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Fostering Sustainable Learning via Embodied Intelligence: The E3-HOT Framework for Higher-Order Thinking in the AI Era

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Abstract

Artificial intelligence (AI) can help students accelerate assignment completion, but it may also foster cognitive outsourcing and learning detached from authentic contexts. This paper presents E3-HOT, a conceptual framework that leverages embodied intelligence to sustain learners' cognitive agency and higher-order thinking for sustainable learning, aligned with SDG 4 (Sustainable Development Goal 4) and its emphasis on inclusive and equitable quality education and lifelong learning. Using an iterative conceptual synthesis, we distill three embodied pathways—situational embedding, embodied participation, and cognitive creation—and translate them into a practical system design with a three-module E3 core. It includes a virtual–real integrated learning environment for rich scenarios, embodied interaction for action and sensing, and an intelligent core that provides bounded and teacher-controlled support. To facilitate equitable adoption across resource-diverse settings, we specify multi-fidelity enactment options and an auditable set of evidence artifacts for subsequent expert review and future validation studies. We further provide an illustrative university human–AI design project that outlines a week-by-week workflow and corresponding evidence plan, presented as a worked example rather than a report of an implemented study. E3-HOT offers a traceable design-and-evidence blueprint without claiming measured learning gains.

Keywords: higher-order thinking; embodied intelligence; E3-HOT framework; sustainable learning; SDG 4; human–AI collaboration

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1. Introduction

Today, AI-powered conversational systems have made it easier for students to access information and complete tasks, but they may encourage cognitive offloading and cognitive outsourcing, raising concerns about sustainable learning and the long-term development of higher-order thinking in AI-intensive classrooms. Some students routinely rely on these systems to automatically generate answers for assignments and papers, particularly by developing a habit of using AI to polish their academic writing [1,2]. Even in routine email communication with teachers, students increasingly rely on AI-generated drafts. This has led teachers to often question whether such messages reflect students' own voice and intent. In effect, students have become less inclined to engage in independent critical thinking. Over time, this may weaken critical reflection and creative ideation, resulting in diminished innovation capabilities and homogenized expression [3–5]. Meanwhile, many students no longer rely on specific contexts for learning; they proactively seek knowledge through online searches or AI tools [6]. People tend to focus on remembering the source rather than encoding and retaining the content. This can undermine deep learning by encouraging cognitive offloading and reducing effortful processing [7–9]. If such cognitive outsourcing becomes normalized, it may create an unsustainable learning pattern in which performance can be improved while the capacity for deep reasoning and creative work gradually erodes.

To situate this work in sustainability-oriented education, we adopt SDG 4 as the normative anchor, emphasizing inclusive and equitable quality education and lifelong learning opportunities for all. In this paper, sustainability is operationalized as the long-term sustainment of this capability under AI-intensive conditions. It also foregrounds inclusive participation under diverse learner needs and institutional constraints. It further requires feasibility through multi-fidelity enactment, so that mechanism–objective alignment can be preserved from high-tech to low-tech implementations. Finally, it emphasizes responsible evidence governance, ensuring that multimodal data collection remains bounded by pedagogical purposes rather than drifting toward surveillance.

Relevant studies indicate that to achieve interaction with humans in real or virtual environments, intelligent systems must be embedded within bodies possessing sensory and motor capabilities [10–12]. The core concept involves using technology to establish connections between students and specific contexts, enabling them to construct knowledge through hands-on participation rather than relying solely on abstract information acquisition. Driven by this philosophy, the integration of embodied intelligence holds promise for addressing limitations in digital learning environments, particularly the lack of contextual diversity, thereby refocusing learning on cultivating higher-order thinking skills. This approach promotes learners' long-term cognitive development in a more sustainable manner [13]. This perspective aligns closely with the 4E (embodied, embedded, extended, and enacted) cognitive framework, which emphasizes the coupling of mind, body, and environment, focusing on strategies that enable complex learning activities to be driven by context and action [14]. It should be noted that within 4E research, there remains disagreement over whether environmental factors are constitutive of cognition or merely exert causal influence on it [15,16]. Therefore, educational research must formulate mechanisms in testable terms and define evidence criteria in operationalizable ways. This motivates an auditable design-and-evidence blueprint that can be enacted under different fidelity levels while maintaining comparable evidence signals.

The higher-order thinking discussed in this paper is operationalized using the cognitive process dimension of the revised Bloom's taxonomy, where Analyze, Evaluate, and Create are defined as complex, higher-level cognitive processes [17–19]. Moreover, research on assessing higher-order thinking frequently designs tasks and rubrics around these three processes as the top tier of this taxonomic framework [20,21]. Accordingly, this paper focuses on these three dimensions, which are widely used as operational definitions in the literature, and examines how embodied intelligence can support them as sustainable learning capacities under AI-rich conditions.

Therefore, this paper proposes E3-HOT, a systematic framework to cultivate students' higher-order thinking skills for sustainable learning in the AI era. Here, E3 refers to the Virtual–Real Integrated Environment, Embodied Interaction, and Intelligent Core; HOT denotes the Higher-Order Thinking that this paper focuses on. It should be noted that E3 represents the three runtime modules of the embodied intelligence core, whereas

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Profile and Learn, introduced later, are orchestration-layer components for configuring constraints and combining activity sequences. This separation is intended to improve feasibility and transfer. The same mechanism pathways can be enacted at different resource levels via Profile constraints and Learn templates, while keeping AI support bounded and teacher-governed.

Compared with conventional AI tutoring systems, E3-HOT does not center on automated explanation delivery or answer optimization. Instead, it treats AI as bounded scaffolding within teacher-governed tasks and requires auditable intermediate artifacts. Compared with immersive or VR-centered instructional designs, E3-HOT does not treat immersion itself as the primary goal; rather, it treats context, action, and evidence as the key conditions for sustaining higher-order thinking. Compared with general higher-order thinking frameworks, E3-HOT adds a mechanism-to-module mapping, a Profile/Learn orchestration logic, and a reproducibility layer that makes enactment and evidence governance explicit.

To develop E3-HOT, we used an iterative conceptual synthesis rather than an intervention study. We scanned representative literature on embodied cognition, embodied intelligence, and higher-order thinking aligned with SDG 4, focusing on claims that can be operationalized in classroom tasks. We then extracted recurring mechanisms and design levers, clustered them into three embodied pathways, and mapped each pathway to Analyze, Evaluate, and Create. Finally, we translated these mappings into implementable specifications, including an E3 runtime core with a virtual–real integrated environment, embodied interaction, and an intelligent core engine, plus a lightweight orchestration layer for task requirements, Profile constraints, and Learn activity templates. This paper is positioned as a design-and-evidence blueprint. It specifies what should be observed and collected in future validation studies, rather than reporting measured learning gains at the current stage.

The contributions of this paper are threefold: First, it proposes E3-HOT as an alignment framework that links embodied mechanism pathways to HOT objectives under an explicit sustainability framing. Second, it specifies an engineering-implementable architecture by clarifying the E3 runtime core and the orchestration-layer components, together with their interfaces and deployment logic. Third, it provides an illustrative workflow for translating theoretical constructs into pedagogical activity pathways and identifying auditable evidence artifacts. It also clarifies the multi-fidelity enactment and governance assumptions required for inclusive and sustainable classroom adoption, thereby supporting subsequent expert review and future validation.

To sharpen the design-oriented positioning of this study, we formulate two explicit design questions rather than effect hypotheses.

Design Question 1 (DQ1). How can embodied intelligence be translated into a teacher-governed framework for fostering analysis, evaluation, and creation as sustainable higher-order thinking processes under AI-intensive educational conditions?

Design Question 2 (DQ2). What design elements, evidence artifacts, and bounded-AI governance rules are needed to make such a framework auditable, reusable, and enactable across different fidelity levels?

In simplified terms, E3-HOT can be read at three linked layers. Mechanism pathways define what kinds of higher-order thinking processes should be supported, the E3 runtime modules define how those processes are enacted in instructional systems, and the Profile/Learn layer defines how tasks, constraints, and activity templates are configured for classroom use.

2. Materials and Methods

Building on the sustainability concerns raised in Section 1, this section describes how E3-HOT was developed and then summarizes the theoretical inputs used to ground its mechanism pathways [22–24]. Because this study is positioned as a design-and-evidence blueprint rather than an intervention report, the Materials and Methods section emphasizes transparency, traceability, and auditability in the framework construction process.

