S-A I-EDU: A BIO-INSPIRED AND MODULAR SPARSE AI ARCHITECTURE FOR ADAPTIVE AND SYMBOLIC INTELLIGENT EDUCATIONAL SYSTEMS

Said Slaoui

Mohammed V University, Rabat, Morocco

ABSTRACT

This paper introduces S-AI-EDU, a bio-inspired, modular, and parsimonious AI architecture designed for adaptive and symbolic intelligent educational systems. Unlike data-centric black-box models, S- AI-EDU employs hormonal modulation and symbolic agent orchestration to adaptively select pedagogical, motivational, and evaluation agents while maintaining transparency, interpretability, and cognitive economy.
The architecture integrates a MetaAgent for global orchestration, specialized educational agents for targeted interventions, and Gland Agents simulating artificial educational hormones (e.g., Curiosin, Confusionin, Attentionin, Fatiguin, Dopaminin) to dynamically regulate instructional intensity.
A symbolic memory module preserves learner paths, misconceptions, and engagement patterns, enabling explainable trace-based pedagogy.
Experimental validation in simulated learning scenarios over 120 instructional cycles demonstrates the system's capacity to:

1. *Detect cognitive instability (confusion, disengagement) early;*
2. *Activate only the necessary agents to avoid cognitive overload;*
3. *Produce interpretable learning traces for pedagogical review.*

S-AI-EDU offers a resource-aware, emotionally adaptive, and ethically aligned approach to intelligent education, bridging symbolic reasoning with neuro-inspired regulation.

KEYWORDS

Sparse Artificial Intelligence (S-AI), Adaptive Learning, Symbolic Pedagogy, Hormonal Modulation, Educational Agents, Neuro-Symbolic AI, Intelligent Tutoring Systems (ITS), Explainable AI (XAI), Learning Analytics, Cognitive Economy.

1. INTRODUCTION

1.1. The Rise of Intelligent Education

In recent years, education has undergone a paradigm shift fueled by the exponential growth of Educational Technologies (EdTech), online learning platforms, and AI-driven analytics. Traditional classrooms have evolved into hybrid, data-rich learning ecosystems where learners interact with intelligent systems capable of providing content, feedback, and assessment at scale. Massive Open Online Courses (MOOCs), Learning Management Systems (LMS), Intelligent Tutoring Systems (ITS), and adaptive platforms now reach millions worldwide, offering flexible access, automated evaluation, and real-time analytics. The demand for personalized and adaptive learning is driven by multiple factors:

- Global learner diversity in background, prior knowledge, and learning goals.

- The shift toward lifelong learning, requiring support for non-linear and self-paced trajectories.
- The explosion of multimodal data sources, including clickstream logs, keystroke dynamics, eye- tracking, and affective computing signals. Yet, despite these advances, many systems remain dominated by opaque, black-box AI models—often deep neural networks—whose lack of interpretability and pedagogical transparency undermines trust, especially in high-stakes educational contexts where instructors must justify feedback and learners must understand the rationale behind guidance.

1.2. Challenges in Educational AI

Educational AI operates in environments marked by extreme heterogeneity and rapidly shifting learner states. Four critical challenges stand out:

1. Learner Variability

Cognitive abilities, motivation levels, cultural contexts, and emotional resilience vary widely. One-size-fits-all algorithms risk over-instructing some learners while under-supporting others, leading to disengagement or overload.

2. Ethical and Socio-Technical Constraints

Educational AI must comply with strict ethical and legal frameworks (e.g., GDPR, FERPA), ensuring fairness, privacy, and non-discrimination—particularly for children and marginalized groups.

3. Attention and Cognitive Load Management

Empirical findings from educational psychology show that sustained attention often declines after 10–15 minutes of passive engagement, and excessive cognitive load impairs retention. Overactivation of AI tutoring agents—continuously delivering hints, feedback, or new content—can overwhelm learners instead of supporting them.

4. Deficit of Symbolic and Interpretable Models

Statistical models excel at pattern recognition but often lack symbolic reasoning capabilities that support explainable, pedagogically aligned feedback and foster metacognitive skills.

