

Cognitive AI Learning Environments for Ethical, Adaptive, and Context-Aware Tutoring in Higher Education

Divesh Sarkar¹ and Manish Sarkar²

¹Senior Software Engineer and ²Software Engineer

¹Sikkim Professional University

²South Andaman, Bamboo/flat, shore point ward no 7

¹diveshsarkar70@gmail.com (Corresponding Author)

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Abstract

AI has revolutionised education by enabling personalised learning, but current AI tutoring systems struggle with a fundamental challenge: they can't fully grasp how humans think, learn, and interact in different situations. This paper presents CAL-E (Cognitive AI Learning Environment), a new theoretical framework that addresses these limitations by combining cognitive flexibility, personalised learning, and ethical safeguards. CAL-E consists of seven integrated components. At its heart, a Cognitive Processing Core interprets how students learn and adjusts teaching in real-time. This core works alongside a Context Analyser that tracks emotional states and learning conditions, while a Learner Model Repository continuously updates student profiles. The system's Knowledge Base aligns with academic standards, and its Adaptive Learning Engine delivers customized content. A Feedback Generator provides ongoing assessment, while an Ethical Governance Layer ensures the system remains fair, transparent, and compliant with international AI ethics guidelines. This architecture directly addresses pressing educational challenges, from digital access inequalities to algorithmic bias and the growing demand for scalable personalised education. Built on foundations in cognitive science, international AI ethics frameworks (including UNESCO and EU guidelines), and recent advances in generative AI, CAL-E provides a roadmap for future research and implementation. The paper includes two detailed architectural diagrams that show how the system's components work together, mapping data flows, agent interactions, and decision-making processes. CAL-E aims to guide the development of AI tutoring systems that aren't just smart, but also ethical, fair, and responsive to each student's unique learning context.

Keywords: cognitive adaptability, personalised learning, ethical AI, higher education, Educational Technology.

Introduction

In the last decade, Artificial Intelligence (AI) has emerged as a transformative force in education, reshaping the way learners interact with knowledge and how educators engage with pedagogical processes. The integration of AI into digital learning environments—often referred to as “AI in Education” (AIED)—has given rise to intelligent tutoring systems (ITS), adaptive learning

platforms, and generative tools that support a more personalized, scalable, and data-driven form of instruction (Hooshyar et al., 2025). However, despite these advancements, contemporary AI systems remain constrained by structural limitations. They often lack the ability to understand learners in a holistic manner, process cognitive and emotional states dynamically, and produce multi-level, context-sensitive feedback in real time (Gadekallu et al.,

2025). The CAL-E (Cognitive AI Learning Environment) architecture proposed in this paper seeks to address these limitations by introducing a modular, ethically grounded design that prioritises adaptability, personalisation, and oversight. The global shift toward hybrid and online learning has accelerated the demand for responsive and intelligent systems capable of addressing diverse learner needs. Educational institutions worldwide are grappling with the challenges of learner disengagement, inequity in access, rigid instructional formats, and the lack of actionable insights into learner cognition (Eaton, 2025). These challenges have only intensified in the post-pandemic era, where large-scale digital learning implementations have exposed the fragility of current systems and the urgent need for transformation (Maine, 2024). In response, the concept of cognitive adaptability has gained prominence, urging the design of learning systems that can flexibly respond to fluctuations in learner motivation, emotion, and context (Roig-Vila and Cazorla, 2024). Despite progress in the field, most AI tutoring architectures adopt narrowly defined learner models or operate on static representations of user data. This results in shallow personalisation—where learners receive different sequences of the same content rather than a fundamentally tailored instructional pathway (Filippone et al., 2024). Moreover, while commercial AI education platforms demonstrate viability, they often do not fully integrate multi-modal context awareness, such as emotional or temporal conditions, which are critical to learning efficacy (Jindal and Kumar, 2024). Furthermore, ethical dimensions of AI use—including transparency, data fairness, and psychological safety—remain underexplored in architectural blueprints, especially when the target audience comprises vulnerable learners (Kollar, 2024). To navigate these gaps,

the CAL-E framework builds on existing AIED models but expands them along three axes:

- (1) Cognitive Intelligence, via a Processing Core that dynamically interprets cognitive-affective learner states;
- (2) Contextual Awareness, via a multi-input Context Analyser that considers time of day, learning fatigue, emotional signals, and environmental constraints;
- and (3) Ethical Governance, ensuring that decision-making, learner profiling, and feedback generation are explainable, accountable, and aligned with global AI ethics standards. These components are designed not as isolated systems but as part of an interconnected architecture where modules update and communicate continuously. The central innovation lies in how CAL-E orchestrates a personalised learning journey, guided by a constantly updating Learner Model Repository, which is enriched by real-time interaction data and long-term academic records. Drawing from advances in reinforcement learning, affective computing, and large language models (LLMs), the system can adapt the complexity, pacing, and modality of content presentation (Slattery, 2024). Simultaneously, the Feedback Generator component ensures learners receive actionable, formative responses based on cognitive benchmarks and engagement metrics (Clowser, 2024). In this architecture, personalization is not just content-based but cognitively and ethically situated. By addressing ethical concerns at the architectural level, CAL-E aligns with international frameworks for responsible AI development (Gadekallu et al.,

2025). The system not only logs decision paths and data sources but also includes mechanisms for bias detection, explainability, and consent management. As AI becomes more entrenched in pedagogical decision-making, these safeguards ensure that technology enhances rather than diminishes human agency and learner autonomy (Hooshyar et al., 2025).

This paper presents CAL-E as a theoretical architecture meant to guide both researchers and developers in designing the next generation of AI tutors. The design is not prescriptive but inspirational, providing a conceptual framework that can be adapted across educational levels, subject domains, and national contexts. In doing so, it contributes to the growing body of literature that seeks to position AI as a pedagogical partner, rather than a tool, in the pursuit of deeper, fairer, and more human-centered learning experiences.

To address the gaps identified in current AI tutoring systems, this theoretical paper is guided by the following questions:

1. How can an AI tutoring architecture integrate cognitive adaptability, contextual awareness, and ethical governance to overcome the limitations of shallow personalisation and lack of holistic learner understanding in existing intelligent tutoring systems?
2. What modular components and interconnections are necessary to enable real-time interpretation of learner cognitive-affective states while ensuring alignment with international AI ethics frameworks, such as those from UNESCO and the EU?
3. In what ways can a dynamic learner model repository, informed by

multi-modal data inputs, facilitate personalised instructional pathways that account for emotional, temporal, and environmental factors in higher education?

4. How might the proposed CAL-E framework mitigate broader educational challenges, including digital access inequalities, algorithmic bias, and the scalability of personalised learning in diverse global contexts?

