

Article

Design Guidelines for Inclusive XR Learning Environments in Higher Education: Integrating Learning Analytics and Educational Psychology Models

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Abstract

Reality (XR) technologies hold significant potential for transforming higher education by enabling immersive, embodied, and data-informed learning experiences within smart campus ecosystems. However, adoption remains uneven, as many implementations are driven by technological availability rather than by educational psychology models, formative assessment logic, accessibility requirements, or sustainable implementation criteria. This study proposes a theoretically grounded set of guidelines for inclusive XR learning environments in higher education, following a Design Science Research methodology in which the guidelines are conceived as a design artifact derived from an interdisciplinary knowledge base. The study covers the design and development phase of the DSR cycle; the evaluation phase, comprising expert review and field deployment, constitutes the planned immediate next step. The literature base integrates recent systematic reviews and empirical studies on cognitive load, multimedia learning, self-regulated learning in immersive environments, Universal Design for Learning 3.0, and learning analytics. The resulting artifact comprises an Integrative Educational Psychology Model, organized across three mutually informing analytical layers connecting constructs such as presence, agency, embodiment, cognitive load, self-regulation, and learner variability, and ten design guidelines linking pedagogical alignment, UX/UI design, accessibility, feedback, analytics, and scalability. Two hypothetical illustrative use cases demonstrate how the framework could be operationalized across individual and collaborative learning scenarios. The proposed framework offers psychologically grounded and practically applicable guidance for educators, instructional designers, and developers seeking to create pedagogically meaningful and inclusive XR environments. Empirical evaluation will be necessary to confirm its effectiveness.

Keywords: extended reality; mixed reality; immersive learning; learning analytics; educational psychology; cognitive load; self-regulated learning; Universal Design for Learning; inclusive education; smart campus



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1. Introduction

Extended Reality (XR) is commonly used as an umbrella term for immersive technologies that combine physical and digital elements across the reality–virtuality continuum,

from Augmented Reality (AR) and Mixed Reality (MR) to fully Virtual Reality (VR) [1]. In recent years, XR has been applied across a broad set of domains, including cultural heritage, rehabilitation, neurocognitive training, and assistive applications [2–5]. In higher education, its relevance is increasing because XR can situate learners inside interactive, manipulable, and contextually rich environments that are difficult to reproduce through conventional lectures, two-dimensional media, or laboratory constraints.

Recent evidence confirms both the scale of this diffusion and the persistence of unresolved design problems. A 2025 systematic review of XR in higher education examined 295 studies published between 2020 and 2024 and found broad international adoption, with research across six continents and 48 countries. The same review reported that VR was the most common XR modality, undergraduate settings were the most frequent context, and XR was mainly used for simulation, visualization, problem solving, and gaming [6]. Another systematic review of immersive VR in higher education similarly shows that the field is expanding, while also emphasizing variability in terminology, study quality, and implementation practices [7].

The pedagogical potential of XR is therefore no longer the central question. The more urgent question is how XR learning environments should be designed so that immersion produces meaningful learning rather than novelty effects, cognitive overload, or inequitable access. Earlier reviews already noted that many XR applications in higher education focus on discipline-specific case studies and design elements without consistently translating learning theory into reusable design knowledge [8]. More recent work confirms that XR can support experiential learning cycles, inquiry-based learning, and collaborative exploration when pedagogical methods are aligned with immersive affordances [9,10]. However, alignment is not automatic: high sensory richness, spatial interaction, and real-time data capture can either support or hinder learning, depending on how they are orchestrated.

This problem is particularly important in smart campus environments, where digital infrastructures, analytics services, immersive laboratories, and cloud-based learning platforms are increasingly integrated. XR can become a pedagogically productive component of such ecosystems only if design decisions are connected to validated constructs from educational psychology, accessibility research, and human–computer interaction. Without this connection, institutions risk investing in experiences that are impressive at the demonstration level but weak in transfer, inclusion, assessment, and scalability.

The framework developed in this study is explicitly scoped to higher education for three interconnected reasons. First, the majority of XR educational research has been conducted in higher education contexts, where institutional infrastructure and student autonomy create distinctive conditions that differ substantially from K–12 or corporate training settings [6,7]. Second, higher education institutions face specific systemic constraints that the guidelines address directly: heterogeneous student-owned hardware ecosystems, institutional review board (IRB) compliance requirements for learning analytics data, integration with existing Learning Management Systems (LMSs) such as Moodle, Canvas, or Blackboard, and the expectation of adult learner self-regulation. Third, higher education emphasizes higher-order cognitive outcomes, such as analysis, synthesis, evaluation, and transfer, that align specifically with the affordances of XR for causal visualization, embodied manipulation, and reflective inquiry. The proposed guidelines are therefore not intended as universally applicable prescriptions across all educational levels, but as a design framework tailored to these constraints and affordances.

The present paper addresses the design and development phases of the DSR cycle. Problem identification and objective definition are addressed in this introduction and in Section 3.1. The artifact design and development are reported in Sections 3 and 4. The demonstration phase is illustrated through two hypothetical use cases in Section 5. The

evaluation phase, comprising expert review panels, heuristic assessment, and empirical field deployment, is not included in the present manuscript but constitutes the planned immediate next step. This delimitation is important: the guidelines presented here are theoretically motivated design propositions, not empirically validated prescriptions.

The contribution of the paper is threefold. First, it updates the literature base with recent reviews and empirical studies published up to 2026 on XR in higher education, immersive learning, cognitive load, self-regulated learning, UDL 3.0, and learning analytics. Second, it develops three structured interpretive models grounded in validated constructs: the Cognitive-Embodied Processing Model, the Motivation-Agency-Regulation Model, and the Inclusive Participation and Analytics Model. Third, it reformulates the design guidelines as an iterative evidence-to-design process that can be used by instructional designers, educators, UX specialists, and developers to produce inclusive and analytically informed XR environments. The paper is organized as follows. Section 2 reviews the literature. Section 3 presents the methods, interpretive models, and guidelines. Section 4 presents results, including the model and the ten design guidelines. Section 5 discusses the implications through hypothetical use cases. Section 6 concludes the paper.

The reality–virtuality continuum addressed by the study is illustrated in Figure 1.

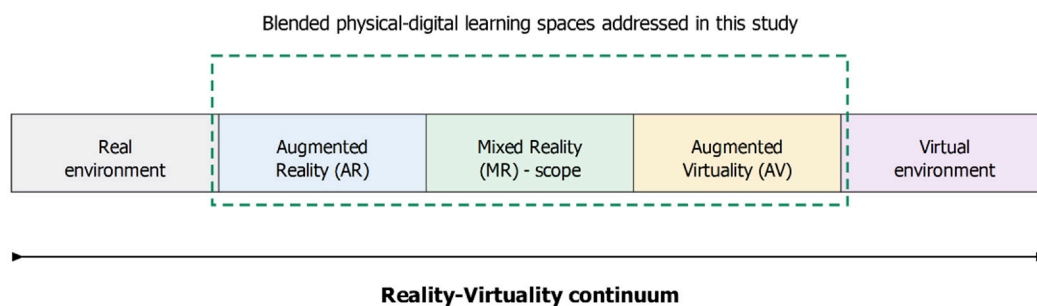


Figure 1. Reality–virtuality continuum and the blended physical–digital scope addressed by the study.

2. Related Work

2.1. XR in Higher Education

XR has been used in higher education to support visualization, simulation, authentic practice, collaborative inquiry, and embodied interaction. The 2025 systematic review by Burke et al. provides one of the most comprehensive recent syntheses because it considers VR, AR, and MR together and identifies knowledge acquisition, psychomotor learning, and affective learning as major domains of use [6]. Stracke et al. complemented this evidence by focusing on immersive VR and highlighting the need for clearer terminology, stronger methodological rigor, and better integration into teaching practice [7].

A central theme in this literature is experiential learning. XR allows students to manipulate virtual objects, navigate simulated contexts, and observe consequences that would be costly, risky, or inaccessible in real life. Fromm et al. argued that VR can support a holistic experiential learning cycle when learners move through experience, reflection, conceptualization, and experimentation rather than remaining passive recipients of immersive content [9]. Won et al. identified diverse approaches to learning with immersive VR, including inquiry-based, simulation-based, and collaborative models [10].

The literature also shows that XR effectiveness depends on instructional design. Radianti et al. identified recurring design elements such as presence, feedback, task authenticity, and interactivity, while also noting that many studies remain fragmented and rely on limited theoretical grounding [8]. These findings suggest that XR design should not be organized

around technological features alone. Instead, the core design question should be how each feature supports a psychological process that contributes to a defined learning outcome.

2.2. Educational Psychology Foundations for Immersive Learning

A stronger educational psychology foundation is necessary because XR environments intensify both the opportunities and the risks of digital learning. The Cognitive Theory of Multimedia Learning (CTML) proposes that meaningful learning occurs when learners select relevant information, organize it into coherent mental structures, and integrate it with prior knowledge [11]. This is directly relevant to XR because immersive environments present visual, auditory, spatial, and interactive information simultaneously. XR design should therefore reduce irrelevant sensory complexity, segment information, coordinate modalities, and support active integration rather than assuming that immersion itself is sufficient.

Cognitive Load Theory (CLT) further clarifies this requirement by distinguishing intrinsic load, extraneous load, and germane load [12,13]. XR can reduce intrinsic difficulty by making abstract or invisible processes manipulable and visible, but it can also increase extraneous load through confusing navigation, visual clutter, motion discomfort, unfamiliar controls, or poorly timed feedback. Consequently, a psychologically robust XR design must manage cognitive load at the level of environment, interface, task structure, and assessment.

The Cognitive Affective Model of Immersive Learning (CAMIL) provides a specific theory for immersive VR. CAMIL identifies presence and agency as general psychological affordances of immersive learning and links them to interest, intrinsic motivation, self-efficacy, embodiment, cognitive load, and self-regulation [14]. This model is important because it avoids technological determinism: immersion is treated as a condition that can facilitate psychological affordances, not as a direct cause of learning. The immersion principle in multimedia learning similarly suggests that immersive media may increase presence, enjoyment, and interest, but that learning gains depend on how immersive affordances are pedagogically organized [15]. Recent AR research also supports the extension of multimedia learning principles to augmented environments, especially for controlling extraneous load [16].

Embodied learning research adds a further dimension. Johnson-Glenberg argues that VR offers two profound affordances for education: presence and embodied interaction through gesture and manipulation in three-dimensional space [17]. In educational terms, embodiment is valuable when physical actions are congruent with the conceptual structure being learned. A gesture or manipulation is not pedagogically meaningful merely because it is interactive; it becomes meaningful when the motor action maps onto a disciplinary relation, process, or causal structure.

The revised framework also preserves established constructivist and sociocultural foundations. Bruner emphasized discovery learning, hypothesis generation, and active knowledge construction [18]. Kolb conceptualized learning as a cycle involving concrete experience, reflective observation, abstract conceptualization, and active experimentation [19]. Lave and Wenger described learning as legitimate participation in situated practices and communities of practice [20]. XR environments can operationalize these theories when learners are placed in authentic roles, interact with consequential tasks, and receive structured opportunities for reflection and conceptualization.

Motivation and self-regulation are equally central. Self-Determination Theory (SDT) identifies autonomy, competence, and relatedness as psychological needs that support intrinsic motivation and internalization [21]. Bandura identified self-efficacy as a key determinant of persistence, effort, and adaptive action [22]. Zimmerman described self-regulated learning (SRL) as cyclical processes of forethought, performance monitoring, and

self-reflection [23]. Recent IVR research shows that SRL strategies can support goal setting, planning, monitoring, and evaluation in immersive environments, while poorly designed environments can increase cognitive load and distract learners from task goals [24,25].

Inclusion is not a secondary add-on to these models. CAST released UDL Guidelines 3.0 in 2024, emphasizing learner agency, barriers rooted in systems of exclusion, and multiple means of engagement, representation, and action/expression [26]. Inclusive XR reviews argue that VR learning applications should be grounded in UDL while also accounting for embodied interaction, collaboration, and the immersive properties of virtual content [27]. Recent accessibility studies further demonstrate the value of spatial audio cues, adjustable text, customizable lighting and contrast, alternative interaction modes, and user-centered evaluation for visually impaired learners and neurodivergent populations [28,29].

2.3. Learning Analytics, Formative Assessment, and Multimodal Evidence

XR environments generate rich traces of learning activity. These traces may include navigation paths, gaze direction, object manipulation, time on task, collaboration patterns, verbal interaction, physiological signals, and responses to embedded prompts. A recent systematic review of learning analytics in immersive virtual learning environments reported that the field has expanded from outcome evaluation and behavior analysis toward performance prediction, self-regulation, social interaction, and affective states, but also noted uneven theoretical grounding, limited use of multimodal data, and challenges related to interpretability, privacy, and adoption [30].

Earlier work showed that interaction data in immersive learning environments can be used to provide real-time student feedback and to support automated evaluation of user behavior [31,32]. In higher education, formative assessment supported by learning analytics can help educators monitor learning processes rather than only final outcomes [33,34]. Assessment frameworks for immersive learning emphasize that analytics should be linked to learning tasks, feedback, and evidence of competence rather than collected as isolated behavioral metrics [35].

From an instructional perspective, learning analytics should be interpreted as formative evidence. This means that data should support feedback, reflection, adaptive scaffolding, and design improvement. Technical standards such as xAPI can make XR interaction data more interoperable with learning record stores and institutional systems, but the educational value of instrumentation depends on mapping events to theoretically meaningful constructs [36]. Ethical considerations are essential: learning analytics should be transparent, proportionate, interpretable, and beneficial to learners, with privacy and power asymmetries explicitly addressed [37].

2.4. Design Frameworks and Existing Guidelines

Several instructional design frameworks can inform XR learning design. ADDIE supports systematic analysis, design, development, implementation, and evaluation, while the Successive Approximation Model (SAM) emphasizes agile iteration and rapid prototyping [38,39]. TPACK highlights the need to integrate technological, pedagogical, and content knowledge, a principle that is particularly important when immersive technologies are introduced into disciplinary teaching [40].

More XR-specific frameworks have attempted to capture the distinctive features of immersive learning. Mulders et al. proposed a framework for the use of immersive VR in learning environments, while more recent design-oriented work connects immersive technologies to learning outcomes and competence frameworks [41,42]. These contributions are valuable but often focus on selected aspects of XR design. The following subsection positions the proposed framework relative to these existing approaches.

2.5. Positioning the Proposed Framework Within Existing XR Design Approaches

Although several frameworks address aspects of XR learning design, no single existing framework simultaneously integrates cognitive-embodied processing, motivational-regulatory scaffolding, inclusive accessibility from inception, and ethics-compliant theory-driven learning analytics within a single design artifact. Table 1 compares the proposed framework with four representative existing approaches across five dimensions.

Table 1. Comparison of the proposed framework with existing XR and instructional design frameworks. (✓ = explicitly addressed; ○ = partially addressed; – = not addressed).