2.1. Framework Development Protocol: Iterative Conceptual Synthesis

E3-HOT was developed through an iterative conceptual synthesis that translates multidisciplinary theoretical claims into classroom-operational mechanisms, design elements, and evidence artifacts. The goal of the protocol is not to estimate learning effects, but to make the framework construction process inspectable and reusable under diverse instructional constraints.

The process began with literature identification and scoping. We searched representative scholarship on embodied cognition and embodied intelligence, higher-order thinking and its assessment, and learning theories that clarify how analysis, evaluation, and creation can be fostered in authentic activity [25–27]. We also reviewed literature that discusses AI-mediated learning risks, particularly cognitive offloading and cognitive outsourcing, in order to define design constraints for bounded AI support [28,29].

We then applied screening and selection criteria centered on classroom enactability. Eligibility was assessed using titles, abstracts, and keywords only; full texts were not systematically retrieved or assessed. This study focused on extracting design-relevant mechanisms, constraints, and observable evidence cues. It did not aim to synthesize effect sizes or offer exhaustive coverage. Therefore, the literature review was carried out as a design-oriented scoping process based on titles, abstracts, and keywords. Priority was given to sources that stated mechanisms in actionable terms, described conditions under which a mechanism is expected to operate, or implied observable signals that could serve as evidence in future validation. When a mechanism, design lever, or evidence artifact was not explicitly described in the available record fields, it was coded as not stated rather than inferred. Sources that remained purely descriptive without clear implications for task design or evidence planning were treated as background rather than drivers of the final mapping. To audit coding reliability under this abstract-based protocol, two coders independently double-coded a randomly sampled subset of records (n = 25). Percent agreement was 92% for situational embedding, 96% for embodied participation, and 96% for cognitive creation. Disagreements were resolved by consensus adjudication.

Next, we extracted candidate concepts and coded them into three information types. The first type captured mechanism claims about how context and action shape cognition. The second type captured design levers that can be implemented as task scripts, interaction rules, or platform affordances. The third type captured evidence artifacts that could be collected during enactment, such as structured analysis traces, justification records, or iterative revision histories.

After iterative coding and consolidation, we clustered recurring mechanisms into three pathways, situational embedding, embodied participation, and cognitive creation. Each pathway was then mapped to the higher-order thinking targets used in this study, namely, Analyze, Evaluate, and Create. The mapping was guided by whether the pathway primarily supports context deconstruction and structure identification, evidence-based judgment and criteria use, or generative exploration and iterative refinement.

Finally, we translated the pathway-to-HOT mapping into implementable specifications. This translation produced the E3 runtime core with a virtual–real integrated environment, embodied interaction, and an intelligent core, alongside an orchestration layer that supports task requirement modeling, Profile constraints, and Learn activity templates. Throughout development, we maintained a traceable chain from theoretical claims to pathway assignment, from pathway assignment to module design, and from module design to proposed evidence artifacts. To make later validation work comparable across resource levels, the protocol also checked whether each mechanism could be enacted with different fidelity options while preserving the same evidence signals.

2.2. Theoretical Inputs: Embodied Intelligence

Embodied intelligence is a new research direction that has developed from reflections on and extensions of traditional artificial intelligence. It emphasizes that the body, brain, and environment of an intelligent agent form an inseparable whole. Unlike traditional perspectives that regard intelligence as merely information processing within the brain, embodied intelligence proposes that cognition gradually forms through the interaction between the body, brain, and environment [10,30,31]. In this study, embodied intelligence is further viewed as a means to sustain learners' cognitive agency by reconnecting thinking with action and context, rather than replacing thinking with automated outputs.

The concept of embodied intelligence aligns with the four characteristics of the 4E cognition framework, which are embodied, embedded, enacted, and extended (See Figure 1).

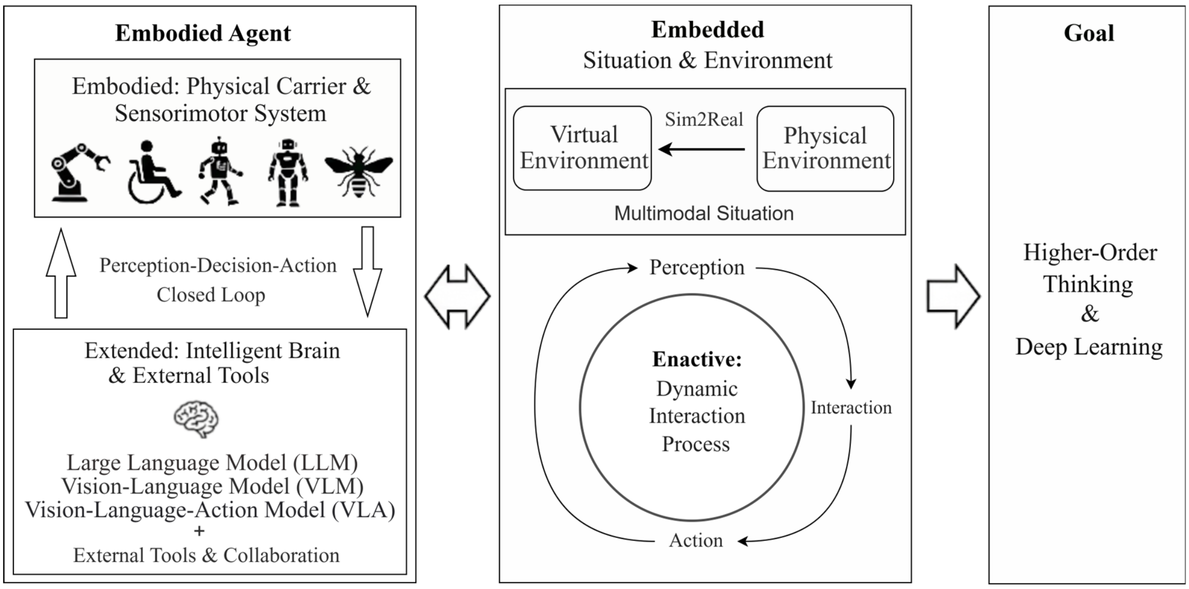

Figure 1. The conceptual framework of embodied intelligence.

Based on the above theoretical framework, this paper identifies three mechanisms through which embodied intelligence empowers the cultivation of higher-order thinking. These are the situational embedding mechanism, the embodied participation mechanism, and the cognitive creation mechanism. These three mechanisms are clearly related: situational embedding supports students' analytical thinking, embodied participation supports evaluative thinking, and cognitive creation supports creative thinking.

The situational embedding mechanism refers to using concrete or simulated scenarios to carry knowledge and learning tasks, making them more aligned with real-world contexts. This form of learning aligns with the cognitive view of situational embedding, which helps overcome the disconnection between knowledge and its real-world application, and supports the analytical dimension of higher-order thinking.

The embodied participation mechanism initiates cognitive processing through bodily engagement and multisensory experience. It aligns closely with embodied cognition and action cognition, and emphasizes the role of bodily movement and hands-on practice itself.

The cognitive creation mechanism is mainly realized through artificial intelligence, which extends and amplifies human intelligence, thereby enabling AI-mediated support for learning. The cognitive creation mechanism can be viewed as the creative dimension of higher-order thinking, in which students use AI-provided knowledge support, strategic suggestions, and generative materials to extend their thinking and generate new ideas [5,32].

It is important to note that these three mechanisms are not independent but work in an interrelated and integrated manner.

2.3. Theoretical Foundations

Embodied intelligence can be integrated with classical cognitive theories to support students' cognitive development. These theories clarify which forms of thinking should be cultivated, while embodied intelligence offers mechanisms for implementing them in learning scenarios. In this study, these theories are used as theoretical inputs that inform pathway definitions and evidence planning, rather than as competing explanatory accounts.

Constructivist learning theory posits that learning is a process in which learners actively construct meaning based on their prior experiences and engagement [33]. With the support of embodied devices, students' learning processes can be recorded in real time, which can trigger feedback based on their learning outcomes. In addition, such traceable, action-linked learning processes can support long-term monitoring and iterative improvement of instruction, which is consistent with the idea of sustaining educational quality rather than optimizing one-off performance.

Situated learning theory points out that knowledge is inherently contextual, with the context itself constituting a vital component of cognition [34]. In the situational embedding of embodied intelligence, learning activities are placed in simulated or real scenarios to establish a close connection between knowledge and the application environment. When knowledge and contexts are tied together, students are more likely to move from merely memorizing facts to explaining mechanisms and making judgments.

Self-regulated learning theory emphasizes that learners should regulate their learning activities to achieve goals, monitor their learning processes, and adopt strategies to improve their performance [35]. The development of higher-order thinking also requires strong metacognitive and self-regulatory skills [36–38]. Within this framework, embodied intelligence environments create favorable conditions for students' self-regulated learning, offering rich visual and operational feedback, which allows students to verify and revise their understanding through action.

3. From Theory to Platform: E3-HOT Educational Design for Sustainable Learning

3.1. Empowerment Hierarchy Model and Pathways for Cultivating Higher-Order Thinking

3.1.1. Situational Embedding Level

This level focuses on cultivating students' analytical thinking through situational creation. Teachers can use technologies such as virtual reality and situational simulation to create teaching scenarios that closely resemble real-life situations so that students can integrate the knowledge they have learned into these concrete contexts. Students need to recognize their situational context and understand what they should do within it as a whole, preparing them for further cognitive processing. In teaching practice, this level should guide students to analyze through contextualized questions. This allows them to explicitly demonstrate their understanding of the situational structure and reduces context-free answer seeking that may arise from overreliance on generative AI. To make analysis inspectable, teachers can require students to externalize key assumptions, constraints, and causal links in written or diagrammatic form, and to submit intermediate reasoning artifacts before any final response is produced. These artifacts provide stable evidence cues that can be preserved even when the fidelity of scenarios changes across classrooms.

3.1.2. Embodied Participation Level

After completing basic situational analysis training, students enter the second level. The embodied participation level emphasizes guiding students toward deep engagement through bodily involvement, prompting them to reflect on and evaluate the meaning embedded within the context. As students engage in interactions, they will experience cognitive conflicts and engage multiple senses, thereby activating evaluative processes central to higher-order thinking [39–41]. Teachers can design specific activities to encourage students to question their operational results and support or revise their original judgments with evidence. For instance, in role-playing and situational simulations, students are encouraged to argue and defend their positions from different perspectives, thus training evaluative thinking as a sustainable capability rather than a one-off performance outcome. To prevent AI-driven shortcutting, evaluation is framed as evidence-based judgment under explicit criteria. Students are asked to explain why a claim is acceptable, what evidence supports it, and what counterevidence would change the decision. The resulting artifacts can serve as auditable evidence that evaluation occurred through action-linked inquiry rather than answer acceptance.

3.1.3. Cognitive Creation Level

The main focus of this level is cultivating students' creative thinking. The knowledge, experience, and skills acquired in the previous two levels will be integrated and applied to practices of innovation and creation at this stage. In a blended virtual–real teaching space, the various functions of the intelligent core are utilized to assist students in generating innovative new solutions. In the cognitive creation level, teachers need to provide open-ended tasks. They also provide multi-round feedback and examples through the intelligent core module, supporting them to refine their work through multiple iterations. In addition, the evaluation criteria should shift from whether the answer is correct to the novelty, rationality, and sufficiency of the arguments in creative work, promoting the continuous development of students' creative thinking. To avoid AI replacing human thinking, this level is more suitable for human–AI co-creation with human-determined rules, with humans determining the final task solution so that extended cognition remains bounded and educationally sustainable. At this level, creation is treated as iterative design rather than one-shot generation. Students are required to document decision rationales across iterations, and the intelligent core is constrained to provide prompts rather than a final deliverable. Teachers retain authority over the rules of acceptable assistance and over the final evaluation of student work.

In conclusion, the situational embedding level helps students develop a structured analytical viewpoint within complex scenarios, and the embodied participation level drives them to make evidence-based judgments through action and experience. The cognitive creation level then guides students to generate new solutions, creations, or representations based on the experiences from the first two levels. The three levels are not a one-time linear process but can circulate multiple times around the same learning theme, gradually advancing students' higher-order thinking through the interplay of analysis, evaluation, and creation. Therefore, the pathway is not simply divided into three layers but is a continuous learning system that evolves. Across cycles, the mechanism–objective alignment remains stable, while enactment media can be adapted to local constraints without changing what is counted as evidence of analysis, evaluation, and creation.

3.2. Task Requirement Modeling

Before proceeding to system implementation, it is necessary to objectify the target outcomes that classroom tasks are expected to achieve. Following a declarative modeling approach led by instructional designers, E3-HOT treats task requirement modeling as the entry point of the platform. Instructional designers provide functional descriptions of the target tasks and select the most relevant competency elements from the E3-HOT element checklist. The task requirements modeling process emphasizes support rather than substitution. The system provides element prompts and consistency checks, yet the final selection and interpretation remain the prerogative of the teacher. The modeling results will serve as shared inputs for subsequent persona scenario filtering and learning activity generation. This helps ensure consistency across activities, competencies, and evidence while establishing a sustainable evidence pathway for later expert review and validation. Specifically, these requirements parameterize the Profile constraints (Section 5) and guide activity retrieval and sequencing in Learn (Section 6). In addition, task requirement modeling specifies the minimal evidence cues expected from the activity sequence, so that future validation studies can audit whether higher-order thinking was enacted through observable processes and artifacts. This also enables multi-fidelity enactment, because teachers can change media and tools while keeping evidence cues and scoring rubrics comparable across contexts.

3.3. System Design for Supporting Higher-Order Thinking Through Embodied Intelligence

To operationalize higher-order thinking through embodied intelligence, this paper constructs a layered architecture from a systems engineering perspective. This framework comprises three core modules: the virtual–real integrated environment, embodied interaction, and the intelligent core. These three modules respectively realize the mechanisms of situational embedding, embodied participation, and cognitive creation. For clarity, the remainder of this paper refers to the virtual–real integrated environment, embodied interaction, and intelligent core as modules, and to situational embedding, embodied participation, and cognitive creation as mechanism pathways. The proposed architecture is designed to sustain learners' higher-order thinking under AI-intensive learning conditions by keeping teachers in the loop and constraining AI to scaffolding roles. It is also designed for equitable adoption across resource-diverse classrooms by allowing different enactment fidelity options while preserving the same mechanism–objective alignment and evidence pathway. The overall system architecture is illustrated in Figure 2.

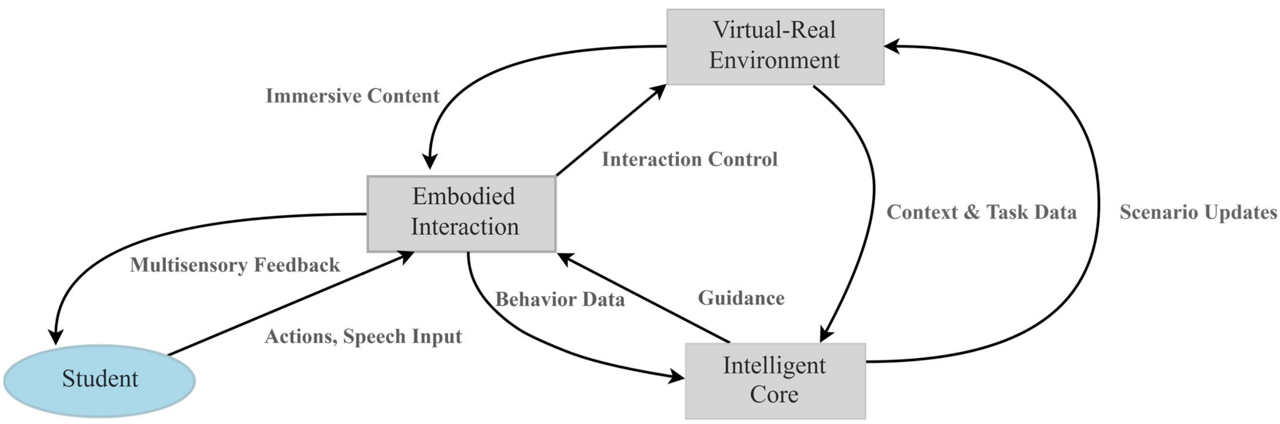

Figure 2. System architecture of embodied intelligence empowering students' higher-order thinking. The architecture is teacher-governed: teachers authorize task rules, evidence boundaries, and acceptable AI assistance; student teams produce the required intermediate artifacts; and the Intelligent Core provides bounded scaffolding rather than autonomous final-output generation.

3.3.1. Virtual–Real Integrated Environment Module

By creating educationally meaningful learning scenarios and using a virtual–real integrated environment as the medium, situational embedding can support higher-order thinking while providing a carrier for diverse learning activities. The environment integrates elements of physical space and digital virtual space. It uses mixed reality, augmented reality, and virtual reality to create immersive scenes that present the contextual and material elements required for learning tasks in digital form while retaining the necessary physical elements. Key components include a virtual environment generation engine, physical space positioning devices, and a scenario script and storyline manager. Through these subcomponents, the environment module can load pre-designed instructional scenario scripts and present virtual objects alongside projection and audio equipment in the physical space, thereby constructing an immersive scenario that integrates the virtual and the real. When immersive devices are unavailable, the same mechanism can be enacted through lower-fidelity media. In these cases, the design requirement is not immersion itself, but the presence of a coherent context that supports analysis through explicit structure, constraints, and causal relations.

3.3.2. Embodied Interaction Module

This module is responsible for capturing and providing feedback on students' bodily postures and multisensory behavioral data, enabling these inputs to function as dynamic controllers of the learning environment and content. Students interact naturally with the virtual–real integrated environment and the intelligent core through bodily actions. The embodied interaction module consists of a set of sensing and feedback subcomponents. Position tracking and motion capture devices collect students' movements and spatial postures; speech recognition and facial expression recognition interfaces capture verbal commands and affective cues; and haptic and force-feedback devices enhance immersion. These subcomponents work in coordination to digitize various forms of students' inputs and send them to the virtual–real integrated environment and the intelligent core module. To support responsible evidence governance, data collection is bounded to what is necessary for the task and is configurable by teachers. When sensing devices are not feasible or appropriate, embodied participation can still be evidenced through structured observation checklists and student reflection logs that document action, outcome, and judgment.

3.3.3. Intelligent Core Module

The intelligent core module is not only the core of the embodied intelligent system, but also the main intelligent support component. This module comprises artificial intelligence units and data-processing components that understand learning contexts, analyze student behavior, deliver personalized support and feedback, and co-create with students during creative tasks. In this part, AI is designed as a Socratic guide rather than a direct answer provider. This design ensures that the system focuses on higher-order thinking rather than low-level knowledge retrieval. The intelligent core is constrained to provide prompts, critique, and strategy suggestions, and it can require students to articulate rationales and cite evidence before accepting a claim or finalizing a solution. Teacher confirmation remains the gate for applying system recommendations to subsequent task configurations. The intelligent core module can be decomposed into several units:

Learner Modeling and Cognitive Diagnosis Unit: This unit mainly focuses on collecting students' behavior data generated during interactions within the virtual–real environment and embodied interaction processes. After analyzing the data, the system constructs profiles of students' cognitive states, forming the basis for understanding what students are thinking and doing.

Generative Intelligence Unit: This unit uses large language models and image generation models to provide content support as needed.

Intelligent Tutoring and Feedback Unit: This unit provides dialogic guidance, enabling the system to engage students through Socratic dialog or direct conversation.

Coordination and Regulation Unit: This unit manages coordination among the above components, including dynamically adjusting task difficulty and interaction pacing based on diagnostic results. It also manages access control, logging, and teacher-facing settings that bound what assistance can be generated and what evidence can be stored.

Through the intelligent core module, the system establishes a co-learning interaction with students, essentially supporting exploration and inquiry. As students generate creative ideas, the system continuously refines its strategies based on feedback, gradually guiding and stimulating higher-order thinking across the levels of analysis, evaluation, and creation. The primary objective is not to maximize automation, but to sustain learner agency through guided inquiry that remains auditable across iterations.

3.3.4. Module Coordination

Each of the three modules plays a distinct role: the virtual–real integrated environment supports context creation and material provision, embodied interaction supports action and communication, and the intelligent core provides analytical support and regulatory control. Together, these modules form a coordinated instructional system that establishes tasks and scenarios, externalizes reasoning and peer questioning, and then adjusts subsequent tasks through a combination of intelligent-core rules and teacher-defined rules. Through iterative cycles, students' thinking develops within a feedback loop that links perception, decision-making, and action. Each round of system feedback is designed to guide rather than replace student thinking, ensuring that training consistently targets higher-order thinking goals. Notably, the closed loop referred to here denotes a feedback loop between instructional design and evidence, rather than real-time algorithmic adaptation. In the current version, automated strategy updates are not deployed, system recommendations must be confirmed by teachers before being applied in subsequent task configurations. This coordination logic supports multi-fidelity enactment because teachers can select different environment and interaction configurations while keeping the same evidence pathway and governance constraints. Table 1 summarizes the design elements and representative tasks associated with the three modules, providing a reference for future instructional design and for building sustainable educational ecosystems aligned with SDG 4.

Table 1. Design Elements and Representative Tasks.

Module	Key Design Elements	Typical Task Type
Virtual–Real Integrated Environment	VR and AR scenarios, immersive projection and audio, scenario scripts and storylines.	Contextualized problem solving, virtual experiments, case-based discussions.
Embodied Interaction	Motion capture and embodied sensing devices, speech and facial expression recognition interfaces.	Experimental operations, role-playing, collaborative dialog, and embodied challenge-based activities.
Intelligent Core	Learner models and diagnostic algorithms, generative-AI–based intelligent tutoring dialog interfaces.	Intelligent tutoring, adaptive learning, human–AI co-creation projects.

4. Putting the Framework into Action: An Illustrative Vignette

The primary challenge in bringing the three-module architecture of E3-HOT and its higher-order thinking pathway into classroom practice is translating system-level design into concrete tasks and activities. Since there is no single solution applicable to all contexts, it is necessary to clearly articulate assumptions and allow teachers to adjust parameters according to instructional conditions. This section is an illustrative worked example and an evidence specification. It reports no completed pilot, no participant recruitment, no data collection, and no empirical findings. Its purpose is to make the E3-HOT workflow, evidence artifacts, and governance constraints reproducible for later expert review and classroom validation. Accordingly, the subsections below specify classroom roles, auditable evidence artifacts, multi-fidelity enactment options, and a machine-readable Profile/Learn interface.

4.1. Illustrative Worked Example and Evidence Specification

The worked example is framed as a four-week university human–AI co-creation design project that can be enacted with or without immersive devices. The teacher uses task requirement modeling (Section 3.2) to define the challenge and success criteria, then parameterizes the classroom context through Profile (Section 5) and selects activity templates from Learn (Section 6). These choices configure the Virtual–Real Integrated Environment, Embodied Interaction, and Intelligent Core as a teacher-led workflow rather than as an autonomous AI tutoring system.

Role responsibilities are made explicit to support auditability and to ensure clear governance boundaries. The teacher authorizes task rules, evidence boundaries, and acceptable assistance. Student teams produce the required intermediate artifacts and record iteration rationales. The Intelligent Core provides prompts, critique, and strategy suggestions within teacher-approved bounds and does not generate a final deliverable for direct submission.

Teacher governance is implemented through pre-defined checkpoints that gate changes to criteria, tool use, and final submissions. Each checkpoint is recorded as a Teacher Gatekeeping Record, allowing later reviewers to inspect how bounded AI use and evidence requirements were enforced.

4.2. Evidence Specification: Artifacts, Mandatory Fields, and Rubric Stubs

E3-HOT operationalizes evidence as auditable artifacts that externalize analysis, support evidence-based evaluation, and document iterative creation. Because this study does not report participant data, the evidence plan below is presented as reusable templates and minimal rubric stubs for future validation studies and expert audits. Evidence collection remains purpose-bounded and teacher-configurable so that logs and traces do not drift toward routine surveillance.

Table 2 specifies the evidence artifacts, mandatory fields, and rubric stubs that connect mechanism pathways to interpretable evidence cues.

Table 2. Evidence artifact specification for auditable enactment.

Artifact	Mandatory Fields	Example Cue for Audit	Rubric Stub
Context Structure Map	Scenario ID; stakeholders; constraints; causal links; open questions; author/team; timestamp	Constraints and causal links are explicit and connected to the task prompt	Adequate when the map identifies key constraints and at least one causal chain; strong when it includes alternatives and uncertainty notes
Assumptions & Source Log	Claim; assumption; evidence source; confidence note; alternative explanation; author/team; timestamp	Evidence is traceable to sources, and uncertainty is recorded	Adequate when sources are cited and assumptions stated; strong when counterevidence and revisions are documented

Table 2. *Cont.*

Artifact	Mandatory Fields	Example Cue for Audit	Rubric Stub
Criteria–Evidence Matrix	Criteria; weights (optional); evidence; counterevidence; decision; rationale; author/team; timestamp	Judgments reference criteria and evidence, not authority or AI output	Adequate when criteria align with the task; strong when trade-offs and counterevidence are addressed
Embodied Trial Observation Sheet	Trial ID; action; observable outcome; measurement/notes; interpretation; safety note (if needed); timestamp	Action–outcome links are documented and interpreted	Adequate when observations are recorded and interpreted; strong when interpretations are revised after new trials
Peer Critique Record	Target artifact/version; critique claim; evidence; suggestion; response; revision decision; timestamp	Teams respond to critique with evidence-based revisions	Adequate when critique is specific; strong when critique triggers documented revisions
Iteration & Change Log	Version; change summary; rationale; evidence used; decision owner; linked artifacts; timestamp	Multiple versions show purposeful refinement rather than one-shot generation	Adequate when versions and rationales are logged; strong when changes are tied to evidence and criteria
AI Assistance Disclosure Log	Step; assistance type; prompt summary; what was accepted/rejected; student rationale; teacher gate (if applicable); timestamp	AI use is transparent and bounded, with student rationale recorded	Adequate when assistance types are disclosed; strong when rationales show independent evaluation of AI suggestions
Teacher Gatekeeping Record	Checkpoint; compliance check; decision; required revision; approving teacher; timestamp	Teacher approval is recorded at pre-defined checkpoints	Adequate when decisions are documented; strong when decisions cite evidence artifacts and safety/ethics constraints

Illustrative synthetic examples of these evidence traces are provided in Supplementary File S5. These examples are included only to clarify the intended artifact structure and do not represent participant data or completed pilot records.

4.3. Multi-Fidelity Enactment and Substitution Map

In this study, multi-fidelity enactment refers to using alternative media at different resource levels to implement the same mechanism pathway and evidence cues, so that evidence remains comparable across classrooms. This definition supports inclusive adoption by allowing high-tech and low-tech implementations while preserving what counts as evidence of Analyze, Evaluate, and Create.

Table 3 provides a substitution map that maintains the required evidence cues when immersive environments or embodied sensing are not feasible.

Table 3. Multi-fidelity enactment substitution map preserving evidence cues.

Mechanism Pathway/Module	Higher-Fidelity Enactment Option	Lower-Fidelity Substitution Option	Evidence Cue Preserved
Situational embedding/Virtual–Real Integrated Environment	VR/MR scenario with interactive digital objects	Scenario script with physical props, photos, or printed maps; role cards	Context Structure Map; Assumptions & Source Log
Embodied participation/Embodied Interaction	Wearables, motion capture, haptics, sensor-based trials	Structured observation checklist; manual trial log; photo/video only if teacher-approved	Embodied Trial Observation Sheet; Peer Critique Record

Table 3. *Cont.*

Mechanism Pathway/Module	Higher-Fidelity Enactment Option	Lower-Fidelity Substitution Option	Evidence Cue Preserved
Cognitive creation/Intelligent Core	Teacher-governed LLM coach embedded in the platform	Teacher-approved prompt cards; peer critique protocol; offline ideation with disclosure	Iteration & Change Log; Criteria–Evidence Matrix; AI Assistance Disclosure Log
Evidence governance/logging	Automated system event logs (purpose-bounded)	Timestamped version history and manual submission checklist	Iteration & Change Log

4.4. Machine-Readable Profile/Learn Artifacts and Reproducibility Package

To improve transparency and reuse, Profile constraints and Learn activity templates can be expressed in machine-readable form. Table 4 presents a selected human-readable subset of the Week 1 specification, showing how classroom context, HOT focus, evidence artifacts, and bounded-AI rules can be parameterized. Full JSON and YAML schema files are provided in Supplementary Files S2 and S3.

Table 4. Selected human-readable subset of the machine-readable Profile/Learn specification for the illustrative vignette (Week 1).

Component	Field	Example Value
Profile	language	zh; en
Profile	duration_weeks	4
Profile	modality	hybrid
Profile	group_size	5
Profile	resources.vr_ar	optional
Profile	resources.sensing	optional
Learn template	week	1
Learn template	goal	Framing & Exploration
Learn template	hot_focus	Analyze; Create
Learn template	evidence_artifacts	context_structure_map; assumptions_source_log
Bounded AI rules	allowed	prompting; critique; missing-element check
Bounded AI rules	disallowed	drafting final deliverable; fabricating citations
Bounded AI rules	teacher_gate	criteria_approval; final_submission_approval

Detailed reproducibility materials supporting the illustrative vignette are provided in Supplementary Files S1–S8.

4.5. Illustrative Case Scenario: "Human–AI Co-Creation Design Project"

The vignette below is illustrative and is not extracted from participant data; it is provided to demonstrate how the workflow and evidence specification can be instantiated.

This example focuses on cultivating creative higher-order thinking within a human–AI co-creation design challenge situated in a university-level interdisciplinary project. Students would participate in an open-ended group project over four weeks. The project could be enacted in an immersive environment that blends physical and digital elements, supported by simulation tools and a shared resource library. Within this setting, students would assemble prototypes, test solutions in an immersive sandbox environment, and discuss their findings through verbal communication. The generative AI-driven Intelligent Core would provide prompts and guidance when teams encounter roadblocks. Teachers would act as supervisors and coordinators, providing materials and feedback from multiple perspectives to keep the project aligned with sustainable learning goals under SDG 4.

According to the requirements of this creative task, we selected 12 relevant E3-HOT facets that cover cognitive, conative, and knowledge dimensions. The selected facets are listed below.

4.5.1. Divergent Thinking (Cognitive Dimension—Expert Level)

Divergent thinking refers to the ability to generate diverse and novel ideas, which constitutes the core of creative thinking. This facet encourages students to produce a wide range of unique perspectives, laying the foundation for subsequent design work.

4.5.2. Convergent Thinking (Cognitive Dimension—Advanced Level)

Through human–AI collaboration, students can systematically converge from a broad idea space to a limited set of optimal solutions.

4.5.3. Interdisciplinary Knowledge Integration (Knowledge Dimension—Expert Level)

Innovative projects always involve the integration of knowledge from multiple disciplines.

4.5.4. Technical Practice Skills (Sensorimotor Dimension—Advanced Level)

Translating ideas into prototypes requires hands-on technical skills.

4.5.5. Initiative and Perseverance (Conative Dimension—Advanced Level)

Long-term creative projects test students' motivation and persistence.

4.5.6. Collaborative Communication (Conative Dimension—Advanced Level)

Creative activities are typically team-based. Effective collaboration and communication ensure idea sharing and collective decision-making.

4.5.7. Emotional Experience and Empathy (Affective Dimension—Advanced Level)

A positive emotional atmosphere helps inspire and maintain team cohesion during creative projects.

4.5.8. Tolerance for Uncertainty (Affective Dimension—Intermediate Level)

Innovation often comes with uncertainty. Students need to remain calm in the face of the unknown and risks, and be able to make rational judgments.

4.5.9. Metacognitive Reflection (Cognitive Dimension—Intermediate Level)

Throughout the project, students engage in continuous metacognitive reflection and adjust their creative strategies accordingly. This enhances the quality of their work and makes the final outcomes more innovative.

4.5.10. Iterative Improvement (Conative Dimension—Intermediate Level)

Creative achievements rarely reach their ideal state in a single attempt. They require continuous experimentation, refinement, and further optimization.

4.5.11. Contextual Adaptation (Knowledge Dimension—Intermediate Level)

Situational adaptation refers to the ability to adjust ideas and plans according to specific contexts. By establishing contextual constraints, teachers compel students to respond to external demands and conditions.

4.5.12. Outcome Articulation (Knowledge Dimension—Intermediate Level)

Clearly articulating the creative process and its outcomes is a crucial step in closing the innovation loop. Through expression, students learn to organize complex ideas, making the value of innovation easier for others to understand and evaluate.

Table 5 maps these facets to a week-by-week workflow, clarifying when each facet is activated and what evidence artifacts would be produced in a future implementation.

Table 5. Mapping of E3-HOT facets to the illustrative case workflow (Week 1–4).

Week	Core Goal	Representative Activities	Key Activated Facets	HOT Focus	Sustainability Signal
Week 1: Framing & Exploration	Open the problem space and ground it in context	Scenario briefing; stakeholder walkthrough; rapid ideation	Divergent Thinking; Emotional Experience & Empathy; Tolerance for Uncertainty	From Analyze to early Create	Resists answer-first AI use; builds context-grounded inquiry
Week 2: Synthesis & Selection	Narrow options with criteria and integrate knowledge	Concept clustering; criteria setting; feasibility screening	Convergent Thinking; Interdisciplinary Knowledge Integration; Collaborative Communication	Evaluate	Builds reasoned judgment and accountable decision-making
Week 3: Prototyping & Testing	Embodied making, testing, and evidence-based iteration	Prototype build; embodied trials; data logging; peer critique	Technical Practice Skills; Metacognitive Reflection; Iterative Improvement; Contextual Adaptation	From Evaluate to Create	Sustains learning through action-linked feedback loops
Week 4: Articulation & Reflection	Communicate outcomes and reflect for transfer	Demo day; design rationale write-up; retrospective reflection	Outcome Articulation; Initiative & Perseverance; Metacognitive Reflection	Create & reflection	Makes learning transferable; supports long-term capability

5. E3-HOT Profile

The Profile component of the E3-HOT framework is designed to provide a contextual foundation for instructional design. It enables instructional designers to define the pedagogical context for training, thereby laying the foundation for subsequent E3-HOT activity recommendations. After a set of parameters is predefined, the Profile component filters instructional strategies that are relevant and feasible in the given context. This helps ensure that the designed learning activities are not only theoretically sound but also practically implementable under real classroom conditions. It also supports inclusive and sustainable adoption across resource-diverse settings by making contextual assumptions explicit.

The output of the Profile component is not a psychological assessment of individual learners, but rather a set of configuration constraints for combinations of contexts, groups, and resources. The system cross-references this with task requirement modeling outcomes to identify areas of direct alignment and potential areas of tension. This output serves as a filter for the Learn component, allowing it to adjust teaching activities and map theory to practice. By treating context as an explicit and auditable configuration, Profile records the constraints that shape activity selection, thereby supporting sustainable implementation, reuse, and cross-cohort comparison. In this study, classroom task contexts are summarized into six key parameters (a–f), each of which has a significant impact on instructional design:

(a) Language (e.g., if learners come from multilingual backgrounds, the E3-HOT Profile will consider providing multilingual materials or real-time translation support; in contrast, in a monolingual context, instruction may focus on in-depth materials in the target language);
(b) Time Duration (e.g., the total amount of time available for training and its pacing, including whether the training is completed in a short, intensive period or distributed across a longer time span, such as an entire semester);
(c) Spatial Environment (e.g., whether learning is conducted online, on-site, or in a hybrid format; whether activities take place in a classroom, lab, maker space, or field setting; and what embodied-interaction affordances are available);
(d) Social Setting (e.g., whether learning is undertaken independently, in small-group collaboration, or as a whole-class activity; typical group size and role structure; and how collaboration, peer feedback, and accountability are organized);
(e) Instructional Culture (e.g., whether the training is initiated by learners' own needs, mandated top-down by institutional management, or driven by examination reforms or policy directives—capturing the motivation for the program and the level of institutional support);
(f) Practical Constraints (e.g., class size, equipment and resources, premises, curriculum standards, and safety and ethical restrictions, among others, which constitute additional hard constraints within the teaching context).

Once these parameters are explicitly defined and formalized, E3-HOT automatically generates a structured profile output corresponding to the context. Consequently, subsequent teaching recommendations are no longer based on abstract judgments but on actual contextual conditions. The system employs a dual-layer rule structure for policy selection: hard constraints define non-negotiable conditions, while soft preferences express adjustable tendencies. Building upon this foundation, the system compares multiple alternative solutions and selects an implementation path that balances efficiency and adaptability. In subsequent validation work, the Profile output can also serve as a standardized context descriptor for reporting transfer conditions, thereby improving the interpretability and reusability of evidence.

Suppose there is a university innovation practice course on human–machine collaboration. The course spans four weeks. Students come from multidisciplinary backgrounds, including international students. The course organizes weekly in-person workshops and combines online collaboration to advance team tasks. Due to the bilingual Chinese-English environment, teaching materials and communication methods must accommodate both languages. Learning occurs in teams of five, and the course operates within an elective framework. Teachers favor exploratory teaching approaches and can provide support. From a sustainability standpoint, the scenario also requires maintaining inclusive participation across linguistic backgrounds and ensuring that AI use supports learning rather than replacing thinking.

Under these classroom conditions, Profile guides the Learn component to prioritize project-based learning and open-ended creative activities. The system first recommends asynchronous components. Teams can brainstorm online using AI platforms while simultaneously conducting literature reviews and background research. Synchronous sessions are structured as weekly in-person workshops, emphasizing role-playing, prototype demonstrations, and immediate feedback. AR devices enhance the immersive quality of creative experiences. When immersive devices are unavailable, the same workflow can be enacted through scenario scripts and structured reflection while preserving the same mechanism–objective alignment. Finally, this profile optimizes activity sequencing to ensure the training plan remains imaginative yet fully implementable. To align with SDG 4, the configuration emphasizes sustained capacity building and inclusive participation, rather than short-term output maximization. In sum, Profile translates broad instructional goals into explicit contextual constraints that improve feasibility, guide Learn activity selection, and support sustainable implementation under local classroom conditions.

6. E3-HOT Learn: Building and Applying a Pedagogical Activity Repository

The E3-HOT Learn component functions as a repository of pedagogical activities that translates E3-HOT's mechanism pathways into classroom-deployable instructional units. It is designed to help teachers select activities that cultivate higher-order thinking as a sustainable learning capacity under AI-intensive conditions, thereby contributing to SDG 4. It also supports inclusive and equitable adoption under resource-diverse constraints by providing multi-fidelity enactment options and purpose-bounded evidence governance. Methodologically, this section describes a conceptual design blueprint within a preliminary DBR phase, rather than a deployed system with measured learning gains.

6.1. Design Goals of E3-HOT Learn

E3-HOT Learn is guided by three design goals:

- Teacher agency and bounded AI support. The module is designed to support teachers' instructional decision-making rather than automate it. Recommendations are presented as editable options, and final adoption remains teacher-confirmed. This design goal also requires teacher decision rights and responsibility boundaries to remain explicit throughout recommendation and revision.
- Context feasibility and maintainability. Activities are parameterized so they can be adapted to different constraints and reused across contexts, while preserving mechanism–objective alignment and comparable evidence cues under both high-tech and low-tech enactment.
- Sustainability framing and SDG 4 alignment. Each activity template explicitly states its targeted HOT process, evidence artifacts, and a brief sustainability rationale that clarifies how the activity supports inclusive participation and long-term capability building.

6.2. Construction Pipeline of the Pedagogical Activity Repository

To ensure the scientific rigor and practicality of the teaching activity library, E3-HOT Learn follows this construction process:

Step 1: Compilation of teaching strategy list.

The research team first reviewed representative literature to compile a broad inventory of instructional strategies and documented the conditions under which each strategy is applicable. To balance coverage and maintainability, the initial inventory is recommended to start with a manageable set that can be expanded iteratively in later Design-Based Research (DBR) cycles.

Step 2: Mapping strategies to competency dimensions and facets.

With the assistance of generative AI, the research team mapped each instructional strategy to the competency dimensions and specific facets defined in the E3-HOT model. This prevents the repository from becoming a black box and keeps it aligned with teacher judgment. A bounded AI use field is added to specify what AI is allowed to do and what it must not do. This field specifies permitted assistance types, prohibited shortcut behaviors, and teacher confirmation points, so that AI support remains transparent and pedagogically bounded.

Step 3: Parameterize each activity as a reusable template.

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After completing the strategy–competency mapping, E3-HOT Learn enters the key phase of repository generation. For each facet and proficiency level, the system pre-selects 4–6 candidate strategies and contextualizes them into synchronous and asynchronous activity templates by referencing Profile constraints. These templates are later filtered and integrated into teacher-facing instructional plans, and each template records a multi-fidelity enactment note that preserves the same mechanism target and evidence cues under lower-tech alternatives.

Step 4: Define evidence artifacts and minimal evaluation cues.

Each activity template additionally records a minimal set of evidence artifacts and evaluation cues that can support later validation studies, such as reflection logs, revision histories, and prototype iteration traces. To illustrate how E3-HOT Learn operationalizes higher-order thinking, the examples below focus on three objective categories and select one representative competency facet from each category. These examples should be read as design illustrations rather than evaluated interventions.

Step 5: Expert review, versioning, and DBR refinement.

The repository is treated as a versioned resource that can be iteratively expanded and refined through DBR cycles. Expert review focuses on whether each template remains classroom-executable, whether evidence cues are interpretable for teachers, and whether bounded AI rules prevent shortcutting while supporting learner agency. This maintenance logic supports sustainability by enabling reuse and incremental improvement across cohorts rather than one-off implementation.

Table 6 presents illustrative activity designs for analytical higher-order thinking. The competency element selected is problem analysis capability within a context-embedded mechanism, corresponding to the core of analytical thinking. The table lists activity proposals in ascending order of proficiency level.

Table 6. Layered instructional activity examples for cultivating analytical ability.

Level	Description	Synchronous Instructional Activity Examples	Asynchronous Instructional Activity Examples
Level 1: Beginner	Able to identify key points in basic questions within simple contexts when prompted.	Guided case scan: The teacher presents a short scenario and uses structured prompts to help students identify key issues and list them collectively.	Online annotation: Students highlight and tag key information in a short case; the platform compares with a reference set and returns prompts on omissions.
Level 2: Intermediate	Can independently break down problems and extract key information within familiar contexts.	Small-group decomposition: Groups break a familiar case into sub-problems, then share and refine their decomposition through whole-class feedback.	Scenario analysis brief: Students submit a structured breakdown and evidence list online; AI-assisted feedback flags missing elements and misclassified information.
Level 3: Advanced	Comprehensively analyze problems in complex and unfamiliar contexts, identifying multi-level causal relationships.	Role-based case workshop: In a simulated real-world case, teams analyze multi-level causes from assigned roles and defend their reasoning in a short presentation and Q&A.	Progressive case reasoning: The platform releases case clues in stages; students update hypotheses each round and submit a final coherent analysis report.
Level 4: Expert	Capable of navigating highly complex and open-ended scenarios, adept at pinpointing the core of issues and conducting structured analysis of the broader context.	Timed expert simulation: Teams act as consultants to pinpoint the core issue, propose an analytic framework, and respond to challenge questions under time and information constraints.	Open-ended case project: Over several weeks, teams research a real issue, submit milestone briefs, receive automated analytic support, and deliver a rigorous final report.

Minimal evidence artifacts for Table 6 include a structured problem decomposition sheet, annotated case highlights, and an analysis brief that records assumptions and causal links. Bounded AI support is limited to prompts, missing-element checks, and structure consistency feedback, and it is prohibited from generating a complete final report on behalf of students.

Table 7 illustrates a set of activity design examples for "evaluative" higher-order thinking objectives. The selected competency facet is critical evaluation within an embodied participation framework—that is, the ability of students to assess viewpoints or solutions based on evidence and criteria, aligning with the key focus of developing evaluative thinking. The activities at different levels are designed to progressively cultivate students' judgment and reflective abilities.

Table 7. Layered instructional activity examples for cultivating evaluative ability.

Level	Description	Synchronous Instructional Activity Examples	Asynchronous Instructional Activity Examples
Level 1: Beginner	Be able to make basic judgments on simple viewpoints under clear standards.	Criteria-based judgment: Students evaluate simple claims using provided criteria, discuss in groups, and justify their decisions with brief evidence.	Validity-judgment quiz: Students judge claims with supporting materials and short justifications; auto-scoring provides model rationales for comparison.
Level 2: Intermediate	Be able to provide simple evaluations of the strengths and weaknesses of viewpoints or solutions within familiar domains based on evidence.	Paired solution critique: Pairs compare two solutions, identify strengths/weaknesses with course evidence, state a preference, and respond to peer challenges.	Peer review task: Students submit a short evaluative memo and review two peers using an evidence-based rubric; selected comments are discussed in class.
Level 3: Advanced	Be able to critically analyze various positions on open-ended issues, make well-founded judgments, and clearly articulate reasons.	Structured debate: Teams defend opposing positions on an open issue; students evaluate logic and evidence in real time using a rubric, followed by a guided debrief.	Case review report: Students analyze competing perspectives in a real case, assess source reliability, and defend a conclusion; the system scaffolds search and citation.
Level 4: Expert	Ability to weigh multiple factors in complex and uncertain situations, make comprehensive and prudent evaluative decisions, and confidently assume responsibility for the consequences of judgments.	Panel review simulation: Students pre-read a complex proposal, score it across multiple criteria, negotiate a consensus decision, and draft a concise review under time pressure.	Comprehensive evaluation project: Students develop a policy/proposal, model consequences of options with platform tools, and submit a decision rationale; grading emphasizes prudence and accountability.

Minimal evidence artifacts for Table 7 include an evidence-based rubric, justification records that cite criteria and evidence, and peer critique notes that capture counterarguments and revisions. Bounded AI support is limited to helping students restate criteria, surface counterevidence, and improve clarity of justification, while teacher-defined criteria remain the final authority.

Table 8 shows a set of activity design examples for "creative" higher-order thinking objectives. The selected competency facet is inventive capability under the cognitive creation mechanism, representing the core of creative thinking.

Minimal evidence artifacts for Table 8 include iteration logs, design rationales that explain why changes were made, and a final reflection on transfer. Bounded AI support is limited to critique, alternative generation under constraints, and Socratic prompting, and it is prohibited from producing the final deliverable without student-authored rationales and revisions.

Table 8. Layered instructional activity examples for cultivating creative ability.

Level	Description	Synchronous Instructional Activity Examples	Asynchronous Instructional Activity Examples
Level 1: Beginner	Capable of making simple improvements or imitative creations to existing things under guidance from others.	Micro-innovation warm-up: Given an everyday object or scenario, students propose one improvement or new use with prompts; the class provides quick feedback.	Remix-and-reflect task: Students adapt a provided example using a checklist and submit a short reflection on one change that increases novelty.
Level 2: Intermediate	Ideas or works that can independently generate a certain degree of novelty, yet remain confined within familiar boundaries.	Constraint prototyping sprint: In a short workshop, teams build a simple prototype with limited materials and demonstrate it, followed by a rapid feedback round.	Semi-structured mini-project: Students design a product combining two course concepts and submit proposal; the system prompts when stuck and provides rubric-based draft feedback.
Level 3: Advanced	Capable of producing works with a high degree of originality and complexity under open requirements, and able to iterate and refine them multiple times.	Creative design salon: Brainstorming, poster sharing, and revision rounds help teams iterate quickly; the teacher and AI coach provide targeted prompts and resources.	Prototype sprint with change log: Over two weeks, teams upload iterations to a project space, receive peer comments, and submit a final demo video plus revision log.
Level 4: Expert	Capable of independently conceiving unprecedented innovative ideas and fully realizing works of practical value.	Open innovation studio: Teams choose topics, run validation updates in seminars, and present final products; external experts may co-evaluate originality and practical value.	Competition or venture engagement: Students join external innovation programs; the platform collects reflection logs and provides periodic scaffolds and checkpoints to support execution.

The three tables above correspond to teaching activity design examples for the three higher-order thinking objectives. Teachers may further adapt these plans based on their professional judgment and course objectives. In this way, E3-HOT Learn combines a carefully curated activity repertoire with intelligent matching, while teachers provide secondary optimization, jointly enabling the design of effective and feasible instructional plans for higher-order thinking development. Through the Learn component, complex competency cultivation requirements are translated into concrete instructional action lists, effectively bridging theoretical models and classroom practice and providing robust support for students' higher-order thinking development. Future DBR cycles will examine enactability and evidence quality under realistic constraints, consistent with SDG 4 and the sustainable education framing. This emphasis on reusability, multi-fidelity enactment, and teacher-governed evidence supports sustainable and equitable classroom adoption aligned with SDG 4.

7. Discussion

In the sustainability framing adopted in this study, the core objective is to sustain learners' cognitive agency under AI-intensive conditions. This objective is aligned with SDG 4's emphasis on inclusive and equitable quality education and lifelong learning opportunities for all.

The primary challenge is translating the three-module architecture of embodied intelligence and its higher-order thinking pathway into concrete classroom tasks. While the system architecture logically emphasizes closed-loop feedback, division of labor, and interfaces, students engage only in concrete activities. System design often proves feasible at the macro level, but classroom implementation demands micro-level executability. To ground mechanisms in practice without overstating empirical validation, the present study provides a design blueprint that specifies course units and proposed evidence artifacts for later expert review and future validation studies. Situational embedding, embodied participation, and cognitive creation must be explicitly incorporated into course units, task scripts, and assessment evidence. Different courses will make different choices—some employ contextual scripts to drive analysis, while others use embodied operations to guide evaluation. These choices shape distinct student experiences and consequently alter interpretations of learning outcomes. There is no single solution here, but underlying assumptions must be explicitly articulated, and teachers must be empowered to adjust critical parameters. To keep this approach sustainable across diverse institutions, these parameters should support multi-fidelity enactment, allowing high-tech implementations to be replaced by low-tech alternatives while preserving mechanism–objective alignment and comparable evidence cues. Simultaneously, data challenges become harder to ignore. Embodied systems rely on multimodal process data, yet classroom data is often highly noisy. More crucially, the data must be interpreted through a learning lens to generate meaningful feedback. Otherwise, it devolves into surveillance-like documentation, failing to drive genuine instructional improvement [42–44]. From a sustainability perspective, this implies that data use must be bounded by pedagogical purpose and governance rules, so that evidence collection supports learning improvement rather than routine monitoring. This bounded use also requires transparency about what is collected and why. It further requires teacher-governed configuration of logging and sensing, as well as a clear separation between evidence for instructional improvement and data that could be repurposed for non-educational control. In a human-centered governance stance, human oversight is treated as part of instructional design rather than post hoc compliance, and responsibility boundaries remain explicit.

Another key challenge stems from resource constraints and crowded curricula. Most course frameworks are already tightly packed. Adding sensors, generative tutoring, and learning analytics as extra modules is therefore difficult in practice [45,46]. A more feasible approach is to integrate systems thinking training directly into existing exercises rather than adding extra class hours. The issue lies not in credits but in faculty time. For true implementation, teaching teams must collectively rewrite examples, adjust assessment criteria, and equip themselves with necessary digital tools. Without institutional support and long-term planning at the school level, such systems often remain confined to pilot demonstrations and struggle to transition into routine application [47]. From a systemic perspective, this is not a reform that any single teacher can accomplish alone, but rather a collaborative endeavor involving both social and technological systems [48,49]. To keep the approach scalable, E3-HOT should also support multi-fidelity enactment: high-tech embodied implementations can be substituted with lower-cost embodied activities while preserving the same mechanism–objective alignment. Because infrastructure is uneven, this is not only a feasibility concern but also an equity concern that directly affects who can benefit from embodied and AI-supported learning designs.

E3-HOT implies that sustainable learning in the AI era requires a shift from answer production to capacity preservation and growth. In practical terms, this means designing activities so that students repeatedly engage in context-grounded analysis, evidence-based evaluation, and iterative creation, rather than treating generative tools as a shortcut to finished outputs. Such a design orientation directly addresses the sustainability concern that cognitive offloading may accumulate over time and gradually weaken learners' agency. Under bounded AI rules, the goal is not to eliminate AI, but to ensure that extended cognition supports thinking rather than replaces it.

At the ecosystem level, sustainability also concerns maintainability and reuse. The framework's value is not only in proposing a three-module architecture, but also in offering reusable task scripts and activity templates that can be adapted to different contexts through teacher-defined parameters. This supports the formation of a sustainable educational ecosystem in which practices can be iteratively refined across cohorts rather than implemented as one-off demonstrations. This reuse logic matters for institutions with limited staff time, because sustainability depends on whether designs can be maintained, updated, and adopted without continuous external support.

Sustainable education requires inclusive and accountable deployment. Because immersive infrastructure is uneven, multi-fidelity enactment is not optional but a sustainability constraint. In addition, embodied systems rely on multimodal data, so evidence collection must remain aligned with educational purpose. Human oversight should therefore be treated as part of instructional design rather than as post hoc compliance. In this sense, inclusive deployment requires both accessibility in implementation and accountability in how evidence is produced, interpreted, and governed across different learner groups and classroom contexts.

Limitations and Future Directions

It should be noted that this paper focuses on framework modeling and design demonstration. Comparative empirical research across different disciplines and classroom settings has not yet been conducted. Therefore, conclusions regarding learning gains should be interpreted with caution. This paper aims to propose a designable and testable baseline, not to claim significant improvements. The sustainability claims in the present article are positioned at the level of design intent and scope alignment, rather than at the level of demonstrated long-term impacts. In addition, the conceptual synthesis was conducted as a design-oriented scoping process using titles, abstracts, and keywords rather than a systematic full-text review; therefore, the framework should be interpreted as a structured and auditable design baseline rather than as an exhaustive synthesis of all relevant literature.

Future work will therefore focus on staged validation. Possible validation designs include small-scale design-based studies, quasi-experimental comparisons across bounded-AI and conventional conditions, and rubric-based expert audits of student artifacts. Outcome measures may include process-based indicators of analysis, evaluation, and creation, quality of intermediate artifacts, revision depth across iterations, and teacher-rated interpretability of evidence. The evidence artifacts proposed in Section 4 can serve as structured sources for assessing whether higher-order thinking was enacted through observable reasoning, judgment, and iterative creation rather than through answer acceptance alone. One stream of work will organize expert review and small-scale validation studies to examine whether the three mechanisms remain stable across disciplines and whether the mechanism–objective mapping is interpretable and usable for teachers. Another stream will develop an indicator system aligned with analysis, evaluation, and creation that integrates process and output evidence, while explicitly addressing noise handling and fairness procedures for multimodal data. A third stream will compare human–AI division-of-labor strategies under bounded AI rules, examining how different scaffolding modes influence students' quality of creative outputs, with the goal of producing replicable design principles for sustainable classroom adoption. Across these streams, validation will treat multi-fidelity enactment and purpose-bounded evidence governance as first-class design constraints, because long-term sustainability depends on whether the approach remains inclusive, interpretable, and maintainable under realistic resource variation.

8. Conclusions

This paper proposes E3-HOT as a theory-to-practice framework for fostering higher-order thinking through embodied intelligence in contemporary education. The paper frames sustainability as the long-term maintainability of learners' cognitive agency in

AI-enabled learning environments and explicitly aligns the contribution with SDG 4, which emphasizes inclusive and equitable quality education and lifelong learning opportunities for all.

Building on embodied cognition and the 4E perspective, E3-HOT specifies three mechanism pathways—situational embedding, embodied participation, and cognitive creation—and translates them into an implementable three-module architecture. Rather than presenting a completed intervention with measured learning gains, this study contributes a design blueprint. It includes a mechanism–objective mapping, a contextual profiling logic, and an activity-repository approach that can be enacted at different implementation levels under realistic constraints.

Overall, E3-HOT suggests a sustainability-oriented design stance for the AI era. It uses AI as bounded scaffolding while keeping teachers in control of task rules and evaluation criteria, so that extended cognition supports thinking rather than replaces it. This stance is consistent with the Sustainable Education and Approaches scope, which emphasizes educational approaches that are meaningful, actionable, and capable of supporting long-term educational development.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su18073469/s1, Supplementary File S1: Four Tables workbook, including the search log, screening log, included-record map, double-coded subset audit trail, and agreement summary used in the abstract-based screening and coding workflow; Supplementary Files S2 and S3: Full JSON and YAML schema files for the machine-readable Profile/Learn specification; Supplementary File S4: Evidence artifact templates; Supplementary File S5: Teacher-governed bounded AI rules and governance checkpoints; Supplementary File S6: Mock evidence traces aligned with the artifact types specified in Section 4.2; Supplementary File S7: Multi-fidelity substitution map summarized in Section 4.3; Supplementary File S8: Abstract-based coding protocol and codebook, including a de-identified worked coding example.

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