The paper is organised as follows: Section 2 reviews related work; Section 3 details CAL-E's architecture and components; Section 4 examines integration and data flow; Section 5 proposes an evaluation framework; Section 6 discusses implications for policy and research; and Section 7 concludes.

Background and Related Work

The convergence of artificial intelligence and education is reshaping teaching and learning, marking a significant shift since the traditional classroom model (EdTech Magazine, n.d.; Stanford HAI, n.d.). Early digital platforms delivered static lessons via computer-assisted instruction, but modern systems use adaptive algorithms, cognitive modeling, and generative AI to simulate personalised tutoring. Intelligent tutoring systems (ITS) have advanced, employing cognitive task modeling and real-time feedback, often outperforming traditional methods in targeted areas (Jia, Sun, and Looi, 2024). However, most ITS adopt a behaviorist approach, failing to capture learner motivation, emotion, and context (Azevedo and Aleven, 2013). The field has integrated cognitive science, data analytics, affective computing, and large language models (LLMs) like ChatGPT and Gemini (Brown et al., 2020; Stanford HAI, n.d.), fueling the "Fourth Education Revolution" (World Economic Forum,

n.d.). Yet, generative AI risks shallow learning, opacity, and errors (Poth, 2024; Stanford HAI, n.d.). Current adaptive platforms personalise based on prior knowledge or scores but overlook emotional, fatigue, or socioeconomic factors (Wang et al., 2024; Poth, 2024; Azevedo and Aleven, 2013). CAL-E addresses this by combining a Cognitive Processing Core and Context Analyser for dynamic interpretation of biometric, behavioral, and contextual signals. Ethics are paramount amid concerns over bias, surveillance, and autonomy (UNESCO, 2021; Poth, 2024). UNESCO's guidelines emphasize transparency, fairness, and inclusion (UNESCO, 2021), while the EU's 2024 framework stresses accountability and privacy (European Commission, 2024). CAL-E's Governance Layer embeds these principles as core architecture, not add-ons. Existing AI tutoring blueprints—rule-based, ML-driven, or multimodal—excel in domain modeling but lack real-time integration across modules (Zhou and Wang, 2024; Restack, 2025). CAL-E offers modular, interconnected design with shared data for coherence. Affective computing enhances engagement by responding to emotions like boredom or frustration (Azevedo and Aleven, 2013; Zhou and Wang, 2024), integrated centrally in CAL-E's Context Analyser.

Learning analytics predict performance but often serve teachers post hoc (Kay and Kummerfeld, 2019). CAL-E embeds them in the Adaptive Learning Engine and Feedback Generator for real-time decisions. Overall, CAL-E advances AIED by centering cognitive adaptability, context sensitivity, and ethical integrity (World Economic Forum, n.d.; Stanford HAI, n.d.).

AI Tutoring Systems: Evolution and Limitations

AI tutoring has evolved from rigid rule-based systems to probabilistic and generative models. Early ITS like AutoTutor and Cognitive Tutor

mimicked problem-solving in domains like algebra or physics (VanLehn, 2011), providing tailored guidance but limited to narrow scopes and fixed ontologies (Roll and Wylie, 2016). Machine learning enabled deeper personalisation via knowledge space theory and Bayesian inference in platforms like ALEKS (Chen et al., 2021), yet many remain opaque (Kay and Kummerfeld, 2019). LLMs like ChatGPT generate fluent responses but lack structured pedagogy and introduce biases or inaccuracies (Zawacki-Richter et al., 2019; Brown et al., 2020). CAL-E combines ITS strengths with ML and LLMs, using a Cognitive Processing Core and Context Analyser for balanced, domain-grounded instruction.

Learner Modelling and Contextual Personalisation

Effective AI tutors rely on learner models mapping knowledge, learning styles, and motivations. Early models used overlay frameworks treating student knowledge as expert subsets (Mitrovic, 2010), missing non-linear progress and factors like emotion or context. Advances incorporate biometric signals for real-time emotion-sensitive responses (Baker et al., 2019; Graesser et al., 2022). However, most systems analyse elements in silos, with reactive personalisation (Roll and Wylie, 2016). CAL-E's Learner Model Repository synthesizes multi-source inputs for proactive, context-aware profiles, including emotional volatility and deadlines. It supports transparency, allowing users to view interpretations and foster self-regulation (Bull and Kay, 2016; Luckin et al., 2021).

Ethical Frameworks and Responsible AI in Education

AI in education raises issues of bias, privacy, and equity, demanding ethical safeguards (UNESCO, 2021). UNESCO's AI Ethics Recommendation prioritises inclusion, agency, and non-discrimination (UNESCO, 2021), while

OECD principles focus on transparency and robustness (OECD, 2019). Many tools collect data without

clear consent, risking surveillance (Slade and Prinsloo, 2013). CAL-E’s Ethical Governance Layer operationalises these via bias audits, fairness constraints, transparency logs, and consent interfaces, using Value Sensitive Design

(Friedman and Hendry, 2019). It promotes AI literacy through prompts on ethical dilemmas (Williamson and Eynon, 2020) and complies with GDPR, FERPA, and emerging standards (Eubanks, 2018), enabling audits for accountability.

In sum, the Ethical Governance Layer prevents harm while building trust and equity.

Table 1: Comparative Gaps Between Traditional Intelligent Tutoring Systems and CAL-E Architecture

Feature / criterion	Traditional ITS	CAL-E architecture
Standards compliance	Often limited	Explicit alignment with global education and ethical AI frameworks
Personalisation depth	Mostly surface-level (based on quiz scores or rules)	Deep personalisation using emotional, temporal, and situational cues
Learner modelling	Static or periodically updated	Continuously updated in real-time using contextual and cognitive data
Feedback mechanism	Post-activity or at fixed checkpoints	Real-time formative, and dynamically responsive
Ethical oversight	Rarely addressed	Built-in ethics governance layer ensuring transparency and fairness
Emotional awareness	Absent or rudimentary	Integral, through the emotional recognition layer
Decision-making logic	Rule-based	AI-driven with contextual reasoning and logic pathways
Content alignment	Fixed content structure	Dynamic sequencing via adaptive learning engine + knowledge base
Cognitive adaptability	Minimal (based on pre-defined learner types)	High, through a cognitive processing core

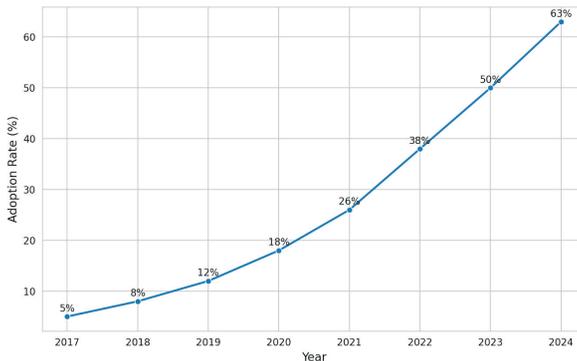


Fig. 1: Adoption Rate of AI Tutoring Tools From 2017 to 2024

Note. Trend data extrapolated from meta-reviews of AI adoption in EdTech (Hanid Ghazali, 2025); Jia, F., Sun, D., Looi, C. (2024).

The CAL-E Conceptual Architecture

The Cognitive AI Learning Environment (CAL-E) is proposed as a modular, ethical, and cognitively grounded architecture for AI-powered tutoring in higher education. Its core premise is that effective AI-driven instruction must not only respond to learner behaviour, but also understand and anticipate learner cognition, context, and development across time. To this end, CAL-E integrates advanced components from cognitive science, machine learning, affective computing, and ethical AI, all structured within a layered, interoperable architecture designed for flexibility, transparency, and scalability.

Unlike conventional tutoring systems that focus on task accuracy or domain completion, CAL-E seeks to facilitate adaptive cognitive development. It operates on the principle that each learner possesses a unique constellation of prior knowledge, emotional states, situational contexts, and goals. Consequently, AI tutors must evolve from static content delivery platforms to cognitively interactive, ethically aware companions that can adapt in real-time and over time.

At a high level, CAL-E comprises seven interdependent modules, each with a distinct function yet deeply integrated into a unified decision-making and learning pipeline.

Design Methodology

The CAL-E architecture was conceptualised through an iterative

process of literature synthesis and theoretical modeling, drawing from interdisciplinary sources in AI in education (AIED), cognitive science, affective computing, machine learning, and ethical AI frameworks. Specifically, the development began with a comprehensive review of existing intelligent tutoring systems (ITS) and their limitations, as detailed in Section 2, identifying key gaps in cognitive adaptability, contextual personalisation, and ethical oversight. These insights were synthesised to define the seven core modules, ensuring modularity for scalability and interoperability. The architectural diagrams (Figures 2 and 3) were created using standard systems modeling techniques, including data flow diagrams (DFDs) and component interaction maps, to visualise module interconnections, data flows, decision pathways, and real-time updates. Tools such as UML (Unified Modeling Language) were employed to represent agent interactions and hierarchical structures, aligning with best practices in software architecture design (e.g., Bass et al., 2012). Analysis of the diagrams involved mapping theoretical principles—such as reinforcement learning for adaptability (Sutton and Barto, 2018) and value-sensitive design for ethics (Friedman and Hendry, 2019)—onto the components, simulating hypothetical learner scenarios to validate logical coherence and ethical compliance. This methodological approach ensures the framework is not only descriptive but also analytically robust, providing a blueprint for empirical validation in future implementations.

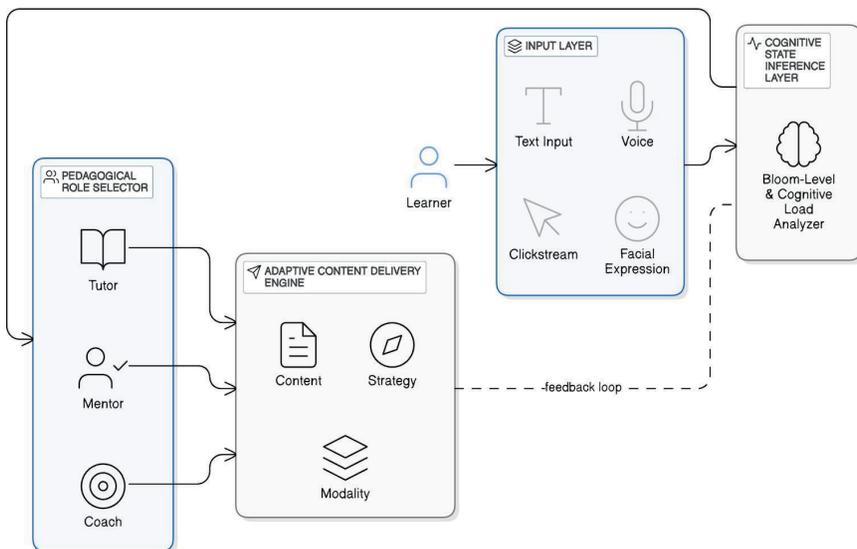


Fig. 2: Basic Architecture of CAL-E (Cognitive-Centered AI Learning Ecosystem)

Note. Illustrates core ecosystem with pedagogical, adaptive, and inference layers for decision-making.

1. Cognitive Processing Core (CPC):

This module is the pedagogical brain of CAL-E. It interprets incoming learner signals (from performance, behaviour, and emotional states), applies instructional strategies based on cognitive theories (e.g., spaced retrieval, dual coding, and metacognitive prompting), and orchestrates the instructional sequence in tandem with the Adaptive Engine. The CPC ensures that content delivery is not only accurate but optimized for deep processing and conceptual transfer (Sweller, Ayres, & Kalyuga, 2011).

2. Context Analyser (CA):

CAL-E's Context Analyser extends learner modelling beyond skill and knowledge levels. It ingests multimodal contextual data—including temporal markers (e.g., time of day, deadlines), emotional cues (e.g., facial micro-expressions, sentiment from responses), and environmental signals (e.g., ambient noise levels)—to enrich decision-making. Drawing on affective computing and

situational awareness frameworks (D'Mello and Graesser, 2015), this module ensures context-aware personalisation, allowing CAL-E to defer, escalate, or modify instruction based on learner well-being or attention fluctuations.

3. Learner Model Repository (LMR):

The LMR functions as CAL-E's evolving database of learner profiles. It continuously synthesises data from the Context Analyzer, the Cognitive Processing Core, and prior learning histories to maintain a longitudinal, explainable learner model. It stores variables such as conceptual mastery, motivation levels, preferred instructional modalities, cognitive load tolerance, and engagement rhythms. This model allows CAL-E to shift from reactive correction to anticipatory scaffolding, tailoring instruction before errors manifest (Rincon-Flores et al., 2023).

4. Knowledge Base (KB):

Aligned with academic standards and ontologies, the Knowledge Base contains

curated instructional content, concept maps, question banks, explanations, and learning objectives. It supports version control, author attribution, and alignment with Bloom's Taxonomy and disciplinary learning outcomes (University of Waterloo, n.d.). The KB is connected to the Adaptive Engine via semantic tagging, ensuring that each instructional unit is discoverable, pedagogically ranked, and domain-consistent (Anohina et al., 2012).

5. Adaptive Learning Engine (ALE):

The ALE serves as CAL-E's optimisation layer. Utilising reinforcement learning and constraint-based planning, it selects, sequences, and times content delivery for maximal cognitive gain. Unlike fixed-path systems, the ALE generates personalised instructional trajectories, factoring in the zone of proximal development, prior effort, and metacognitive status. It collaborates with the Cognitive Processing Core to enact micro-adaptations, such as slowing pacing, switching modalities, or introducing reflective prompts (Kubotani et al., 2021; Vassoyan et al., 2023).

6. Feedback Generator (FG):

Learning without feedback is inert. CAL-E's FG module generates both formative and summative feedback tailored to learner profile, task difficulty, and emotional state. Drawing from natural language generation techniques and pedagogical feedback literature (Shute, 2008), the module provides real-time clarifications, error-specific hints, and motivational reinforcement. It supports multiple feedback modalities, including text, audio, visual cues, and dialogic conversation, enhancing feedback richness and learner receptivity.

7. Ethical Governance Layer (EGL):

This layer acts as the ethical firewall and compliance framework of CAL-E. It enforces bias mitigation, transparency requirements, data privacy standards, and learner agency protocols. It

monitors decision processes across modules, ensuring fairness in adaptivity and explainability in learner-facing actions. The EGL also logs ethical events, supports third-party audits, and provides mechanisms for learner appeal or data opt-outs, operationalising principles from UNESCO and GDPR within the system's daily operation (UNESCO, 2021; UNESCO, n.d.).

Cognitive Processing Core (CPC)

The CPC serves as the pedagogical brain of CAL-E, interpreting learner signals (performance, behavior, emotional states) and applying instructional strategies based on cognitive theories like cognitive load theory (Paas et al., 2020) and dual-process models (Evans and Stanovich, 2013). It collaborates with the Context

Analyser and Learner Model Repository to infer states such as confusion or engagement, optimising content for deep processing (Sweller et al., 2011).

The CPC operates via a hybrid decision-making loop:

- **Signal Reception:** Aggregates data from modules, including stats, contextual factors, and affective signals.
- **Cognitive-State Inference:** Employs probabilistic models to estimate working memory load and strategies (Chi, 2020).
- **Instructional Orchestration and Learning Path Calibration:** Selects methods (e.g., guided questioning) and updates trajectories with the Adaptive Learning Engine.
- **Feedback Integration:** Coordinates with the Feedback Generator to avoid overload.

Context Analyzer

The CA extends learner modelling by ingesting multimodal data—temporal

(e.g., time of day), emotional (facial expressions), and environmental (noise levels)—to inform decisions (D’Mello & Graesser, 2015).

It processes inputs through:

- Temporal data (Yusuf et al., 2023).
- Affective data (Alam and Roy, 2023).
- Environmental data (Chavhan and Chavhan, 2023).
- Behavioural cues (Luo, 2023).

The CA creates a dynamic context profile (DCP) via:

1. Cognitive-Affective State Vector (CASV): Combines tone, frustration, and engagement.
2. Context Stability Index (CSI): Assesses environmental consistency.
3. Interruption Risk Predictor (IRP): Predicts disruptions.

It includes socio-cultural metadata (Nasir and Hand, 2006), ethically filtered by the Ethical Governance Layer. The CA supports metacognition with nudges and trends for instructors (Roll and Winne, 2015).

Overall, the CA makes CAL-E situationally aware (see Table 2).

Learner Model Repository (LMR)

The Learner Model Repository (LMR) serves as CAL-E’s dynamic memory system, maintaining a continuously evolving profile of each learner. It encapsulates cognitive, behavioural, affective, and contextual dimensions, enabling deep personalisation over time. Unlike static models, the LMR functions as an intelligent scaffold that interprets and adapts to the learner’s journey, addressing critiques of AI tutors that often generalise learners into overly abstract categories (Bull and Kay, 2016

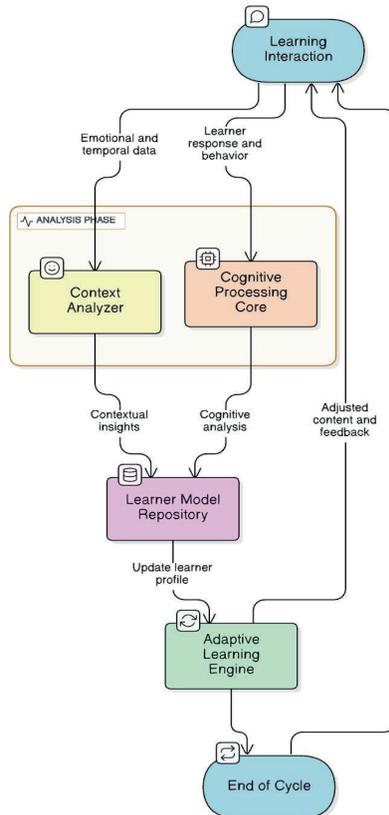


Fig. 3: High-Level Modular Architecture of CAL-E

Note. Diagram illustrates the seven core components and their interconnections for cognitive adaptability and ethical governance.

Multi-Dimensional Learner Representation

The LMR organises learner data into an interconnected schema comprising:

- Cognitive Competency Profiles: Tracking knowledge mastery, misconceptions, metacognitive skills, and learning strategies.
- Behavioural Signatures: Monitoring engagement styles, pacing preferences, task-switching patterns, and help-seeking behaviours.
- Affective Trajectories: Documenting emotional patterns, motivational fluctuations, and indicators of burnout over time.
- Contextual Histories: Integrating environmental and situational data from the Context Analyzer to situate learning episodes within real-world conditions.

Each learner is modelled as a probabilistic agent, with profiles updated through Bayesian inference and reinforcement learning techniques. This approach enables CAL-E to predict future performance, adaptively sequence tasks, and anticipate risks of disengagement (Koedinger et al., 2015).

Continuous and Recursive Updates

The LMR is designed for incremental intelligence, continuously integrating new data without overwriting prior insights. Through a recursive updating pipeline, each interaction contributes to:

- Skill Mastery Estimation: Utilising knowledge tracing models, such as Deep Knowledge Tracing, to assess and predict learner understanding (Piech et al., 2015).
- Affective State Calibration: Comparing predicted versus actual emotional

responses to refine the model's accuracy.

- Strategy Shift Detection: Identifying transitions from rote learning to conceptual exploration or from guessing to hypothesis-driven problem-solving.
- This ongoing calibration supports CAL-E's capacity to personalise not only the content but also the instructional strategies, aligning with the learner's evolving profile.

Individualisation Without Overfitting

A central design challenge in learner modelling is balancing granularity with generalisability. Highly individualised models risk overfitting, limiting the transferability of learning paths. The LMR addresses this through:

- Federated Modelling Layers: Balancing global pedagogical templates with local learner variations.
- Confidence Thresholding: Assigning weights to model inferences based on interaction richness and signal clarity.
- Similarity Clustering: Identifying peer clusters with similar learning trajectories to inform collaborative and comparative interventions.

These techniques allow CAL-E to retain personalisation while leveraging pedagogical insights at scale, ensuring efficient use of AI resources and interpretability (Bull and Kay, 2016).

Pedagogical Reflexivity

A unique feature of the LMR is its pedagogical reflexivity—the system not only models the learner but also evaluates the impact of its own strategies on the learner's profile.

If certain instructional techniques consistently correlate with regression in confidence or rising cognitive load, the LMR flags these relationships for review. This supports an iterative co-evolution between the system's pedagogical intelligence and the learner's development, making CAL-E not only adaptive but also accountable.

Transparency and Learner Control

Aligned with CAL-E's Ethical Governance Layer, the LMR is designed for interpretability and learner agency. Learners can view and challenge elements of their profile—such as flagged misconceptions, assigned confidence levels, or affective interpretations—via a dashboard interface. This supports epistemic transparency, combats over-reliance on the system, and fosters metacognitive awareness (Bull and Kay, 2016).

Conclusion

The Learner Model Repository transforms CAL-E into a memory-enriched, reflective learning partner, capable of shaping pedagogical experiences that

resonate with each learner's journey. By integrating cognitive, behavioural, affective, and contextual data, and by ensuring transparency and adaptability, the LMR addresses the complexities of personalised education in dynamic contexts.

Knowledge Base

The Knowledge Base (KB) in CAL-E serves as the foundational academic resource layer, designed not only to store content but also to curate, align, and reason over academic knowledge in a manner congruent with pedagogical standards, learner goals, and disciplinary structures. It addresses a critical shortcoming in conventional educational AI systems—their dependence on fragmented or static content banks—and reimagines the knowledge layer as a dynamic, intelligent academic scaffold that integrates domain precision with instructional adaptability (Merrill, 2002; Luckin, 2010). below summarizes the core functions of each module and highlights their individual contributions toward CAL-E's adaptive and ethical learning framework.

Table 2: Core Functions of CAL-E Modules and Contributions to Personalisation/Ethics.

Module name	Core functions	Contribution to personalization/ ethics
Learner profile engine	Collects user preferences, Cognitive states, and behavioural data	Enables adoptive content delivery and personalized pathways
Cognitive contextual layer	Interprets real-time context using situational signals	Enhances relevance and timing of instruction
Adaptive Tutoring engine	Adjusts content difficulty and style dynamically	Supports inclusive and learner-specific teaching
Emotional recognition layer	Analysis tone, sentiment, and emotional cues	Ensures affective alignment, reducing learner anxiety
Ethics governance layer	Filters decisions through fairness and transparency rules	Mitigates bias and maintains trust
Knowledge graph manager	Aligns concepts, curriculum, and learner paths semantically	Provides structured, explainable learning trajectories
Feedback optimisation unit	Generates real-time formative and summative feedback	Ensures clarity and improves learner engagement

Note. Functional roles derived from architecture design inspired by adaptive learning frameworks (Troussas et al., 2020; see Section 3 for details).

This structure allows each module to interact modularly yet ethically, with transparent decision paths and adaptive orchestration.

Standards-Aligned Content Ontology

At its core, the CAL-E Knowledge Base (KB) is structured around a standards-aligned content ontology, ensuring that learning objects (LOs) map onto curricular frameworks and academic taxonomies (Zhao and Wang, 2024). Key components include:

Concept Graphs: These represent prerequisite relationships, conceptual dependencies, and semantic proximity across knowledge domains. Recent AI-assisted systems such as the ACE framework demonstrate how knowledge graphs can enhance learning personalisation and content navigation (John and Ahmed, 2023).

Curriculum Maps: Content is aligned with formal educational standards, including CEFR, U.S. Common Core, and local accreditation systems. This supports both global competencies and local adaptability in instruction (Council of Europe, 2020).

Instructional Metadata: Learning objects are tagged with metadata detailing complexity, modality compatibility (e.g., text, video), cognitive demand, and alignment to learner profiles. Metadata-driven systems help optimise instructional sequencing and reduce extraneous load (Seufert et al., 2024).

This semantic infrastructure enables CAL-E to deliver modular content dynamically—decomposing and recomposing instructional units in real

time to match learners' evolving needs and goals (Smith and Li, 2023).

Integration with Authoritative Sources and LLMs

To maintain epistemic accuracy and currency, the KB is connected to:

Authoritative academic databases (e.g., JSTOR, ERIC, PubMed, ArXiv) for verified content ingestion. Open educational repositories (e.g., OpenStax, MIT OCV) for modular, peer-reviewed resources.

Language models and AI-generated summaries used cautiously and always filtered through a content validation layer—ensuring that generative outputs do not replace vetted materials but augment explanation clarity or fill granularity gaps (Zhou et al., 2023).

This dual-channel model—curated human knowledge plus AI-assisted augmentation—allows CAL-E to respond flexibly to diverse knowledge needs without compromising content integrity.

Knowledge Reasoning and Adaptive Structuring

The KB is not simply a warehouse of content but a knowledge reasoning engine. It performs functions such as: Adaptive content restructuring based on learner misunderstanding patterns, leveraging graph traversal algorithms to identify alternative explanation paths.

Cognitive gap diagnosis, using performance data to flag misalignments between perceived and actual competency levels.

Path dependency analysis, which helps the Adaptive Learning Engine select sequences that build concept mastery efficiently, avoiding redundancy or premature escalation.

Such reasoning capabilities transform the KB into a living, pedagogically intelligent resource, rather than a passive digital textbook.

Domain-Specific Customisation

Recognising the diversity of disciplinary epistemologies, CAL-E allows domain-specific KB customisation. For example:

In STEM fields, the KB supports symbolic logic representation, simulation-based experimentation, and computational problem-solving frameworks.

In humanities and social sciences, it emphasises argumentative structure, interpretive depth, and epistemological pluralism.

In professional and vocational learning, the KB integrates with real-world tools (e.g., lab simulators, design environments) and certification standards.

This discipline-sensitive design supports deep, context-aware instructional delivery that respects domain authenticity (Shulman, 1986).

Semantic Traceability and Explainability

CAL-E's knowledge base enables semantic traceability, so learners can ask, "Why am I learning this now?" or "What should I study next to achieve my

goal?" and receive clear, logical answers. These responses are grounded in transparent reasoning that connects current lessons to previous learning and future objectives, fostering explainable AI (XAI) in education and enhancing both trust and learner empowerment (Lindner et al., 2023).

Adaptive Learning Engine (ALE)

The ALE personalises content delivery based on integrated signals (VanLehn and Brunskill, 2021). It balances progression and responsiveness, selecting content, formats, and interventions (Holstein et al., 2020). The ALE tailors outputs, e.g., gamifying or rephrasing (Winkler and Söllner, 2023). Sequencing employs Bayesian modelling and reinforcement learning for zone of proximal development alignment (Rafferty et al., 2019). Decisions promote agency with options and explanations, refining via feedback (Ifenthaler, 2023). Ethically governed, the ALE ensures equitable personalisation (see Table 2 and Figure 3).

Feedback Generator

The Feedback Generator operationalises CAL-E's commitment to formative, timely, and context-aware guidance. Unlike systems that give only binary or static hints, CAL-E's feedback adapts to cognitive, affective, and metacognitive states. Research shows that such adaptive, multi-level feedback yields strong learning gains, especially when feedback intensity increases in response to need (Wisniewski et al., 2020).

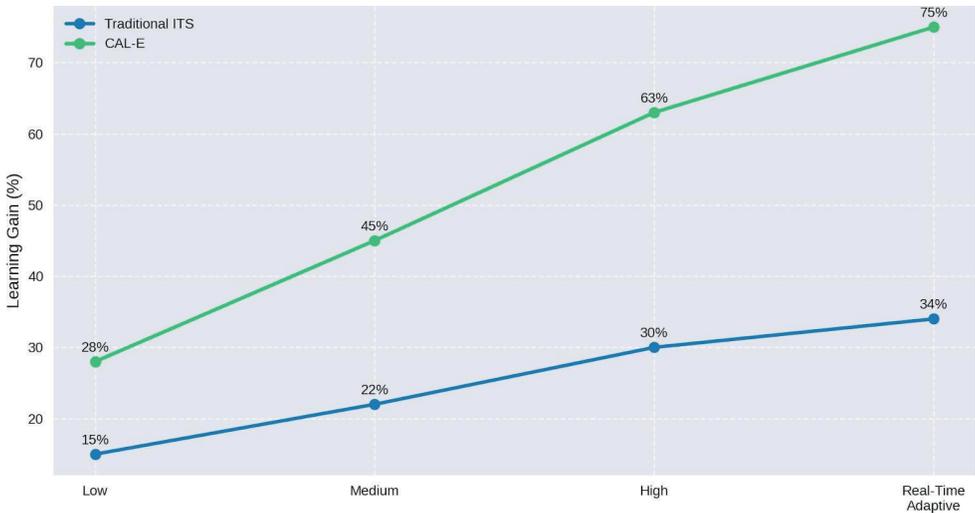


Fig. 4: Learning Gain vs. Feedback Loop Intensity

Note. Data modeled conceptually using engagement/effectiveness findings from (Bognár Khine, 2025). Multi-Tiered Feedback Framework..

Multi-Tiered Feedback Framework

CAL-E employs a multi-tiered feedback framework grounded in contemporary educational psychology and instructional design theories. Feedback is categorised into three hierarchical levels:

1. **Task-Level Feedback:** Focuses on the accuracy of the learner’s response, providing immediate corrections or affirmations. This level addresses the question, “Is my answer correct?”
2. **Process-Level Feedback:** Offers insights into the learner’s approach or strategy, guiding improvements in problem-solving methods. It addresses, “How can I improve my approach?”
3. **Self-Regulation-Level Feedback:** Encourages learners to reflect on their learning processes, fostering skills like goal-setting, self-monitoring, and strategic planning. This level tackles, “How can I monitor and direct my learning?”

This structured approach ensures that feedback not only corrects errors but also promotes deeper understanding and autonomous learning, aligning with the principles outlined by Hattie and Timperley (2007).

Real-Time and Delayed Feedback Coordination

Feedback in CAL-E is not uniformly immediate; instead, the system intelligently times its responses based on learning phase, task complexity, and cognitive load. For instance:

During exploratory learning, CAL-E may delay corrective feedback to promote discovery and critical thinking.

In high-stakes or scaffolded instruction, it delivers real-time prompts to prevent entrenchment of misconceptions.

This timing is dynamically orchestrated by the Adaptive Learning Engine, using indicators from both the Learner Model and Context Analyzer.

Affective and Motivational Feedback

Drawing from affective computing and emotionally intelligent tutoring systems (DMello and Graesser, 2012), CAL-E tailors feedback to the learner's emotional context. For example:

If frustration is detected, feedback may include empathic encouragement or offer a step-by-step walkthrough. If overconfidence emerges, it might include challenge feedback to recalibrate difficulty and promote deeper engagement.

Such emotion-sensitive feedback helps preserve motivation and engagement—key factors in sustained learning (Pekrun, 2006).

Feedback Personalisation and Linguistic Adaptation

CAL-E adapts not only the content of feedback but also its linguistic style and tone, adjusting for: Learner language proficiency, using simplified syntax or domain-specific vocabulary as needed. Cultural expectations, varying formality and directness to align with diverse educational contexts. Learner preferences, allowing customisation (e.g., choosing concise vs. explanatory feedback modes).

This conversational personalisation increases feedback receptivity and user trust, turning generic messages into dialogic interactions.

Feedback as Knowledge Contribution

In CAL-E, feedback is not a terminal event but a contribution to the system's knowledge and learner model. Every

feedback interaction is logged and analysed to:

Improve future feedback strategies (e.g., identifying which feedback type leads to quicker mastery). Update the learner's confidence and persistence profiles.

Provide teachers or administrators with dashboard-level insights on group learning progress and misconception trends.

Thus, feedback serves as both an instructional tool and a diagnostic artifact, critical for adaptive intelligence and educational accountability.

The Feedback Generator elevates CAL-E's instructional design from reactive correction to reflective scaffolding, transforming learner interaction into a rich, emotionally aware, pedagogically structured conversation. It ensures that feedback is not merely information, but transformation—guiding learners toward mastery with insight, empathy, and clarity.

Ethical Governance Layer

The Ethical Governance Layer functions as the regulatory conscience of the CAL-E system, embedding ethical intelligence directly into its operational core. Unlike most AI tutoring platforms that approach ethics as a checklist or add-on—often audited after deployment—CAL-E integrates ethical reasoning into every layer of its decision-making process (Jobin et al., 2019). This ensures that adaptive capabilities remain tightly aligned with foundational principles such as fairness, transparency, inclusivity, and learner autonomy.

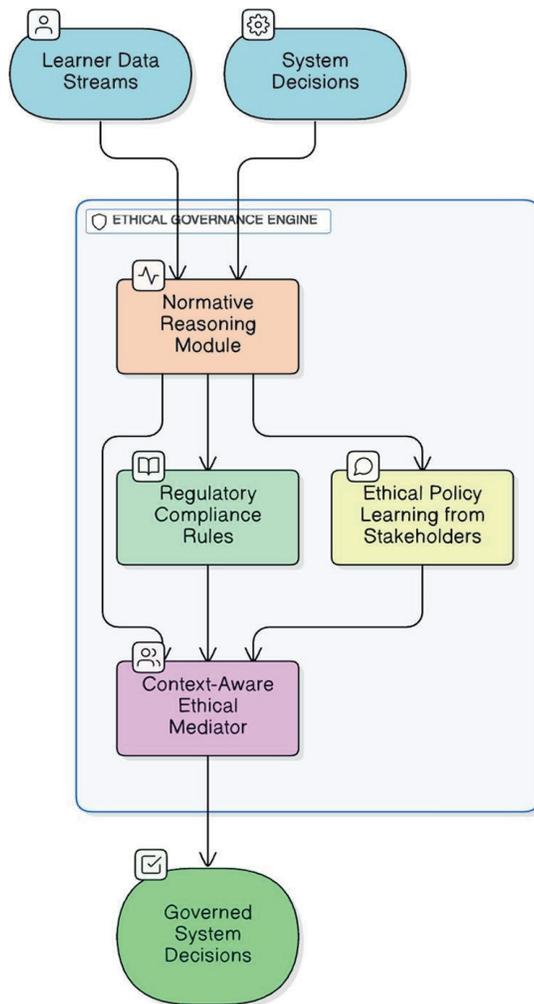


Fig. 5: Ethical Decision Pipeline in CAL-E

Note. Inputs (learner data, system choices) are filtered through compliance rules and evaluated for transparency and fairness, then returned to the instructional core (Bognár Khine, 2025).

Systemic Flow: Unified Architecture of CAL-E

CAL-E's modules form a cohesive system, with data flowing bidirectionally for real-time adaptation. The Cognitive Processing Core initiates by processing inputs from the Context Analyzer and Learner Model Repository, querying the Knowledge Base for content. The Adaptive Learning Engine sequences materials, while the Feedback Generator

delivers responses—all moderated by the Ethical Governance Layer for compliance and fairness. This flow supports proactive personalisation, e.g., adjusting for fatigue or bias. Interconnections enable scalability, with updates propagating across components (see Figures 2 and 3). Aligned with ethical standards (UNESCO, 2021), CAL-E transforms AI into an integrated, human-centred tutoring framework.

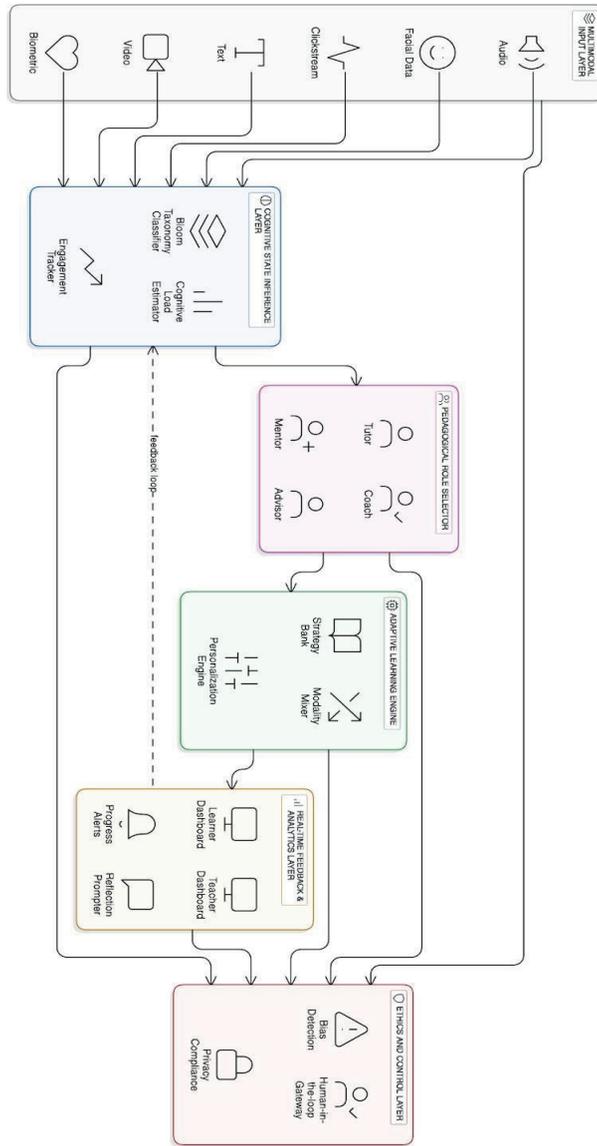


Fig. 6: Systemic Coordination in CAL-E Architecture

Note. Visualises how CAL-E's modules communicate, coordinate, and function in **real-time** to deliver intelligent, ethical, and context-aware tutoring (Hanid Ghazali, 2025)

This unified architecture ensures CAL-E is not a linear instructional system but a living, learning infrastructure, one that adapts with the learner and remains accountable to ethical and pedagogical standards throughout the entire tutoring process.

Integration Logic and Data Flow

The architecture of CAL-E is a dynamically orchestrated system where components interact through defined data flows and decision pathways. This section outlines how raw learner data transforms into ethical, adaptive tutoring interactions.

At the core is the Cognitive Processing Core (CPC), the central coordinator. Incoming data—from learner actions, sensors, or triggers—passes through the CPC, which interprets it using cognitive-affective ontologies. Enriched with metadata from the Context Analyzer, this data updates dynamic profiles in the Learner Model Repository, mapping knowledge, emotions, and engagement. The Adaptive Learning Engine then selects optimal sequences from the Knowledge Base, integrating standards and scaffolding. Responses—content, feedback, or prompts—are generated via the Feedback Generator. All decisions are reviewed by the Ethical Governance Layer, which overrides sequences to prevent harm (e.g., high cognitive load scenarios). This bidirectional ecosystem supports reactive (immediate feedback) and proactive (anticipated interventions) processes, with synchronous and asynchronous pipelines. CAL-E interoperates with external platforms (e.g., LMS) via standards like xAPI and LTI, embedding its intelligence in broader environments. Overall, CAL-E's integration reflects a neuro-symbolic cognition model—combining symbolic reasoning (rules, profiles) with real-time recognition (affective signals)—ensuring accuracy, resilience, and trust (Evans and Stanovich, 2013; Hanid and Ghazali, 2025).

Evaluation Criteria and Validation Framework

To ensure CAL-E's architecture is robust and actionable, this section outlines evaluation across performance, value, ethics, and adaptivity. As a theoretical construct, validation emphasises design-based research and mixed methods for future prototypes.

Multi-Dimensional Evaluation Model

CAL-E's success is assessed across five dimensions:

1. **Cognitive Effectiveness:** Improves understanding, retention, and higher-order thinking
2. **Personalisation Accuracy:** Aligns with individual needs and trajectories
3. **Ethical Compliance and Transparency:** Upholds fairness, bias mitigation, and explainability
4. **System Responsiveness:** Timely and context - appropriate adaptations
5. **User Satisfaction and Trust:** Perceived as supportive and respectful

These pillars integrate learning efficacy and AI ethics, positioning CAL-E as a cognitive partner.

Validation Methodology

To Adopt Design-Based Research (DBR) for iterative refinement in real-world settings (McKenney and Reeves, 2019). Use quasi-experimental designs to compare CAL-E against traditional methods (Wang and Hannafin, 2005). Incorporate multimodal learning analytics (MMLA) for holistic insights, integrating eye-tracking, sensors, and logs (Zhou and Kang, 2023; Yan et al., 2024).

Ethical frameworks guide deployment: AI Assessment Scale (AIAS) for transparency (Perkins et al., 2023); FATE for fairness and ethics (Jin et al., 2024); ENAI recommendations for integrity (Foltynek et al., 2023).

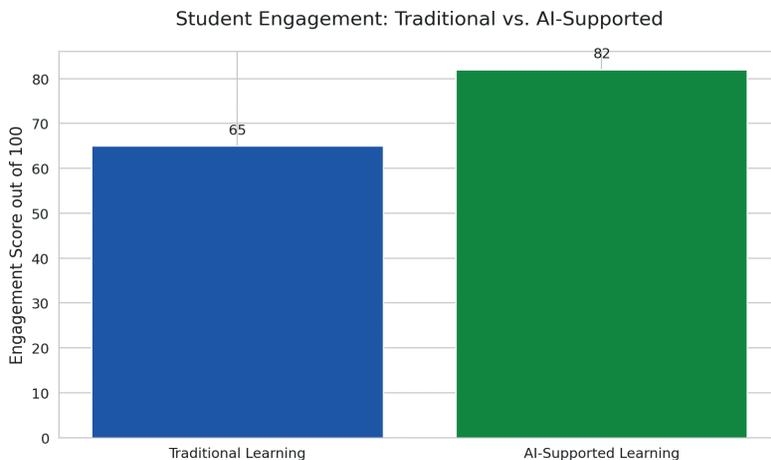


Fig. 7: Student engagement scores comparison between traditional and AI-supported learning systems

Note. Data modeled conceptually using engagement/effectiveness findings from (Bognár Khine, 2025).

Performance Indicators and Benchmarking

Define KPIs: knowledge gains (pre/post assessments), state detection accuracy, fairness ratios, response latency, ethical flags, and satisfaction scores. Use a multi-tier dashboard for real-time monitoring.

Cross-Cultural and Contextual Adaptability

Validate equity across settings via localisation testing for language, curriculum, and culture (Mushtaq et al., 2025; Ye, 2024). Ensure access in low-resource environments (Llego, 2023; AI in Cross-Cultural Education, 2025), making CAL-E globally deployable.

Discussion and Implications

CAL-E reflects a shift in educational AI, functioning as a cognitive-ethical mediator engaging learners' mental models, emotions, and values (Nguyen and Dror, 2024; Ye, 2024). This aligns with discourses on learner agency and situated intelligence (Mushtaq et

al., 2025; Llego, 2023), emphasizing contextual and ethical adaptability.

Reframing Educational AI Through Cognitive-Ethical Alignment

CAL-E integrates cognitive adaptivity and ethical responsibility, addressing non-linear learning via emergent states and feedback. The Ethical Governance Layer ensures transparency and accountability (UNESCO, 2021; Floridi, 2019), intertwining adaptivity with moral logic.

Implications for Higher Education Policy, Infrastructure, and Assessment

As hybrid models grow, CAL-E blueprints AI strategies: ethical checkpoints for policy on integrity and autonomy; Knowledge Base for curriculum alignment; transparent maps for faculty collaboration. Requires interoperable LMS, data governance, and AI-literate teams. The Feedback Generator redefines assessment as formative and multi-modal, promoting metacognition,

reduced anxiety, and personalised growth over static evaluations (Carless et al., 2020).

Implications for Global and Inclusive Education

CAL-E suits diverse environments, calibrating for cultural and accessibility variables: low-bandwidth systems, multilingual classrooms, neurodiverse groups, refugee populations. Complies with global standards (OECD, 2022; EU AI Act, 2024).

Limitations and Future Improvements

Challenges include scalability (edge computing), emotional inference accuracy (multicultural settings), explainable UI/UX, and balancing protection with autonomy. These provoke interdisciplinary research for engineers, scientists, ethicists, and educators.

Conclusion

The Cognitive AI Learning Environment (CAL-E) presents a bold theoretical proposition for the future of AI in higher education—one that goes beyond automation and personalisation, toward a deeply contextual, ethically grounded, and cognitively responsive system. This architecture recognizes that learning is not simply a sequence of content delivery steps, but a dynamic, multi-layered process shaped by learner states, socio-emotional contexts, evolving knowledge structures, and ethical implications of algorithmic intervention. By integrating a Cognitive Processing Core, Context Analyzer, Learner Model Repository, Adaptive Learning Engine, Formative Feedback Generator, and a dedicated

Ethical Governance Layer, CAL-E introduces a modular and interpretable framework that addresses many of the limitations faced by current educational AI tools. Unlike conventional adaptive systems that react based solely on user interaction data, CAL-E is proactive, sensitive to learning trajectories, and reflective of ethical standards, such as fairness, transparency, and user autonomy.

In aligning with global frameworks like UNESCO's guidelines for human-centered AI, national digital education strategies, and scholarly discourse on generative AI, CAL-E offers not just a technical blueprint, but a socio-technical paradigm—one that is flexible enough to be localised yet principled enough to offer global relevance.

The theoretical contributions of CAL-E extend across multiple domains:

In AI research, it demonstrates the feasibility of embedding ethical logic into cognitive systems.

In education theory, it highlights the role of AI in shaping reflective, agency-driven learning cultures.

In practice, it serves as a conceptual springboard for developers, educators, and policymakers aiming to design next-generation AI tutors.

Future work will involve validating this architecture through iterative design-based research, empirical field trials, and cross-cultural evaluations. The ultimate goal is to bridge theory with implementation, enabling a future where AI doesn't just support learning—it learns to care, adapt, and act responsibly within the complex landscape of human education.

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