1.3. The Promise of Sparse AI in Education

Sparse Artificial Intelligence (S-AI) provides a bio-inspired, modular, and parsimonious alternative to conventional AI in education. Rather than activating all components at once, S-AI deploys specialized agents selectively, based on learner state, context, and hormonal modulation:

- Modular Agent-Based Architecture — Distinct agents for concept explanation, misconception detection, engagement regulation, progress monitoring, and curriculum alignment.
- Hormonal Regulation — Artificial hormones (e.g., Curiosin, Confusionin, Fatiguin, Attentionin, Dopaminin) dynamically modulate agent activation thresholds, inspired by neuroeducational principles.
- Symbolic Memory & Trace-Based Pedagogy — Detailed traces store conceptual pathways, emotional signals, instructional strategies, and feedback loops, enabling explainable replay, targeted remediation, and teacher-in-the-loop adaptation. By activating only what is needed, when it is needed, S-AI-EDU reduces cognitive overload, enhances transparency, and ensures context-aware, emotionally sensitive, and resource-efficient tutoring.

1.4. Contributions

This paper introduces S-AI-EDU, a bio-inspired and modular Sparse AI framework for adaptive, explainable, and ethically aligned intelligent educational systems. Its main contributions are as follows:

1. Novel Architecture for Adaptive Education
   A framework combining symbolic reasoning, hormonal modulation, and parsimonious agent orchestration to personalize learning without overwhelming learners.
2. Hormonal Orchestration of Pedagogical, Motivational, and Evaluation Agents
   A real-time Artificial Hormonal Engine regulating agent activation and priority based on learner state, enabling affect-aware adaptivity and energy-efficient operation.
3. Symbolic Memory of Learning Paths, Misconceptions, and Effort Patterns
   A semantically rich trace structure enabling targeted review, transparent feedback, longitudinal learner modeling, and progress tracking.

S-AI-EDU represents a step toward building transparent, adaptive, and cognitively coherent educational ecosystems capable of supporting human learning in ethically responsible and resource- conscious ways.

2. Related Work

This section reviews the foundational research and recent advances that underpin S-AI-EDU, spanning Intelligent Tutoring Systems (ITS), knowledge tracing and learner modeling, learning analytics in MOOCs/LMS, modular architectures, affective and socio-cognitive agents, explainable and ethical AI, and Neuro-Symbolic approaches. We conclude with the gaps that motivate the S-AI-EDU framework.

2.1. Foundations of Intelligent Tutoring Systems

Over four decades, ITS research has evolved from rule-based systems to cognitive tutors and, more recently, to modular and conversational multi-agent architectures.
Early work formalized the four core components—domain model, student model, pedagogical model, and interface—while establishing principles for adaptive feedback and content sequencing [1], [5].
The shift from step-based cognitive tutoring to dialogue-based scaffolding introduced richer interaction models and Socratic questioning strategies [3], [4].
Meta-analyses indicate that, in certain domains, ITS can approach the effectiveness of one-on-one human tutoring [2].

2.2. Knowledge Tracing and Open Learner Models

Knowledge Tracing (KT) methods estimate evolving mastery—ranging from probabilistic Bayesian KT (BKT) to neural Deep KT (DKT) and hybrid approaches. These methods balance predictive accuracy with interpretability.Open Learner Models (OLM) make these internal states visible to learners and instructors, promoting reflection and shared control [5], [6]. Interface design for OLMs focuses on actionable transparency without cognitive overload.

2.3. Learning Analytics, MOOCs, and Reinforcement Learning

Large-scale Massive Open Online Courses (MOOCs) and Learning Management Systems (LMS) have enabled fine-grained Learning Analytics (LA) and Educational Data Mining (EDM), supporting early- risk detection, adaptive sequencing, and personalized interventions [7]. While powerful, these systems are often data-centric, with limited symbolic pedagogy encoding. Reinforcement Learning (RL) has been applied to optimize tutoring policies in both domain-specific and interpersonal skills training [8], but remains challenging to align with explainable pedagogical strategies and teacher oversight.

2.4. Modular Architectures and the GIFT Framework

The Generalized Intelligent Framework for Tutoring (GIFT) exemplifies modular, service-oriented design, enabling reusable components for learner modeling, content delivery, and assessment [14]. The extensible Problem-Specific Tutor (xPST) model further demonstrates problem-specific modularization with symbolic reusability [13].

2.5. Affective and Socio-Cognitive Tutoring Agents

Affective computing highlights how states like confusion, boredom, and engagement mediate learning outcomes. Affective tutoring agents adapt pacing, difficulty, and style based on inferred emotional states [15], [4]. Recent conversational agents show significant gains when dialogue is pedagogically grounded rather than purely reactive [16].

2.6. Explainable and Ethical AI in Education

Educational Explainable AI (XAI) goes beyond model interpretability, requiring pedagogical explainability—actions must be justifiable in learner and teacher terms [17].
Ethical guidelines emphasize human oversight, transparency, privacy, and alignment with learning goals, with concrete recommendations for the responsible use of generative AI in schools and research as outlined by UNESCO [15], [18].

2.7. Neuro-Symbolic AI and Multi-Agent Orchestration

Neuro-Symbolic AI (NSAI) combines symbolic reasoning with neural perception, balancing interpretability and adaptivity [21], [22].
Recent educational NSAI systems integrate meta-orchestration of specialized agents, selecting them based on learner context and performance.

2.8. Gaps Motivating S-AI-EDU

Across these domains, persistent gaps include:
- Resource-aware parsimony to avoid cognitive overload.
- Symbolic traceability of instructional decisions.
- Affect-aware global coordination of agents.
- Pedagogically meaningful explanations accessible to humans.

S-AI-EDU addresses these through hormonal orchestration, sparse agent activation, and symbolic memory producing interpretable learning traces [27], [28].

This extends the S-AI paradigm [27], the conversational orchestration of S-AI-GPT [28], and its refined agent-level modulation [29]—bringing these innovations into the educational domain.

3. Bio-Inspired And Symbolic Foundations Of S-AI-Edu

The S-AI-EDU framework draws from biological systems, cognitive psychology, and symbolic AI to design an educational architecture that is adaptive, parsimonious, and pedagogically aligned. This section outlines the theoretical foundations and contrasts them with traditional AI in education.

3.1. Principle of Parsimony in Learning Support

Parsimony in instructional design advocates delivering only the necessary intervention at the optimal moment. Over-instruction risks cognitive overload, reducing engagement and retention [27], [28]. In biological systems, energy is conserved for critical functions—a principle echoed in Sparse AI [27], [28]. In educational contexts, parsimony translates into:

- Avoiding repetitive explanations when mastery is evident.
- Reducing simultaneous activation of multiple pedagogical agents.
- Prioritizing interventions with the highest predicted learning gain per effort unit.

S-AI-EDU operationalizes this by coupling hormonal modulation with agent selection filters, ensuring interventions occur only when learner state justifies them.

3.2. Hormonal Modulation Inspired by Educational Neuroscience

S-AI-EDU's hormonal engine is inspired by how neuromodulators regulate attention, motivation, and memory in the human brain [15]. Educational neuroscience identifies key affective-cognitive factors— attention, fatigue, confusion, curiosity—as critical to learning outcomes [15].
We model these as artificial hormones:

- Attentionin – Focus intensity.
- Curiosin – Drive to explore new concepts.
- Confusionin – Indicator of conceptual misalignment.
- Fatiguin – Accumulated mental effort.
- Dopaminin – Reinforcement and motivation.

Hormone levels are updated each cycle based on learner behaviors (e.g., response time, error rate, idle periods). Agent activation thresholds depend on these hormone levels, mirroring biological homeostatic regulation and linking affective state to pedagogical orchestration [20].

3.3. Symbolic Pedagogy and Trace-Based Instruction

Symbolic AI represents knowledge in structured, human-readable formats.
In S-AI-EDU, symbolic pedagogy ensures that every instructional action is accompanied by a symbolic trace containing:

- Concept taught.
- Strategy used.
- Learner state (cognitive + affective).
- Outcome of the intervention.

These traces are stored in JSONL format for both system use and teacher review, enabling:

- Replay of specific learning episodes.
- Diagnosis of recurring misconceptions.
- Cross-session continuity in instruction [19], [23].

By encoding both the "what" and the "why" of instructional decisions, S-AI-EDU bridges the gap between automated adaptivity and pedagogical transparency.

3.4. Alignment with Theories of Learning

S-AI-EDU integrates principles from major learning theories:

- Vygotsky's Zone of Proximal Development (ZPD) – Interventions target the learner's "next achievable" step [30].
- Bruner's Scaffolding – Support is gradually withdrawn as competence grows [31].

- Bloom’s Mastery Learning – Sequential mastery before progression [32].
- Constructivist Models – Learners actively construct meaning; agents stimulate engagement rather than passively deliver content [4].

Hormonal modulation aligns with these theories by dynamically adjusting challenge level and support intensity [15], [20].

3.5. Comparison with Classic ITS Architectures and Deep Learning Models

Classic ITS architectures are often monolithic and rule-bound, offering high interpretability but limited adaptability [3], [7].BDeep learning-based tutors offer adaptivity but are opaque and resource-intensive [22].
S-AI-EDU positions itself between these extremes by:

- Maintaining symbolic transparency via explicit traces.
- Achieving adaptivity through hormonal modulation.
- Ensuring parsimony with sparse agent activation [27], [28].

This results in a system that is both explainable and efficient, suited for diverse educational contexts, including resource-constrained environments.

4. General Architecture Of The S-AI-Edu System

The S-AI-EDU architecture is designed as a bio-inspired, modular, and symbolic learning ecosystem. Its key components are orchestrated by an Edu-MetaAgent that dynamically activates specialized agents based on artificial hormonal states, pedagogical objectives, and learner context. This architecture ensures parsimony, adaptivity, and explainability while being scalable across both online and blended learning environments.

4.1. Global Overview and System Diagram

At its core, S-AI-EDU follows a layered, modular architecture:

1. Sensing Layer: Captures learner interactions and contextual signals.
2. Hormonal Modulation Layer: Translates behavioral patterns into artificial hormone levels.
3. Agent Orchestration Layer: The Edu-MetaAgent selects and coordinates specialized agents.
4. Instruction & Feedback Layer: Generates pedagogical interventions.
5. Memory & Trace Layer: Stores symbolic learning traces for explainability and longitudinal adaptation.

This separation of concerns mirrors biological nervous systems where central orchestration interacts with peripheral specialized modules [15], [27].

Figure 1: Modular overview of the S-AI-EDU system.

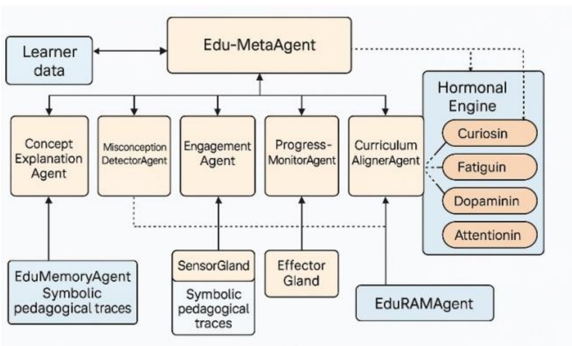

Figure 1. Overview of the S-AI-EDU Architecture

Modular overview of the S-AI-EDU system, illustrating the interaction between the Edu-MetaAgent, Specialized Agents, Gland Agents, the Hormonal Engine, and memory interfaces. Hormonal flows and symbolic feedback loops regulate the adaptive orchestration of personalized pedagogical responses.

Detailed Description:

- Core of the Architecture: The Edu-MetaAgent acts as a conductor, receiving contextual inputs, monitoring hormonal states, selecting relevant pedagogical agents, and ensuring a balance between guidance, autonomy, and cognitive economy.
- Specialized Pedagogical Agents:
  - ConceptExplanationAgent: Delivers targeted symbolic explanations.
  - MisconceptionDetectorAgent: Detects conceptual errors.
  - EngagementAgent: Stimulates attention and motivation.
  - ProgressMonitorAgent: Evaluates learner progress.
  - CurriculumAlignerAgent: Adjusts the instructional sequence to match the curriculum.
- Biologically-Inspired Gland Agents: Simulate educational hormones such as Attentionin, Curiosin, Fatiguin, Confusionin, and Dopaminin. Each hormone activates, inhibits, or modulates specific agents depending on the learner's cognitive and emotional state.
- Hormonal Engine: Dynamic regulation system based on emission and feedback rules, integrating data on inactivity time, number of errors, and learning profiles.
- Memory Modules:
  - EduMemoryAgent: Archives symbolic traces (provided explanations, errors, confusion events).
  - EduRAMAgent: Manages exchanges with the user interface and the system's inputs/outputs.
- Signaling Arrows:
  - Blue arrows: hormonal flows.
  - Yellow arrows: symbolic interactions and pedagogical feedback.
  - Red arrows: agent activations or inhibitions.

4.2. Edu-MetaAgent: Orchestration of Adaptive Learning Paths

The Edu-MetaAgent serves as the central cognitive orchestrator, responsible for:

- Reading the hormonal state and learner context.
- Selecting the minimal set of specialized agents needed for the current cycle.
- Avoiding redundant or conflicting interventions.
- Adjusting the intensity and frequency of interventions.

Unlike static scheduling in traditional ITS [3], [5], the Edu-MetaAgent operates as a dynamic decision-maker, similar to an executive function in cognitive psychology [15].

4.3. Specialized Agents

S-AI-EDU deploys five core specialized agents, each aligned with a distinct pedagogical role:

4.3.1. ConceptExplanationAgent – Delivers symbolic, multi-modal explanations [6], [15].
4.3.2. MisconceptionDetectorAgent – Identifies and corrects conceptual errors [7], [13].
4.3.3. EngagementAgent – Modulates attention and curiosity via adaptive prompts [4], [15].
4.3.4. ProgressMonitorAgent – Tracks mastery levels and suggests pacing adjustments [1], [2].
4.3.5. CurriculumAlignerAgent – Ensures lesson progression aligns with curriculum goals [9], [14].

Each agent is event-driven, activated only under hormonal and contextual triggers.

4.4. Gland Agents

Gland Agents are dedicated modules responsible for hormone emission. They function analogously to biological glands, translating environmental and learner events into quantitative hormonal signals. For example:

4.4.1. AttentionGland – Increases Attentionin when learners interact actively.
4.4.2. FatigueGland – Raises Fatiguin with prolonged activity without breaks.
4.4.3. CuriosityGland – Boosts Curiosin upon novelty detection.
4.4.4. ConfusionGland – Emits Confusionin when errors cluster in a topic.

These signals feed into the Hormonal Engine for regulation and agent activation [15], [20].

4.5. Hormonal Engine

The Hormonal Engine aggregates and regulates hormone levels, applying:

4.5.1. Inhibition – Temporarily suppresses certain agents.
4.5.2. Stimulation – Raises priority of relevant agents.
4.5.3. Decay – Gradually reduces hormone levels over time.
4.5.4. Feedback Loops – Hormones may trigger the emission of others (e.g., high Confusionin can reduce Curiosin).

This mechanism allows for continuous adaptation and parsimonious activation of agents [19], [27].

4.6. EduMemoryAgent

The EduMemoryAgent stores symbolic traces of learning interactions, enabling:

4.6.1. Session-to-session continuity – Recalling past difficulties and successes.
4.6.2. Review recommendations – Scheduling targeted refreshers.
4.6.3. Explainable AI – Providing teachers with transparent reasoning paths [10], [17].

Memory entries include concept IDs, hormonal context, instructional strategy, and learner response quality.

4.7. EduRAMAgent

The EduRAMAgent manages real-time interactions between learners, teachers, and the S-AI-EDU core. It provides:

4.7.1. A user interface for direct interaction.
4.7.2. Data exchange with external systems such as LMS or MOOCs.
4.7.3. Real-time dashboards for progress and engagement monitoring.

This agent bridges machine intelligence with human oversight, ensuring the architecture remains teacher-inclusive [7], [9].

5. Typology Of Educational Agents

S-AI-EDU's pedagogical logic is implemented through a constellation of specialized agents, each with a distinct instructional role. Activation is sparse and symbolic: an agent is engaged only when the learner's cognitive state, hormonal signals, and pedagogical context justify it. This approach prevents redundancy, optimizes cognitive economy, and fosters adaptive, context-aware guidance.

5.1. Extended Agent Classification Table

Category	Agent Name	Role Description	Trigger Hormones	ary Output Format
Cognitive Agents	ConceptExplanationAgent	Provides symbolic, multi-modal explanations using text, diagrams, or analogies [6], [15]	Curiosin, Attentionin	Text, diagram, metaphor
	MisconceptionDetector	Detects and corrects conceptual errors [7], [13]	Confusionin, Fatiguin	Remediation messages
	ProgressMonitor	Tracks learner progression and cognitive plateaus [1], [2]	All hormones	Skill mastery heatmap, summary trace
	CurriculumAligner	Aligns instructional flow with curricular objectives [9], [14]	Normin, Fatiguin	Sequencing suggestions, alerts
	AdaptiveAssessmentAgent	Designs on-the-fly quizzes tailored to the learner's mastery profile [8], [9]	Curiosin, Normin	Adaptive test items
Metacognitive Agents	ReflectionPromptAgent	Encourages self- reflection on errors and strategies used	Dopaminin, Normin	Reflection prompts
	LearningStrategyAdvisor	Suggests cognitive strategies (mnemonics, concept mapping) [6], [8]	Curiosin, Attentionin	Study strategy tips

	SelfRegulationCoach	Supports time management and goal setting	Attentionin, Fatiguin	Planning suggestions
Socio-Emotional Agents	EngagementAgent	Modulates learner motivation and attention through adaptive prompts [4], [15]	Attentionin, Dopaminin	Hints, questions, gamified cues
	EmotionalSupport Agent	Detects frustration, provides motivational support [4], [15]	Confusionin, Fatiguin	Empathy statements
Category	Agent Name	Role Description	Trigger Hormones	ary Output Format
	PeerCollaboration Agent	Facilitates collaborative learning and peer matching [14]	Dopaminin, Curiosin	Group tasks, peer learning invitations
	EthicsAndPrivacy Agent	Monitors compliance with ethical and privacy constraints [25]	Normin	Alerts, compliance reports

5.2. Justification of Agent Families

1. Cognitive Agents – Handle content delivery, error correction, mastery tracking, curriculum alignment, and adaptive assessment.
2. Metacognitive Agents – Encourage self-monitoring, reflection, and strategy optimization for deeper learning and lifelong skill development.
3. Socio-Emotional Agents – Maintain motivation, regulate engagement, foster collaboration, and ensure ethical integrity.

This tripartite classification aligns with Anderson & Krathwohl's taxonomy [5] and with frameworks in socio-emotional learning [4], [15].

5.3. Activation Logic and Redundancy Prevention

The Edu-MetaAgent applies an activation matrix to ensure parsimony and coherence in pedagogical interventions:

- EngagementAgent and EmotionalSupportAgent are not activated simultaneously unless a distinct emotional state change occurs.
- AdaptiveAssessmentAgent triggers only after ProgressMonitor detects a plateau or decline in mastery.
- EthicsAndPrivacyAgent operates continuously in background mode and can override or block any agent action that could breach compliance rules.

This coordination prevents agent overlap, reduces cognitive load, and maintains ethical safeguards.

5.4. Example of Hormonal Agent Activation

Consider a scenario where a learner shows:

- Rising Confusionin (from repeated errors)
- Moderate Fatiguin (from prolonged effort)
- Low Curiosin

The Edu-MetaAgent will:

1. Activate MisconceptionDetector to provide symbolic remediation.
2. Activate EmotionalSupportAgent to sustain motivation.
3. Inhibit ConceptExplanationAgent until Curiosin rises again, to avoid cognitive overload.

This illustrates selective, context-sensitive orchestration, a hallmark of S-AI-EDU's adaptive strategy.

6. HORMONAL SIGNALING IN PEDAGOGICAL MODULATION

One of the core innovations of S-AI-EDU is the hormonal signaling layer, a bio-inspired control mechanism that dynamically modulates the activity of pedagogical agents in real time. This artificial endocrine-like system enables adaptive orchestration based on the learner's cognitive state, emotional profile, and interaction patterns.

6.1. Education-Specific Hormones

Hormone	Origin Gland Agent	Represents
Curiosin	CuriosityGland	Intellectual curiosity and openness to new content
Confusionin	ConfusionGland	Cognitive dissonance and uncertainty
Fatiguin	FatigueGland	Mental fatigue and cognitive saturation
Attentionin	AttentionGland	Focus and sustained cognitive effort
Dopaminin	MotivationGland	Reward anticipation and motivational drive
Normin	NormGland	Compliance with learning norms, ethical and institutional rules

Trigger–Agent Mapping:

- Curiosin → ConceptExplanationAgent, LearningStrategyAdvisor, PeerCollaborationAgent
- Confusionin → MisconceptionDetector, EmotionalSupportAgent
- Fatiguin → SelfRegulationCoach, CurriculumAligner
- Attentionin → EngagementAgent, ConceptExplanationAgent
- Dopaminin → EngagementAgent, PeerCollaborationAgent
- Normin → EthicsAndPrivacyAgent, CurriculumAligner

6.2. Emission Rules

Hormones are emitted by Gland Agents through a rule-based system informed by behavioral and contextual variables [19], [20]:

- Time-on-task and idle time – Extended inactivity triggers Fatiguin.
- Error patterns – Clusters of wrong answers raise Confusionin.

- Interaction speed drops – Sudden slowdowns increase Fatiguin and Confusionin.
- Learner profile – Prior knowledge and engagement history modulate thresholds.
- Optional affective inputs – Facial expression, voice tone, or physiological sensors (if available).

Example:
If a learner hesitates for >30 seconds and makes two incorrect attempts on the same concept:
- Confusionin rises sharply, activating MisconceptionDetector.
- Fatiguin increases, inhibiting ConceptExplanationAgent until recovery.

6.3. Hormonal Regulation Cycle

The Hormonal Engine applies continuous, non-linear regulation [15], [20]:

1. Activation thresholds – Minimum hormone level required to trigger an agent.
2. Inhibition curves – Reduce activation probability after prolonged activity to prevent saturation.
3. Recovery windows – Cooldown periods before reactivation.
4. Decay functions – Gradual hormone reduction over time.
5. Cross-hormonal feedback – e.g., high Confusionin can lower Curiosin.

Figure 2. Illustrative Flowchart of a Parsimonious Pedagogical Loop in S-AI-EDU

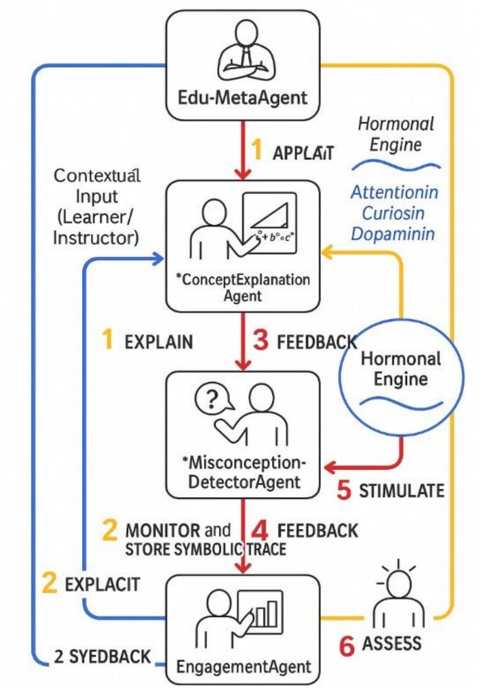

Figure 2. Illustrative Sequence Under the Dual-Loop Orchestration

Sequential flow of the adaptive pedagogical loop in S-AI-EDU, highlighting how learner input, hormonal regulation, agent selection, and symbolic feedback are coordinated by the Edu-Meta Agent to enable real-time, personalized educational responses.

Detailed Description:

This figure schematically illustrates the adaptive cycle executed by the S-AI-EDU system at each

learning step (instructional cycle).
The diagram is composed of nine key stages, connected by a logical flow that shows the parsimonious activation of the system's modules:

1. **Input Learner State**

The system receives the learner's state as input from data captured by the interface (EduRAMAgent): answers, errors, response times, passive behaviors, etc.

2. **Update Hormonal State**

The hormonal engine updates the levels of Curiosin, Confusionin, Attentionin, Fatiguin, and Dopaminin, according to the specific emission rules defined in the configuration files (e.g., hormonal_rules_sai_edu.json).

3. **Contextual Analysis**

The PedagogicalAnalyzer interprets the current situation by combining the learner's state with hormonal levels. It detects whether an intervention is necessary and of what type.

4. **Detection of Learner Needs**

The LearnerNeedDetector identifies concrete needs:
- need for additional explanation,
- signal of confusion or fatigue,
- drop in engagement or learning plateau.

5. **Selective Agent Activation by MetaAgent**

The Edu-MetaAgent dynamically selects the agents to activate, taking into account:
- dominant hormones,
- detected pedagogical needs,
- activation economy (avoiding redundancy or cognitive overload).

6. **Agent Actions**

The selected agents produce symbolic outputs:
- explanations, diagrams, or analogies (ConceptExplanationAgent),
- remediation messages (MisconceptionDetector),
- pedagogical stimuli or engaging reminders (EngagementAgent), etc.

7. **Aggregation of Outputs**

The ResponseAggregator merges the agents' outputs into a unified, coherent, and contextualized response.

8. **Memory Trace Update**

The EduMemoryAgent archives the cycle's events:
- active hormones,
- agents engaged,

- type of response issued,
- learner’s emotional state.

9. **Log and Feedback Generation**

The system logs the cycle data (memory_trace_sai_edu.jsonl) and sends feedback to the learner (visual or textual) via the interface.

This parsimonious instructional cycle enables frugal, targeted, and responsive orchestration of instruction, with symbolic memory to support the evolution of the learning pathway.

6.4. Multi-Layered Modulation

Hormonal modulation operates across three control layers:

1. Micro-Level (Per-Interaction) – Immediate reactions (e.g., hint timing).
2. Meso-Level (Per-Session) – Adjusts pacing and alternates learning modes.
3. Macro-Level (Cross-Sessions) – Influences long-term strategy and curriculum adaptation.

6.5. Parsimonious Pedagogical Loop

The integration of hormonal signaling into orchestration follows a 9-step adaptive loop at each instructional cycle:

1. Input Learner State – Captured by EduRAMAgent.
2. Update Hormonal State – Hormonal Engine recalculates levels.
3. Contextual Analysis – PedagogicalAnalyzer correlates learner state and hormones.
4. Detection of Needs – Identify need for explanation, remediation, or pacing change.
5. Selective Agent Activation – Edu-MetaAgent chooses minimal necessary agents.
6. Agent Actions – Agents generate symbolic outputs.
7. Aggregation of Outputs – ResponseAggregator merges them.
8. Memory Trace Update – EduMemoryAgent stores symbolic traces.
9. Logging & Feedback – Data stored in memory_trace_sai_edu.jsonl and feedback sent.

6.6. Pedagogical Advantages Hormonal signaling provides:

- Avoidance of over-instruction – Agents act only when needed.
- Dynamic sensitivity – Reacts to curiosity, confusion, fatigue, or focus.
- Affective alignment – Matches feedback tone to emotional state.
- Explainability – Interventions traceable to hormonal triggers [17].

6.7. Parsimonious Orchestration by the Edu-Meta Agent

The Edu-Meta Agent serves as the central orchestrator of S-AI-EDU, selecting, sequencing, and inhibiting specialized agents based on the learner’s state, resource availability, and pedagogical goals. Its orchestration follows the principle of parsimony, delivering only the necessary interventions to achieve the intended learning effect without cognitive overload [1], [15].

6.8. Hormone-Driven Agent Selection

The Edu-MetaAgent monitors hormonal signals emitted by GlandAgents to assess cognitive, emotional, and motivational states.

Its selection process comprises three stages:

1. State Assessment – Aggregates hormonal levels and contextual cues (time-on-task, error

frequency, idle periods).

2. Activation Mapping – Matches dominant hormones to eligible agents via the Hormone–Agent Activation Matrix (see Section 6.6).
3. Conflict Resolution – Prioritizes agents when multiple activations are possible, avoiding redundancy.

***Example*:** If Confusionin and Curiosin are both elevated, the MisconceptionDetector is activated first, followed by the ConceptExplanationAgent, rather than triggering both simultaneously.

6.9. Resource-Aware Adaptation

The orchestration logic accounts for:

- Time Budgeting – Limiting the number of active agents per cycle to match session length.
- