knowledge, reflect, and act. This socio-technical interplay reshapes traditional educational roles: learners become active agents within a distributed cognitive system, while AI functions as an adaptive mediating artefact, supporting decision-making, task selection and learning [26]. Authority, responsibility, and agency are thus no longer concentrated solely in the human instructor or the technology but are distributed across human and artificial actors. Framing Human–AI interaction as work foregrounds design concerns such as transparency, trust, ethical adaptive authority, and the preservation of learner agency, aligning the XR classroom with human-centred principles of Industry 5.0.

2.5 Neuro-Adaptive Immersive Environments

Research on adaptive and immersive educational technologies has increasingly examined how intelligent systems can personalise learning in spatial environments. For example, Weerasinghe et al. found that adaptive guidance in an AR language learning system improved learner efficiency and engagement compared to fixed instructional strategies, indicating the pedagogical potential of adaptive instructional agents in XR contexts [27]. In terms of neurofeedback in immersive systems, a pilot study comparing VR-based and traditional neurofeedback demonstrated that VR-based feedback can engage EEG activity patterns associated with emotional regulation, suggesting that immersive neurofeedback may support real-time cognitive state monitoring [28]. More recently, studies integrating EEG biofeedback into VR learning environments have reported improved engagement and proficiency outcomes relative to conventional instruction, highlighting the promise of combining neurophysiological data with immersive adaptive systems [29].

Studies in adaptive immersive environments demonstrate the potential of integrating AI-driven conversational agents and neurofeedback mechanisms within immersive learning contexts. For example, Zhuo et al. [30] combined AR/VR environments with an AI virtual assistant and EEG-based engagement monitoring, showing significantly improved learning outcomes in programming education compared with AR-only and paper-based conditions. Similarly, a large-scale mixed-method study by Hmoud et al. [31], involving 888 high school students, found that AI-enhanced XR environments outperformed traditional, AI-only, and XR-only approaches across cognitive, behavioral, emotional, and social engagement measures.

A growing body of research has evaluated how XR, VR, and AI influence student learning outcomes, engagement, and cognitive processes. Many studies have employed pre- and post-test designs, engagement metrics, and multimodal behavioural or physiological measures similar to the design of the proposed methodology. Experimental studies in immersive environments frequently use quantitative pre- and post-test assessments to measure knowledge gain, which aligns closely with the proposed primary dependent variable in this project: knowledge retention. For example, research on VR-based physics education employed a pre- and post-test design to compare knowledge gains in VR versus traditional slideshow conditions, finding improvements in both and highlighting the utility of immersive environments in assessing learning outcomes [32]. Similarly, a randomized controlled trial demonstrated that college students using a carefully designed AI tutor achieved significantly higher learning gains and engagement than those participating in in-class active learning. The AI tutor, implemented with structured prompts and instructional scaffolding, enabled students to learn more effectively in less time while also reporting increased motivation and engagement [33].

In a comparative study examining XR and desktop modalities for teaching artificial intelligence concepts, Feijoo-Garcia et al. [34] found that participants in the XR condition reported significantly greater engagement, immersion, and satisfaction than those in a traditional desktop environment. However, despite higher engagement and positive user experience metrics, the XR group did not show superior performance on in-lesson comprehension assessments compared with the desktop group. This suggests that while XR technologies can enhance motivational and experiential aspects of learning, these gains do not always directly translate into measurable improvements in knowledge acquisition. These findings suggest that adaptive immersive environments provide synergistic benefits by integrating immersion, AI-driven intelligence, and learner-state awareness derived from pre- and post-quiz performance, highlighting the need for further research into real-time adaptive mechanisms in XR-based education.

3 Identified Research Gap

While prior studies have demonstrated the potential of XR environments and AI tutors to enhance learner engagement and learning outcomes, much of the existing research [26, 31, 33] has focused on static instructional designs or AI interventions that respond only to general user interactions or pre-defined scenarios. In many cases, adaptivity is limited to content sequencing or rule-based feedback, without accounting for learners' moment-to-moment cognitive states during immersive learning activities. As a result, current XR learning systems often lack the responsiveness required to address fluctuations in attention, engagement, and cognitive load as learning unfolds. Despite growing interest in XR and AI-supported learning, several critical gaps remain:

- Most XR learning systems rely on static instructional designs or rule-based AI responses, with adaptation restricted to content sequencing rather than moment-to-moment cognitive states.
- Existing AI tutors typically respond to user interaction patterns or predefined triggers, without incorporating real-time neurophysiological indicators of attention, engagement, or cognitive load during immersive learning.
- Few systems combine pre-session knowledge assessment with continuous cognitive-state monitoring to enable dual-layer personalisation.
- Current research rarely evaluates adaptive XR systems against both XR-only environments, and XR with non-neuroadaptive AI support within a single controlled experimental framework.
- There is little empirical evidence examining how real-time physiological data reshapes the distribution of cognitive work between learner and AI tutor.

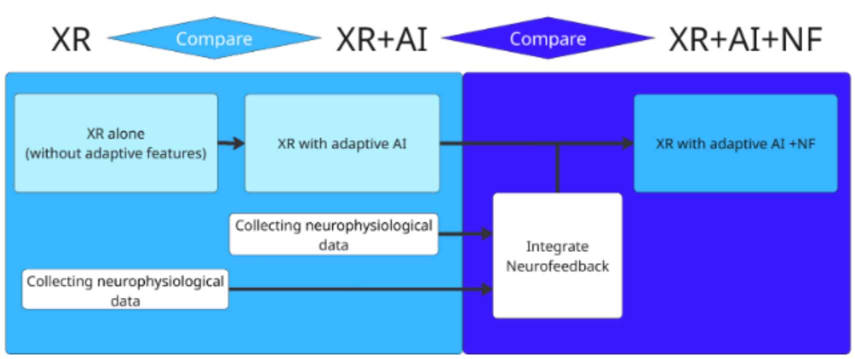

Fig. 2. Proposed comparable XR studies across 3 cohorts

This leads to the following research questions:

- **RQ1:** Does the inclusion of an AI tutor in XR learning affect cognitive load, engagement, and learner agency compared to traditional XR instruction?

- **RQ2:** Does the addition of real-time neurofeedback to an AI tutor enable inclusive human centered learning and autonomy compared to non-neuroadaptive AI support

- **RQ3:** How does the distribution of cognitive work between learner and AI differ across traditional XR, AI-supported XR, and neuroadaptive XR conditions?

The research questions are addressed through the combined system design and evaluation framework of the adaptive XR classroom. Each RQ is operationalised through specific system components and corresponding data collection and analysis methods.

RQ1 (impact on learning outcomes) is addressed through pre- and post-test knowledge gain comparisons across the three experimental conditions (XR, XR-AI, XR-AI-NF), analysed using ANOVA and post-hoc tests.

RQ2 (role of adaptive AI and neurofeedback) is addressed through EEG-derived engagement metrics, interaction logs, and neurophysiological indicators, which are analysed using correlation and regression methods to examine relationships with learning performance.

RQ3 (human–AI interaction dynamics within HWID framing) is addressed through analysis of AI interaction logs and learner behaviour patterns, interpreted within the HWID framework to understand coordination between learners and AI tutors.

3.1 Design Principles for Human-Centric Adaptive XR environments

This section focuses on placing learners' needs, behaviours, and comfort at the centre of the technological experience, rather than allowing technology to dictate pedagogy. The proposed research does not merely test and measure each setting; its intent is to generate design knowledge that can inform the development of future XR classrooms. The following principles are intended to guide the development of adaptive XR environments that integrate AI tutors and real-time cognitive feedback:

Principle 1: Integration of Prior Knowledge [35]

Adaptive interventions should be informed by pre-session assessments to identify each learner's existing knowledge gaps. This allows AI tutors to provide targeted explanations, scaffold tasks effectively, and prevent redundancy or cognitive overload.

Principle 2: Cognitive-State Awareness [36]

Learning systems should continuously monitor learners' engagement and cognitive load, using real-time neurophysiological data where appropriate. Adaptations to content, pacing, and scaffolding should be responsive to fluctuations in attention and focus, supporting sustained engagement and optimal learning outcomes.

Principle 3: Learner Agency and Control [37]

Learners should retain the ability to override or adjust AI-driven adaptations. Preserving autonomy and choice ensures that adaptive systems support, rather than constrain, learners' decision-making and fosters trust in AI-mediated interactions.

These principles collectively aim to create immersive, human-centred XR classrooms where AI tutors act as supportive collaborators, rather than prescriptive instructors, enabling adaptive, engaging, and ethically responsible learning experiences.

4 Proposed Methodology

4.1 Study design

The adaptive XR classroom system used in this study has been developed as a prototype and is currently undergoing preparation for experimental environment. Data collection is planned to commence in a subsequent study phase, enabling the evaluation of the system under controlled experimental conditions. This study aims to support cognitive work in human–AI collaborative and immersive environments aligned with Industry 5.0 principles. A quantitative, between-subjects experimental design will be employed, comparing three learning conditions to examine the incremental contributions of AI support and neurofeedback:

- XR-only instruction
- XR with an AI-enhanced tutor (XR-AI)
- XR with an AI tutor augmented by real-time neurofeedback (XR-AI-NF)

The primary outcome is knowledge retention, operationalised as the difference between pre-test and post-test scores. Secondary outcomes include engagement, cognitive load, and interaction behaviour, measured through neurophysiological indices (e.g., Engagement Index) and user experience questionnaires.

In the XR-AI-NF condition, engagement and cognitive state signals are used to drive real-time system adaptation, enabling dynamic modulation of instructional support when user engagement or cognitive state falls below predefined thresholds. This allows evaluation of how progressively adaptive human–AI interaction influences both task performance and user experience across different levels of system autonomy and support.

4.2 Learning as Work in The Adaptive XR Classroom

The learning scenario is based on a structured and interactive “Solar System exploration” task, in which participants perform spatial reasoning activities such as identifying planetary order, relative scale, and orbital relationships. This scenario serves as a controlled experimental setting due to its well-defined scientific structure and easily reproducible 3D assets. While grounded in an educational context, the framework is designed to model cognitive work processes that extend beyond domain-specific learning environments. From a HWID perspective, the XR classroom conceptualises learning as goal-directed cognitive work within a socio-technical system, where users and an AI agent collaborate in task execution. The structure of the XR task directly maps onto industrial cognitive work scenarios by replicating the decomposition of complex spatial problems into sequential decision-making steps supported by AI-guided information and feedback. This interaction model is transferable to Industry 5.0 environments, including AI-assisted assembly and maintenance tasks, where workers interpret spatial configurations, follow adaptive instructions, and make decisions under uncertainty, as well as inspection and diagnostic scenarios in which AI systems visualise hidden states and guide attention while preserving human decision authority.

Within this system, real-time instruction, feedback, and adaptation are managed by the AI, while domain experts define task structures and knowledge representations. Task performance is constrained by factors such as working memory load, attentional variability (measured via neurofeedback), prior knowledge, and system latency. A central feature of the system is its adaptive instructional strategy, in which the AI dynamically adjusts pacing, feedback granularity, and explanation depth based on user performance and cognitive state. This is designed to enable personalised support ranging from high-level conceptual guidance to detailed step-by-step instruction when required. Through interactive 3D representations, multimodal feedback, and adaptive guidance, cognitive work is distributed between human and AI. The AI regulates scaffolding, explanation depth, and feedback timing, while users retain control over interpretation, decision-making, and action execution. This maintains human autonomy while enabling adaptive support, reflecting the balance between assistance and control required in Industry 5.0 human–AI work systems.

4.3 Measuring Cognitive Metrics

Assessing learners' cognitive state is critical for understanding engagement, workload, and adaptive system performance in XR environments. Neurophysiological measures, such as electroencephalography (EEG), provide objective indicators of attention and mental effort, enabling real-time adaptation in human–AI collaborative systems. Prior research has demonstrated that EEG signals can reliably capture variations in cognitive engagement in immersive learning contexts, supporting the use of neurofeedback as an input for adaptive systems [39–41].

Advances in portable, dry-electrode EEG devices have made it feasible to integrate such measurements into real-world XR environments. In this study, EEG-based indicators of engagement are used to inform adaptive AI behaviour, allowing the system to respond dynamically to fluctuations in user attention. Rather than focusing on precise signal optimisation, the emphasis is placed on how cognitive state estimation can support task coordination and interaction within a human–AI work system. Building on prior work in closed-loop biofeedback systems [43], this approach treats engagement as both a measurable and modifiable state. The system integrates EEG-derived signals into a continuous cognitive state representation that is intended to support real-time adaptation of AI guidance. This is designed to enable a feedback loop in which user state influences system behaviour, and system interventions, in turn, shape user engagement. Neurofeedback functions as a mechanism for dynamic task regulation and coordination, influencing how control, autonomy, and responsibility are distributed between human and AI during cognitive work.

4.4 Neuro-Adaptive Integration

The AI tutor uses real-time brain–computer interface data to adapt the learning experience. EEG and blink signals are processed into a Cognitive State Index (e.g., engagement, fatigue), which functions as a stabilised control signal rather than a direct cognitive label. These signals are discretised into states such as high engagement, cognitive drift, or fatigue risk to reduce noise and ensure stable system responses. These states guide adaptive behaviour by modulating pedagogical support rather than evaluating learner ability. High engagement enables more complex explanations and exploratory tasks, while signs of disengagement or fatigue trigger simplified content, reduced information density, and pacing adjustments. Adaptation also extends to the XR environment, including reducing visual complexity, hiding non-essential elements, and adjusting interaction flow.

Overall, this closed-loop approach integrates cognitive sensing, AI tutoring, and XR adaptation into a multimodal framework that is intended to support learner-centred, human–AI collaboration

4.5 Participants and Procedure

Approximately 90 university students will be randomly assigned to one of the three experimental conditions (approximately 30 per group). This sample size was determined using G*Power, based on a between-subjects design with a single participation constraint per student to prevent knowledge transfer across conditions. A minimum of 30 participants per cohort ensures sufficient statistical power to detect meaningful differences between conditions. Participants will be recruited via university mailing lists and leaflets. Sessions will take place in a controlled XR classroom setting. Each session will include pre-test assessments, immersive learning activities, AI tutor interaction, and post-test evaluations, with engagement and cognitive load monitored continuously via neurophysiological indices.

4.6 Data analysis

Individual knowledge gain will first be calculated by subtracting pre-test scores from post-test scores, providing a direct measure of learning improvement for each participant. This serves as the primary dependent variable in the analysis. To examine differences in learning outcomes across the three experimental conditions (XR-only, XR-AI, and XR-AI-NF), a one-way analysis of variance (ANOVA) will be conducted. If significant effects are found, post-hoc pairwise independent-samples t-tests will be performed to identify specific group differences. Effect sizes (Cohen's d) will be reported alongside p-values to quantify the magnitude of observed effects. In addition to learning outcomes, engagement levels, cognitive load, and AI interaction data will be analysed. Engagement and cognitive metrics will be derived from EEG signals and interaction logs using a consistent computational framework applied across all conditions, with neurofeedback actively influencing system adaptation only in the XR-AI-NF condition. To further explore underlying mechanisms, correlation analyses will be conducted to examine relationships between knowledge gain, engagement, cognitive load, and AI interaction patterns. In addition, regression models will be used to assess the predictive value of these variables for learning outcomes, enabling a deeper understanding of how adaptive XR, AI tutoring, and neurofeedback jointly influence performance.

5 XR System Overview

The adaptive XR classroom is developed in Unity (2022.3.47f1) and integrates multiple SDKs and hardware interfaces to support immersive learning, AI-driven tutoring, and real-time neurofeedback (see Fig. 3). The system is designed to enable personalised interaction while capturing cognitive and engagement metrics for research purposes. Device-level functionality for Meta Quest 3 is provided through the Meta XR SDK (v68.0.1), supporting passthrough, hand tracking, and voice interaction. The Unity XR Interaction Toolkit (v2.6.3) manages object manipulation, ray-based interaction, and navigation for intuitive engagement with virtual and physical elements. Adaptive tutoring is implemented using the Convai SDK, enabling conversational AI avatars as virtual instructors powered by GPT-4o-mini with moderation filtering. The AI tutor dynamically adjusts explanations and guidance based on learner interaction and system metrics. Neurophysiological data is captured using the Interaxon LibMuse library, streaming EEG signals from Muse headbands into Unity. Real-time indices of engagement and cognitive load are computed and used in the XR-AI-NF condition to support neurofeedback-driven adaptation. As shown in Figure 3, participants complete a pre-test before entering one of three conditions: XR-only, XR-AI, or XR-AI-NF. During the session, interaction data, AI dialogue, and EEG metrics are recorded and integrated. In the neuroadaptive condition, a Multimodal Cognitive State Index informs real-time instructional adjustments. Post-test results and session data are aggregated in a central analytics dashboard for comparison across conditions. Overall, the architecture provides a scalable platform for investigating adaptive learning, human–AI collaboration, and the role of AI tutoring and neurofeedback in immersive XR environments.

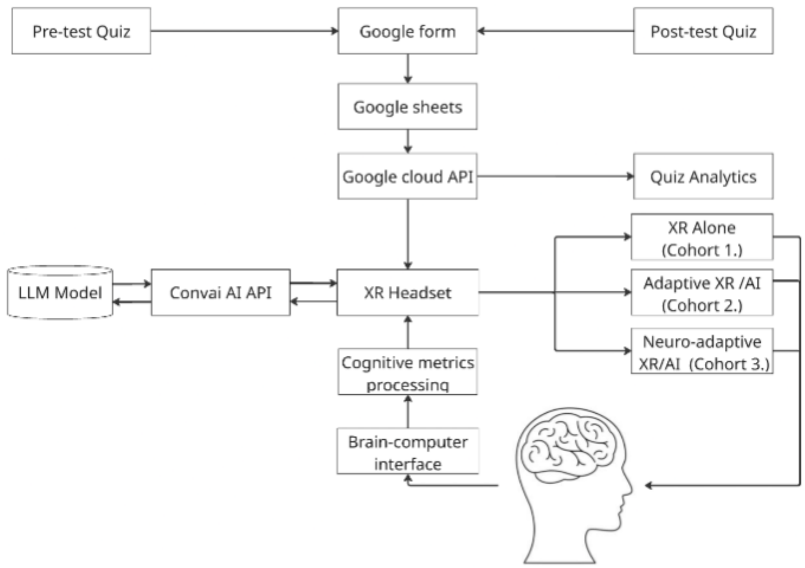

Fig. 3. High-level overview of the research-ready adaptive XR platform

6 Conclusion

This position paper presents a design-stage prototype and argues that adaptive XR classrooms should be understood not merely as educational tools, but as human–AI work systems within a learning-as-work paradigm. From a HWID perspective, learning is conceptualised as coordinated cognitive work, where learners and AI tutors jointly participate in task execution, decision-making, and adaptation. Within this framework, the XR classroom becomes a socio-technical environment in which cognitive processes—such as attention management, problem-solving, and knowledge construction—are distributed between human and AI actors. The AI functions as a co-worker, supporting real-time coordination through adaptive feedback, scaffolding, and workload regulation, while the learner retains an active role in self-regulation and interaction control. By reframing XR learning environments as interactive work systems rather than instructional delivery tools, this paper shifts the focus towards interaction design, coordination, and cognitive work organisation. It demonstrates how immersive XR, conversational AI, and neurofeedback can be integrated to enable adaptive, human-centred collaboration. This work contributes a HWID-oriented conceptual foundation for future Industry 5.0 systems, where human cognitive capabilities are augmented rather than replaced, and where trust, autonomy, and well-being remain central design principles.

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