Framework	Cognitive-Embodied Pedagogy	Motivation and SRL Support	Accessibility (UDL-Grounded)	Theory-Driven Analytics	HE-Specific Constraints
Mulders et al. (2020) [41]	○ (moderate)	–	–	–	–
ADDIE/SAM [38,39]	○ (general)	○ (general)	○ (partial)	–	–
TPACK [40]	○ (general)	–	–	–	–
Pitsikalis et al. (2024) [42]	○ (EQF-focused)	–	–	–	✓
Proposed framework	✓ (CTML, CLT, CAMIL, embodiment)	✓ (SDT, SRL, CAMIL)	✓ (UDL 3.0)	✓ (xAPI mapping)	✓ (LMS, IRB, hardware)

The proposed framework’s primary contribution is therefore not the introduction of new theoretical constructs—CTML, CLT, CAMIL, SDT, SRL, and UDL 3.0 are all well-established—but their systematic integration into a mutually constraining design structure. In existing XR frameworks, pedagogy, accessibility, and analytics are typically addressed separately or not at all. In the proposed framework, they are treated as interdependent: an inaccessible interaction produces biased analytics; analytics without construct grounding produce misleading formative evidence; and motivational scaffolding that ignores cognitive load is self-defeating. The three-layer model (described in Section 4.1) operationalizes these interdependencies as simultaneous design constraints rather than sequential checklist items.

This broader integration is not without cost. Table 1 shows that the proposed framework addresses more dimensions simultaneously than the four comparator frameworks, but breadth of coverage does not eliminate the practical burden of applying five interdependent theoretical perspectives at once. Compared with a single-lens framework such as TPACK or a general process model such as ADDIE/SAM, the proposed framework requires instructional designers to reason simultaneously about cognitive load, motivational scaffolding, accessibility, and analytics governance from the earliest design stages, which increases the conceptual and organizational overhead of adoption, particularly for teams without prior exposure to educational psychology or learning analytics. Institutions with limited instructional design capacity may find the ten guidelines harder to operationalize in full than a narrower, single-dimension checklist. This trade-off between comprehensiveness and ease of adoption is only partially mitigated by the modular structure of the guidelines (Section 4.3), which allows partial application, and it remains an open question for the planned evaluation phase (Section 3.1) whether practitioners can realistically apply all ten guidelines without dedicated training or simplified onboarding materials.

3. Materials and Methods

3.1. Design Science Research Approach

The methodological approach is grounded in Design Science Research (DSR), which focuses on the creation and evaluation of purposeful artifacts that address relevant problems

in information systems and human–computer interaction [43]. In this study, the artifact is a set of design guidelines and an associated educational psychology model for inclusive XR learning environments in higher education.

The research process follows the DSR model proposed by Peffers et al., which includes problem identification, definition of objectives, design and development, demonstration, evaluation, and communication [44]. The problem is the absence of integrated, psychologically grounded, and practically applicable design guidance for XR learning environments in higher education. The objective is to produce guidelines that are educationally meaningful, inclusive, technically feasible, and compatible with formative learning analytics. The design and development activity is carried out through literature-grounded synthesis. The demonstration activity is provided through two hypothetical illustrative use cases.

The present manuscript covers the problem identification, objective definition, design, development, and demonstration phases of the DSR cycle. The evaluation phase (Activity 5 in the Peffers et al. [44] model) is not included but constitutes the planned immediate next step. The guidelines should therefore be understood as theoretically grounded design propositions, not empirically validated prescriptions. The demonstration through hypothetical use cases (Section 5) is intended to establish the applicability and internal coherence of the guidelines, not to provide empirical evidence of their effectiveness.

3.1.1. Planned Evaluation Framework

The next research phase will evaluate the artifact through three complementary methods. First, an expert review panel will be constituted comprising at least six specialists with backgrounds in XR instructional design, accessibility research, and educational technology. Panelists will rate each guideline on clarity, completeness, relevance, and actionability using a structured Likert-scale instrument, and will provide qualitative annotations. Second, a structured heuristic evaluation will apply the ten guidelines as evaluation criteria to existing documented XR learning environments, assessing the degree to which each environment satisfies or violates each guideline. Third, quasi-experimental or design-based studies will compare XR environments developed with and without the framework, measuring learning outcomes, transfer, cognitive load (NASA-TLX or equivalent), motivation (IMI subscales), SRL strategy use (trace data + self-report), and accessibility experiences (user testing with diverse populations). Planned institutional settings include undergraduate STEM courses and humanities seminars in higher education institutions with existing XR infrastructure.

3.1.2. Justification of the Higher Education Scope

The framework is explicitly scoped to higher education rather than K–12 or corporate training for three reasons that are reflected in the guidelines themselves. First, the dominant research context for XR in education is higher education [6,7], providing the empirical literature base from which the guidelines are derived. Second, higher education institutions present a distinctive set of systemic constraints: (a) learning analytics deployments must comply with institutional IRB or equivalent ethics protocols; (b) XR content must integrate with existing LMS infrastructures; (c) student hardware access is highly heterogeneous, ranging from institution-owned HMDs to personal smartphones; and (d) adult learner autonomy means that SRL scaffolding must complement, not replace, independent regulation. Third, the higher-order cognitive outcomes expected in higher education, such as analysis, synthesis, evaluation, and transfer, align specifically with the XR affordances the framework is designed to leverage. These constraints and affordances do not translate directly to K–12 or corporate settings and applying the guidelines in those contexts would require domain-specific adaptation.

3.2. Evidence-to-Guideline Translation Procedure

The guideline development process followed four translation steps. First, theoretical constructs were extracted from educational psychology, including multimedia processing, cognitive load, presence, agency, embodiment, motivation, self-efficacy, self-regulation, situated participation, and learner variability. Second, these constructs were connected to XR design affordances such as spatial visualization, direct manipulation, embodied action, multimodal representation, collaboration, and trace data. Third, each construct–affordance relation was translated into a design requirement that could be implemented and evaluated. Fourth, the requirements were grouped into ten guidelines that reflect the lifecycle of XR design.

Several design requirements were supported by more than one theoretical construct simultaneously; for example, feedback-related requirements were informed jointly by CAMIL, self-efficacy theory, and SRL monitoring processes, and accessibility-related requirements drew on both UDL 3.0 and empirical accessibility studies. Where multiple theories converged on the same design requirement, three decision rules were applied. First, convergent constructs were merged into a single guideline when they pointed to the same concrete design action; for example, CAMIL’s presence and agency affordances and Johnson-Glenberg’s embodied interaction principles were merged into Guideline 4 because both imply that motor action must be conceptually meaningful. Second, when constructs addressed the same requirement at different levels of specificity, the more specific, operationalizable construct was prioritized as the primary rationale, while the broader construct was retained as supporting theoretical grounding; for example, in Guideline 6, Zimmerman’s SRL cycle provided the operational structure for goal-setting, monitoring, and reflection scaffolds, while SDT’s autonomy construct was retained as a secondary justification for the same requirement. Third, constructs that suggested design implications outside the current scope of higher education XR, such as constructs specific to K–12 developmental stages or corporate compliance training, were discarded rather than merged, consistent with the higher education scoping discussed in Section 3.1. This procedure is illustrative rather than fully formalized; a more systematic prioritization protocol, potentially involving expert panel input, is planned as part of the evaluation phase described in Section 3.1.

This translation approach is intended to prevent two common problems in XR educational design. The first is theory without operationalization: citing learning theories without showing how they affect interaction, feedback, accessibility, or analytics decisions. The second is technology without interpretability: collecting behavioral data or adding immersive features without mapping them to valid learning constructs.

Table 2 provides a trace matrix that makes explicit which theoretical constructs and which primary literature sources underlie each guideline, and what the core design requirement is. This matrix is intended to demonstrate that the guidelines are grounded in specific empirical and theoretical literature rather than representing an arbitrary selection.

Table 2. Trace matrix: mapping the ten design guidelines to theoretical constructs, primary literature, and design requirements.

G	Core Construct(s)	Primary Literature	Design Requirement	HE Constraint Addressed
G1	Learner variability; outcome specification; prior knowledge	Hevner et al. (2004) [43]; CAST UDL 3.0 (2024) [26]	Specify knowledge type and accessibility needs before technical development	LMS profile integration; hardware inventory check
G2	Experiential cycle; inquiry-based learning; situated cognition	Fromm et al. (2021) [9]; Won et al. (2023) [10]; Lave & Wenger (1991) [20]	Select XR only when it enables processes inaccessible via conventional media	IRB check for authentic tasks with student data

Table 2. Cont.

G	Core Construct(s)	Primary Literature	Design Requirement	HE Constraint Addressed
G3	CTML; intrinsic/extraneous/germane load	Mayer (2024) [11]; Sweller (1988) [12]; Paas et al. (2003) [13]	Segment content; apply signaling; avoid extraneous detail	Asset optimization for diverse hardware
G4	Embodiment; gesture-concept congruence; agency	Johnson-Glenberg (2018) [17]; Makransky & Petersen (2021) [14]	Motor actions must map onto disciplinary concepts	Alternative inputs for motor diversity; no HMD required
G5	SDT needs; self-efficacy; intrinsic motivation	Ryan & Deci (2000) [21]; Bandura (1997) [22]; Makransky & Mayer (2022) [15]	Provide meaningful choices; calibrate challenge; build competence	Cross-cohort role design; avoid mandatory participation bias
G6	SRL forethought/monitoring/reflection; metacognition	Zimmerman (2000) [23]; Hsu & Lee (2026) [24]; Ader et al. (2025) [25]	Embed goal setting, monitoring tools, reflection prompts in environment	LRS-compatible SRL trace data; LMS feedback loop
G7	UDL 3.0 multiple means; learner agency; accessibility	CAST (2024) [26]; Wehrmann & Zender (2024) [27]; Yensathit et al. (2025) [28]	Apply configurable sensory settings; multiple input modes from first prototype	Assistive technology compatibility; IRB for diverse user testing
G8	Formative assessment; competence-supportive feedback; process evidence	Zhang et al. (2023) [33]; Udeozor et al. (2023) [35]; Schumacher (2019) [34]	Capture choices, errors, strategies, recovery actions alongside outcomes	LMS grade integration; IRB for process data
G9	Theory-driven construct mapping; ethical analytics; interpretability	Tao et al. (2025) [30]; Gorzen et al. (2024) [36]; Slade & Prinsloo (2013) [37]	Create event dictionaries; use xAPI/LRS; apply transparency and minimization	IRB data governance; LMS/LRS interoperability; data minimalist
G10	Institutional feasibility; sustainable adoption; scalability	Burke et al. (2025) [6]; Mulders et al. (2020) [41]	Design for hardware diversity and graceful degradation; use modular assets	LMS deployment; IT support requirements; cost sustainability

4. Results

4.1. Integrative Educational Psychology Model for Inclusive XR Learning

The revised framework proposes an Integrative Educational Psychology Model for Inclusive XR Learning. The model does not replace existing theories; instead, it organizes them into a usable interpretive structure for design. It contains three mutually dependent models: the Cognitive-Embodied Processing Model, the Motivation-Agency-Regulation Model, and the Inclusive Participation and Analytics Model. Together, they explain how XR affordances can become learning opportunities when mediated by validated psychological constructs and inclusive design conditions. The three models are illustrated in Figure 2.

The three models function as mutually informing analytical layers rather than as independent components or sequential processing stages. They are applied simultaneously throughout the design process: the Cognitive-Embodied Processing Model informs the structure of interaction and task design; the Motivation-Agency-Regulation Model guides the motivational scaffolding and self-regulation support; and the Inclusive Participation and Analytics Model establishes the conditions for valid evidence collection and equitable participation. Their interdependence is substantive: design decisions that affect cognitive load also affect the learner's capacity for self-regulation and the validity of analytics evidence; motivational scaffolding that ignores accessibility barriers reaches only part of the learner population; and analytics that are not mapped to construct-valid events are misleading regardless of how ethically they are collected.

In practice, an instructional designer does not apply the three layers as separate stages but moves iteratively between them at each major design decision point. A typical design cycle begins with the Cognitive-Embodied Processing Model to establish what needs to be perceived, manipulated, or understood, for example, segmenting a process or defining a congruent gesture, which fixes a provisional cognitive load budget for the task. The designer then consults the Motivation-Agency-Regulation Model to decide how much choice, challenge, and feedback can be layered onto that task without exceeding the load budget already established, adjusting the cognitive-embodied design if the motivational

requirements would introduce excessive extraneous load. Finally, the designer applies the Inclusive Participation and Analytics Model to check whether the resulting interaction can be perceived and performed through multiple sensory and motor pathways, and to determine which of the interaction events already defined can be mapped to valid analytic constructs; where a required accessibility accommodation is incompatible with the initial cognitive-embodied design, for example, an alternative input mode that changes the gesture-concept mapping established in Guideline 4, the designer returns to the first layer to reconcile the two. This iterative movement, illustrated conceptually in Figure 2 by the mutual dependencies between the three layers, is what distinguishes the model from a linear checklist: each layer constrains and is constrained by the other two throughout the design process, not only at a single review stage.

Integrative Educational Psychology Model for Inclusive XR Learning

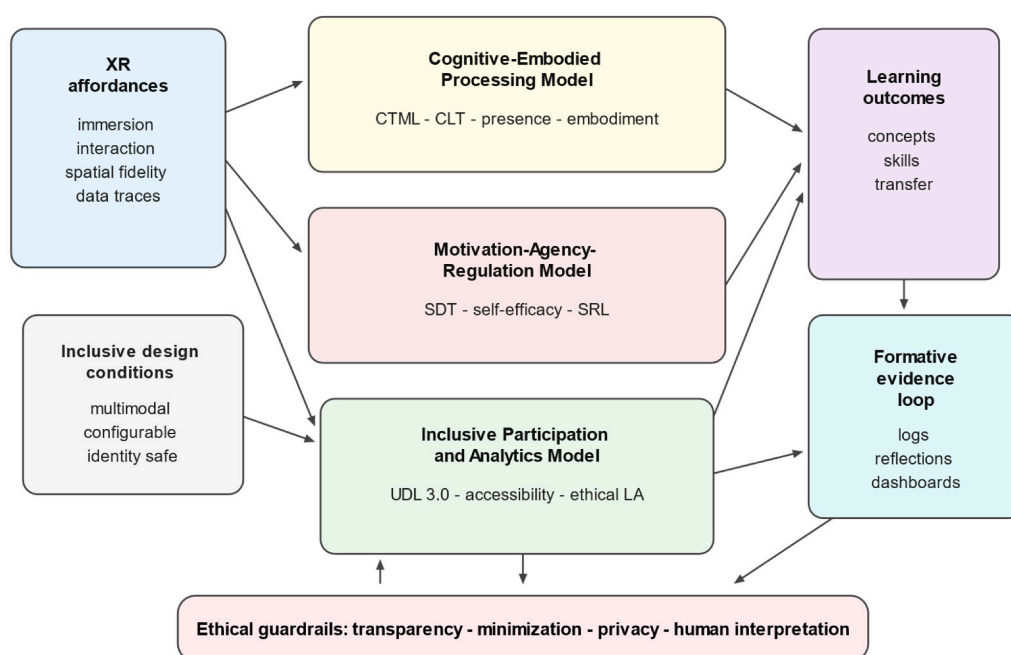


Figure 2. Integrative Educational Psychology Model for Inclusive XR Learning environments. The three layers are mutually dependent: cognitive-embodied processing constraints set the conditions for motivation and regulation, and both depend on inclusive participation for valid evidence.

The first model, the Cognitive-Embodied Processing Model, links CTML, CLT, CAMIL, and embodied learning. It interprets XR as a learning environment in which sensory channels, spatial representations, and bodily actions must be coordinated to support selecting, organizing, and integrating information. In this model, presence and embodiment are productive only when they reduce abstraction, support conceptual mapping, and avoid extraneous load. Design indicators include clarity of spatial cues, congruence between gestures and concepts, segmentation of complex processes, avoidance of seductive details, and provision of reflection prompts that convert experience into conceptualization.

The second model, the Motivation-Agency-Regulation Model, links CAMIL, Self-Determination Theory, self-efficacy, and self-regulated learning. It interprets XR as a motivational environment in which agency, autonomy, competence, and relatedness can sustain engagement. However, motivation must be connected to regulation. Learners need explicit goals, progress information, opportunities to plan actions, feedback for monitoring, and moments for reflection. Design indicators include meaningful choice, calibrated

challenge, role clarity, scaffolded decision points, competence-supportive feedback, and analytics-supported reflection.

The third model, the Inclusive Participation and Analytics Model, links UDL 3.0, accessible design, and learning analytics ethics. It interprets inclusion as a condition for valid learning evidence. If an XR environment excludes learners through inaccessible interaction, sensory overload, unreadable text, rigid locomotion, or identity-insensitive representation, then both participation and analytics become biased. Specific empirical findings support the design indicators: Yensathit et al. (2025) demonstrated the value of spatial audio cues and gaze-based input for visually impaired learners [28]; Valverde Olivares et al. (2025) documented configurable contrast, text, and interaction modes for neurodivergent populations in XR [29]. Design indicators include multiple means of representation, action, and expression; configurable sensory settings; alternative input modalities; accessible captions and transcripts; transparent data collection; and educator dashboards that privilege actionable interpretation over surveillance. Table 3 (below) details the constructs and evidence indicators for all three models.

Table 3. Interpretive educational psychology models, constructs, learning problems addressed, design implications, and evidence indicators.

Model	Core Validated Constructs	Learning Problem Addressed	Design Implications	Evidence Indicators	Primary Informs
Cognitive-Embodied Processing Model	CTML; cognitive load; presence; embodiment; agency	Immersion may increase sensory richness without improving conceptual understanding	Segment complex tasks; align gesture with concept; reduce visual clutter; provide spatial/temporal cues	Task accuracy; transfer; navigation efficiency; cognitive load measures; error patterns	G1, G2, G3, G4
Motivation-Agency-Regulation Model	Autonomy, competence, relatedness (SDT); self-efficacy; SRL; reflection	Learners may be engaged by novelty but fail to plan, monitor, or evaluate their learning	Provide meaningful choices, clear goals, calibrated challenge, progress feedback, reflection checkpoints	Goal completion; strategy changes; persistence; self-efficacy reports; SRL traces	G5, G6, G8
Inclusive Participation and Analytics Model	UDL 3.0; learner variability; accessibility; ethical learning analytics	XR can reproduce barriers and produce biased analytics when participation is inaccessible	Offer multiple modalities, configurable sensory settings, alternative inputs, transparent data use, accessible dashboards	Participation rates; accessibility feedback; option usage; dashboard actions; privacy compliance	G7, G9, G10

4.2. UX/UI and Technical Foundations

The educational psychology model must be implemented through appropriate UX/UI and technical decisions. Affordance theory, originally introduced by Gibson and later adapted for design by Norman, explains how environments signal possible actions to users [45,46]. In XR, affordances are spatial, multimodal, and embodied; they must guide learners toward pedagogically relevant actions without imposing unnecessary cognitive effort.

User experience design emphasizes the perceived quality of interaction between people and systems [47]. In XR education, UX includes comfort, orientation, agency, trust, feedback, collaboration, and the degree to which learners can focus on disciplinary tasks rather than interface management. Nielsen's usability heuristics remain useful when adapted to

immersive contexts, especially visibility of system status, consistency, recognition rather than recall, error prevention, and user control [48].

Presence and immersion should also be distinguished. Immersion is a property of the technological system, whereas presence is the subjective sense of being in the environment [49]. Multimodal interaction principles are relevant because XR combines visual, auditory, haptic, gestural, and spatial channels [50]. Heuristic evaluation of VR applications provides practical mechanisms for identifying interaction and comfort problems before deployment [51].

4.3. Design Guidelines

The ten guidelines are organized as an iterative process rather than a linear checklist. Each guideline includes a pedagogical rationale, psychological interpretation, UX/UI implications, and technical considerations. The iterative process is illustrated in Figure 3. For each guideline, at least one example of a design decision that satisfies the guideline and one that violates it is provided to support practical interpretation.

Iterative evidence-to-design process

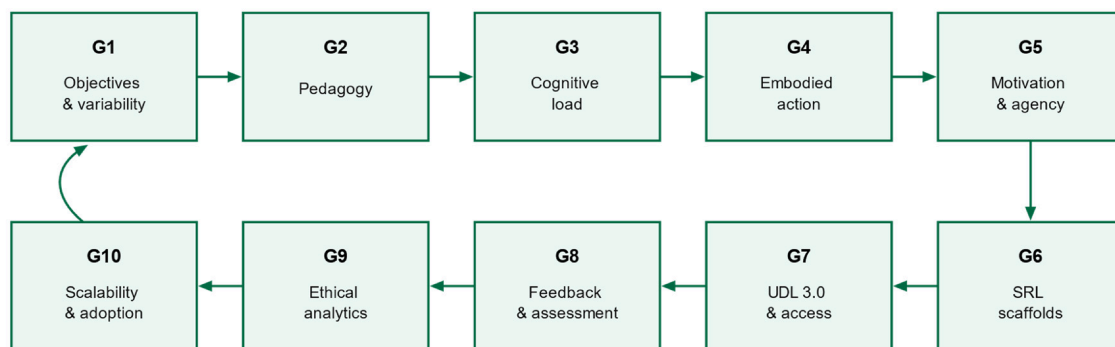


Figure 3. Iterative evidence-to-design process for inclusive XR learning environments.

4.3.1. Guideline 1: Define Learning Objectives, Learner Variability, and Educational Context

Design should begin with learning outcomes, learner profiles, accessibility requirements, and institutional constraints. Objectives should specify what type of knowledge is targeted—factual, conceptual, procedural, or transfer—and which XR affordances are necessary. The psychological rationale is that valid design depends on aligning task demands with learner prior knowledge, cognitive load, and self-regulation needs. UX artifacts such as personas, journey maps, and accessibility scenarios should be produced before technical development begins. In higher education contexts, this phase must also include a hardware inventory (to determine whether HMDs are available or alternatives are needed) and an LMS integration assessment.

Satisfies G1: An instructional designer maps three learner profiles (novice, intermediate, prior disability disclosure) and specifies separate accessibility scenarios before selecting an XR platform.

Violates G1: A development team builds the XR environment and adds accessibility features as post hoc accommodations in response to complaints.

4.3.2. Guideline 2: Align XR Activities with Pedagogical Methods Rather than Technological Novelty

XR should be used when immersion, spatial interaction, or embodied manipulation enable learning processes that conventional media cannot support as effectively. Activities

should be grounded in discovery, experiential, and situated learning while remaining explicit enough to avoid unguided cognitive overload. Designers should specify how each interaction supports hypothesis testing, reflection, conceptualization, or participation in a disciplinary practice.

Satisfies G2: A chemistry course uses XR to allow students to manipulate molecular bonds in 3D, a process that would be impossible to experience spatially in a textbook.

Violates G2: A literature course delivers a linear recorded narration within a VR environment that offers no affordances beyond passive viewing.

4.3.3. Guideline 3: Manage Cognitive Load and Multimedia Processing

The environment should reduce extraneous load, support germane processing, and calibrate intrinsic load to learner expertise. Visual detail, spatial audio, labels, animations, and feedback should be coordinated according to multimedia principles. Segment complex processes, use signaling cues, provide optional explanations, and avoid decorative elements that compete with task-relevant information. Performance targets should include not only presence but also comprehension, transfer, and cognitive load indicators.

Satisfies G3: A biology XR environment segments the cell cycle into distinct phases, each accessed through a deliberate user action, with irrelevant background detail minimized.

Violates G3: A history XR environment simultaneously plays ambient city noise, displays floating text labels, and triggers automatic animations, all without user control.

4.3.4. Guideline 4: Design Embodied Interaction as Conceptually Congruent Action

Embodied interaction should be meaningful, not merely active. Gestures, locomotion, object manipulation, and haptic cues should map onto disciplinary concepts or professional practices. Where embodiment is not pedagogically relevant, simpler interaction may be preferable. Interaction alternatives should be provided for students with motor differences or motion sensitivity.

Satisfies G4: Students physically rotate a 3D geological formation to understand fault line orientation, directly linking the motor action to the spatial concept.

Violates G4: Students are required to 'pick up' and 'carry' objects in a VR environment when a simple point-and-click would achieve the same learning purpose with less extraneous load.

4.3.5. Guideline 5: Support Motivation, Agency, and Self-Efficacy Through Calibrated Challenge

Learners should experience meaningful autonomy, competence, and relatedness. XR scenarios should provide choices that matter, tasks that are challenging but achievable, and feedback that builds self-efficacy. In collaborative settings, roles should create interdependence and mutual recognition. Design should avoid false agency, where learners can move freely but have little meaningful influence on outcomes.

Satisfies G5: A medical simulation allows students to choose the diagnostic sequence and provides competence-informative feedback after each decision step.

Violates G5: An XR environment provides an open virtual space with no goals, no feedback, and no meaningful consequences for learner choices.

4.3.6. Guideline 6: Embed Self-Regulated Learning Scaffolds

XR environments should include goal-setting support, progress indicators, planning prompts, monitoring tools, and reflection checkpoints. These scaffolds should be integrated into the environment rather than added as external questionnaires only. Learning analytics

can support SRL by showing learners what they have explored, which strategies they used, and where conceptual gaps remain.

Satisfies G6: At the beginning of the session, learners set a specific goal; a sidebar indicator updates as they complete sub-tasks; a reflection prompt appears at the midpoint.

Violates G6: RL support consists solely of a post-session survey administered outside the XR environment, with no in-environment feedback or progress indicators.

4.3.7. Guideline 7: Apply UDL 3.0 and Accessibility from the First Prototype

Inclusive design should anticipate learner variability. Information should not be conveyed through a single modality alone; auditory information needs text alternatives, visual information needs verbal or tactile equivalents where feasible, and interaction should support multiple input modes. Sensory intensity, locomotion, contrast, text size, and pacing should be configurable. Accessibility should be evaluated with representative users early and repeatedly. Yensathit et al. (2025) demonstrated that gaze-based selection combined with spatial audio orientation substantially improves XR accessibility for visually impaired learners [28]; Valverde Olivares et al. (2025) documented benefits of configurable contrast and alternative input for neurodivergent users [29].

Satisfies G7: The first prototype is tested with two users who have low vision; spatial audio cues and text labels are implemented based on their feedback before the full development cycle.

Violates G7: Accessibility features are added in the final deployment phase as optional add-ons, after the core interaction model has been fixed.

4.3.8. Guideline 8: Integrate Feedback and Formative Assessment as Part of the Interaction Model

Feedback should be immediate when it supports action correction and delayed or reflective when it supports conceptualization. It should be specific, process-oriented, and competence-supportive. Formative assessment should capture both outcomes and processes: choices made, strategies attempted, errors, recovery actions, and quality of reflection. Feedback mechanisms should avoid interrupting presence unnecessarily.

Satisfies G8: After a student incorrectly applies a surgical procedure step in XR, the system immediately highlights the affected tissue area and asks the student to identify the error before proceeding.

Violates G8: The only feedback is a final score screen displayed after the simulation ends, with no process-level information.

4.3.9. Guideline 9: Instrument Learning Analytics Ethically and Theoretically

XR analytics should collect data that correspond to meaningful learning constructs. Designers should define event dictionaries that map actions to constructs such as exploration, strategy use, collaboration, attention, self-regulation, or task completion. Data collection should follow transparency, minimization, interpretability, and privacy principles. Dashboards should support educator decisions and learner reflection rather than surveillance or simplistic ranking. In higher education contexts, all analytics data collection must comply with institutional ethics requirements (e.g., IRB or equivalent ethics committee approval), and data architectures must be compatible with institutional LMS and LRS infrastructures.

Table 4 provides a sample xAPI event-to-construct mapping for XR learning environments. Each row specifies a raw interaction event, the corresponding xAPI verb-object structure, the psychological construct it operationalizes, and its intended analytic use. This mapping is illustrative; actual event dictionaries must be co-designed with educators and validated against the specific learning objectives of each XR application.

Table 4. Sample xAPI event-to-construct mapping for XR learning analytics (illustrative; requires context-specific adaptation).

XR Interaction Event	xAPI Statement (Actor-Verb-Object)	Psychological Construct	Intended Analytic Use
Gaze fixation on 3D object > 3 s	actor experienced → looked-at → [objectID]	Sustained attention; conceptual exploration	Identify objects/areas receiving sustained focus; flag potential confusion or interest
Object manipulation attempt (success or fail)	actor attempted → interacted-with → [objectID]; result: succeeded/failed	Agency; strategy use; problem solving	Map manipulation sequences to conceptual understanding; detect trial-and-error patterns
Navigation path divergence from optimal route	actor traversed → navigated-in → [zoneID]; deviation: [value]	Spatial orientation; self-directed exploration vs. disorientation	Distinguish intentional exploration from wayfinding difficulty; flag accessibility issues
Reflection prompt response submitted	actor responded-to → [promptID]; duration: [seconds]; length: [words]	Metacognitive processing; self-reflection quality	Assess depth and timeliness of reflection; correlate with learning outcomes
Undo/retry action	actor undid → [actionID]; count: [n]	Error recovery; SRL monitoring phase; self-correction	Identify struggle patterns; flag learners needing scaffolding support
Help resource accessed	actor requested → [helpResourceID]; timing: [elapsed]	Self-efficacy; scaffolding use; help-seeking behavior	Detect learners with low self-efficacy; adapt scaffolding level
Group annotation submitted	actor annotated → [objectID]; in-context: [groupID]	Collaborative knowledge construction; epistemic contribution	Track equitable participation; identify socially peripheral group members

The event-construct mappings in Table 4 should be interpreted as candidate indicators rather than direct or deterministic measures of the underlying psychological constructs. A single behavioral signal, such as gaze fixation duration or undo/retry frequency, can plausibly reflect several different underlying states, for example, sustained attention, confusion, or a deliberate exploratory strategy, and the same construct can be expressed through different behavioral signatures across learners. Consistent with recommendations in the learning analytics literature on interpretability and validity [30,37], each candidate indicator in Table 4 should therefore be triangulated with additional evidence before being used for pedagogical or evaluative decisions, such as assessment performance, the content and quality of reflection prompt responses, or supplementary self-report questionnaires (e.g., self-efficacy or cognitive load scales). Treating xAPI events as sufficient standalone proxies for constructs such as attention, self-efficacy, or self-regulation would risk overly deterministic and potentially misleading interpretations of learner behavior; the mapping is intended as a starting point for construct-informed instrumentation, not as a validated measurement instrument.

All data collected through these events should comply with GDPR or equivalent data protection regulations, be disclosed to learners in plain-language consent forms, and be stored in IRB-compliant LRS systems with defined retention and deletion policies. Dashboards should present cohort-level aggregated patterns to educators rather than exposing individual-level raw traces.

Satisfies G9: The design team creates an event dictionary mapping 12 interaction events to seven constructs, submits the data collection plan for IRB review, and presents the consent process to students.

Violates G9: All controller button presses and gaze data are logged continuously without a construct mapping, consent mechanism, or data minimization policy.

4.3.10. Guideline 10: Ensure Technical Feasibility, Interoperability and Scalability

Design decisions should consider hardware diversity, performance, deployment, maintenance, and institutional integration. The interaction model should degrade gracefully across devices. Analytics infrastructure should avoid degrading runtime performance and

should use interoperable standards where appropriate. Content should be modular so that scenarios, prompts, assets, and assessment rules can be updated without rebuilding the entire environment. In higher education, specific constraints include LMS compatibility, IT support capacity, and sustainable licensing models that do not create long-term vendor dependency.

Satisfies G10: The XR environment is designed for WebXR to support both HMD and desktop browser access; LMS integration is confirmed at the prototype stage using LTI 1.3.

Violates G10: The XR environment requires proprietary HMDs not available to all students and cannot be updated without complete redeployment.

Table 5 provides an expanded summary mapping of the ten design guidelines, integrating educational psychology constructs, UX implications, assessment evidence, technical implications, higher education constraints, and measurable indicators for the planned evaluation phase.

Table 5. Expanded summary mapping of the ten design guidelines to theoretical constructs, UX/UI implications, assessment evidence, technical considerations, HE constraints, and evaluation indicators.

G	Education Psychology	UX/UI	Assessment Evidence	Technical	HE Constraint	Evaluation Indicator
G1	Prior knowledge; learner variability	Personas; journey maps	Baseline profiles; outcome indicators	Platform choice; hardware inventory	LMS profile; IRB scope	Persona accuracy; accessibility scenario coverage
G2	Discovery; experiential; situated	Task authenticity; branching	Hypothesis tests; decision traces	Scenario engine; state tracking	IRB for authentic tasks	% activities with clear XR-specific affordance
G3	CTML; CLT types	Signaling; segmentation	Load reports; error rates; transfer	Asset optimization; frame rate	Diverse hardware constraints	NASA-TLX scores; comprehension test
G4	Embodiment; gesture-concept congruence	Gesture-object mapping; alt inputs	Manipulation quality; action sequences	Input abstraction; haptic APIs	Alternative inputs for all hardware	Motor-concept alignment rating
G5	SDT; self-efficacy	Meaningful choices; calibrated challenge	Persistence; help-seeking; IMI scores	Adaptive task logic	Cross-cohort equity	IMI intrinsic motivation subscale
G6	SRL cycle; metacognition	Progress maps; reflection checkpoints	Strategy traces; reflection quality	LRS; session state	LMS feedback loop	SRL trace coverage; reflection depth rating
G7	UDL 3.0; multimodal	Captions; contrast; multi-input	Option usage; accessibility feedback	Configurable settings; assistive compat.	Assistive technology compatibility	Accessibility audit score; diverse user testing
G8	Formative assessment; competence support	In-environment feedback; debrief panels	Process indicators; misconceptions	Event-based feedback system	LMS grade integration	Feedback specificity rating; process coverage
G9	Theory-driven evidence; ethics; xAPI	Transparent notices; actionable dashboards	Mapped event dictionaries; data quality	xAPI/LRS; data minimization	IRB compliance; LRS compatibility	Construct coverage ratio; IRB approval
G10	Sustainable participation; adoption	Cross-device consistency; graceful degradation	Usage patterns; performance metrics	Cloud deployment; modular assets	LMS compatibility; IT support capacity	Device compatibility rate; LMS integration test

5. Discussion

The following use cases are hypothetical illustrative scenarios presented solely to demonstrate how the proposed guidelines could be operationalized in practice. They do not constitute implemented XR environments, evaluated prototypes, or empirically grounded cases. They are conceptual design plans intended to show the internal coherence of the framework across different disciplinary and collaborative contexts. The illustrative figures (Figures 4 and 5) were generated with Google Gemini and are conceptual visualizations only.



Figure 4. Conceptual illustration of a hypothetical XR cellular biology learning environment. Generated with Google Gemini (3.5 Flash) for illustrative purposes only. This is not an implemented prototype or a real system screenshot.



Figure 5. Conceptual illustration of a hypothetical collaborative XR historical reconstruction scenario. Generated with Google Gemini (3.5 Flash) for illustrative purposes only. This is not an implemented prototype or a real system screenshot.

Table 6 summarizes, for each of the ten design guidelines, whether it is illustrated in the individual cellular biology scenario (Section 5.1), the collaborative historical reconstruction scenario (Section 5.2), or both, so that the mapping between guidelines and use cases is explicit rather than left for the reader to infer from the narrative.

Table 6. Mapping of design guidelines illustrated in each hypothetical use case.

Guideline	Use Case 1: Cellular Biology (Individual)	Use Case 2: Historical Reconstruction (Collaborative)
G1—Learning objectives, learner variability, context	Yes	-
G2—Align XR with pedagogical methods	Yes	Yes
G3—Manage cognitive load and multimedia processing	Yes	-
G4—Design embodied interaction	Yes	-
G5—Support motivation, agency and self-efficacy	Yes	Yes
G6—Embed self-regulated learning scaffolds	Yes	Yes
G7—Apply UDL 3.0 and accessibility	Yes	Yes
G8—Integrate feedback and formative assessment	-	Yes
G9—Instrument learning analytics ethically	Yes	Yes
G10—Ensure technical feasibility and scalability	Yes	Yes

5.1. Hypothetical Use Case 1 (Illustrative Scenario): Cellular Biology Laboratory in XR

The first scenario describes a first-year undergraduate biology course in which students would explore a three-dimensional human cell. Learners would navigate through the cell, interact with organelles, trigger biological processes such as membrane transport and ATP production, and receive feedback about the functional consequences of their actions. The learning objectives would target analysis, causal reasoning, and transfer rather than simple identification of organelles. This scenario is designed to operationalize Guidelines 1–10, as described below and summarized in Table 6.

The Cognitive-Embodied Processing Model (G3, G4) would guide the design by ensuring that spatial navigation and manipulation clarify functional relationships. Students could enlarge organelles, isolate processes, and compare normal and disrupted states. Animations would be segmented and signaled to prevent overload (G3), consistent with the signaling and segmentation principles of CTML [11]. The Motivation-Agency-Regulation Model (G5, G6) would be applied through prediction prompts: before disrupting a membrane or changing a molecular concentration, learners would formulate a hypothesis, test it and compare outcomes with their prediction, supporting agency, self-efficacy, and SRL.

The Inclusive Participation and Analytics Model (G7, G9) would inform accessibility and data collection. The system would provide captions, textual equivalents for audio explanations, adjustable contrast, gaze-based selection, and controller-based alternatives (G7). Learner interactions would be logged through an event dictionary (G9) as illustrated in Table 4: organelle selection events would map to ‘conceptual exploration’; navigation path data would map to ‘spatial orientation’; reflection prompt responses would map to ‘metacognitive processing’. Educator dashboards would summarize patterns at the cohort level and identify concepts requiring further explanation without exposing unnecessary personal data, consistent with ethical analytics principles.

This illustrative scenario addresses the design of Figure 4 below. In this scenario, LMS integration (G10) would be handled through an xAPI-LRS pipeline connected to Moodle, and IRB approval would be required before data collection begins.

5.2. Hypothetical Use Case 2 (Illustrative Scenario): Collaborative Historical Reconstruction in XR

The second scenario describes a second-year undergraduate history course in which groups would reconstruct the social and spatial dynamics of a European city district in the early twentieth century. Students would enter a shared XR environment as role-based investigators: urban historian, social anthropologist, architectural analyst, and primary source specialist. They would explore streets and interiors, examine archival documents, and collaboratively produce a historical interpretation. This scenario is designed to operationalize Guidelines 2, 5, 6, 7, 8, and 9, with particular emphasis on collaborative XR design (see Table 6).

The situated learning rationale (G2) would be explicit: students would participate in a simulated community of historical inquiry [20]. Role-specific affordances would create epistemic interdependence (G5). For example, the primary source specialist could open archival documents, the architectural analyst could reveal building plans, and the social anthropologist could annotate evidence of everyday practices. Group convergence points would require students to compare evidence, negotiate interpretations, and produce a shared account.

Motivation and self-regulation (G5, G6) would be supported through meaningful roles, shared goals, and group reflection prompts. Inclusion (G7) would be addressed through text chat alternatives to voice, adjustable spatial audio, accessible transcriptions of historical documents, and avatar customization. Learning analytics (G9) would operate at both individual and group levels using the event dictionary: navigation, document examination, annotation, speaking turns, and convergence activity would be mapped to constructs from Table 4 and aggregated into a debriefing visualization. The dashboard would be designed to help instructors detect disengagement, imbalance in participation, and weak evidence integration while preserving transparency and proportionality.

5.3. Implications for Instructional Designers and Educators

The guidelines imply a shift from XR as media selection to XR as a learning system design. Instructional designers should begin by defining the psychological processes that XR is expected to support. For example, if the goal is conceptual change, design should emphasize causal visualization, prediction, feedback, and reflection. If the goal is professional practice, design should emphasize authentic roles, situated tasks, and scaffolded participation. If the goal is collaboration, design should include role interdependence, shared artifacts, and group-level feedback.

Educators also need new forms of pedagogical literacy. They must understand how to interpret XR analytics without reducing learning to raw behavioral counts. A high number of interactions may indicate engagement, confusion, or inefficient exploration depending on the task. Long gaze duration may reflect attention, disorientation, or accessibility barriers. Therefore, analytics dashboards should be co-designed with educators and interpreted alongside learning objectives, student reflections, and accessibility data.

The models also strengthen the role of accessibility specialists and students in the design process. Inclusive XR cannot be achieved through final-stage compliance checks. It requires early prototyping with diverse users, systematic review of sensory and motor demands, accessible content authoring, and mechanisms for students to configure the environment to their needs. In this sense, inclusion is both an ethical requirement and a

validity requirement: if participation is not accessible, the learning experience and the data generated by it are incomplete.

5.4. Limitations

The primary limitation of the study is that the guidelines are derived from literature synthesis and illustrated through hypothetical use cases rather than empirically validated in a controlled deployment. The Design Science Research cycle remains incomplete until the evaluation phase, comprising expert review, heuristic assessment, and field testing, is conducted. The proposed models and guidelines are theoretically grounded but have not been tested for effectiveness, usability, or completeness in any real XR learning context.

It is important to note that the term ‘evidence-based,’ used in some prior framings of this research, should be understood here in the specific sense of ‘grounded in systematic literature synthesis’; that is, each guideline is linked to peer-reviewed empirical or theoretical sources (as made explicit in Table 2). It does not mean that the guidelines themselves have been validated through the authors’ own empirical studies. Readers should interpret the guidelines as theoretically motivated design propositions that require empirical evaluation before being adopted as design standards.

A second limitation concerns the generalizability of technical recommendations. Hardware, network infrastructure, institutional policies, and staff expertise vary substantially across universities. Some institutions may not have access to head-mounted displays, learning record stores, or cloud infrastructures. The guideline on scalability is intended to support adaptation, but it cannot eliminate local constraints.

A third limitation concerns collaborative XR. The historical reconstruction scenario illustrates role interdependence and shared interpretation, but the guidelines do not yet fully model conflict, power relations, group emotion, co-regulation, or avatar-mediated identity dynamics. Future versions should integrate computer-supported collaborative learning (CSCL) theory more explicitly.

5.5. Future Research Agenda

Future research should evaluate the guidelines as a DSR artifact through the complementary methods described in Section 3.1. Expert reviews can assess clarity, completeness, and usability. Heuristic evaluations can test the UX and accessibility dimensions. Quasi-experimental or design-based studies can compare XR environments designed with and without the guidelines, measuring learning outcomes, transfer, cognitive load, motivation, self-regulation, and accessibility experiences.

Longitudinal research is needed because many XR studies still focus on short-term novelty and immediate outcomes. Future studies should examine retention, transfer to real-world practice, sustained motivation, repeated use, equity of participation, and instructor adoption. Learning analytics research should move toward theory-driven and multimodal models that combine interaction traces with reflection, assessment, and accessibility indicators.

The technical dimension also requires ongoing revision. XR hardware, authoring tools, AI-assisted content generation, and learning analytics infrastructures are evolving rapidly. Future guideline iterations should include stronger protocols for AI-generated assets, synthetic learner data, privacy-preserving analytics, and interoperability across XR platforms and institutional learning systems.

6. Conclusions

This article has revised and strengthened the design guidance for inclusive XR learning environments in higher education. The updated version integrates recent literature and

develops a more robust educational psychology foundation through three interpretive models: the Cognitive-Embodied Processing Model, the Motivation-Agency-Regulation Model, and the Inclusive Participation and Analytics Model. These models connect XR affordances to validated constructs such as cognitive load, multimedia processing, presence, agency, embodiment, motivation, self-efficacy, self-regulation, situated participation, UDL 3.0, and ethical learning analytics.

The ten design guidelines provide theoretically grounded and practically applicable heuristics for educators, instructional designers, and developers. They emphasize that XR should be used when it supports meaningful learning processes, not when it merely adds technological novelty. They also show that inclusion, feedback, and analytics must be designed from the beginning rather than added after implementation. Two hypothetical illustrative use cases demonstrate how the framework could inform individual inquiry in biology and collaborative interpretation in history.

The proposed artifact contributes to a more systematic and theory-informed approach to XR in higher education. Its value lies not in prescribing a single design template, but in offering a structured way to reason from learning theory to immersive interaction, from learner variability to accessibility, and from behavioral data to formative pedagogical decisions.

The present framework is theoretically grounded through systematic literature synthesis but has not yet been empirically validated. Its value at this stage lies in providing a structured and psychologically coherent basis for XR learning environment design. Empirical validation through expert review, heuristic evaluation, and field deployment constitutes the essential and immediate next step. Future studies will be necessary to refine the model, test its effectiveness, and establish its applicability across disciplines and institutional contexts.

The path from the present conceptual contribution to empirical validation is intended to be systematic rather than open-ended. The three evaluation methods outlined in the Planned Evaluation Framework (Section 3.1)—expert review panels, structured heuristic evaluation, and quasi-experimental field deployment—correspond directly to the measurable evaluation indicators, such as accessibility audit scores, NASA-TLX cognitive load scores, IMI motivation subscales, SRL trace coverage, and construct coverage ratios for the analytics event dictionary. Each of the ten guidelines therefore already carries a pre-specified indicator through which its future evaluation can be operationalized, so that the transition from design proposition to empirically tested guideline will not require the evaluation criteria to be defined post hoc. This explicit linkage between the planned evaluation methods and the guideline-level indicators in Table 5 is intended to close the methodological loop opened in Section 3.1 and to provide a concrete, auditable roadmap for the next phase of this research program.

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Abbreviations

AR	Augmented Reality
CAMIL	Cognitive Affective Model of Immersive Learning
CLT	Cognitive Load Theory
CSCL	Computer-Supported Collaborative Learning
CTML	Cognitive Theory of Multimedia Learning
DSR/DSRM	Design Science Research/Design Science Research Methodology
HMD	Head-Mounted Display
HE	Higher Education
IRB	Institutional Review Board
LMS	Learning Management System
LRS	Learning Record Store
MR	Mixed Reality
SAM	Successive Approximation Model
SDT	Self-Determination Theory
SRL	Self-Regulated Learning
TPACK	Technological Pedagogical Content Knowledge
UDL	Universal Design for Learning
VR	Virtual Reality
xAPI	Experience Application Programming Interface
XR	Extended Reality

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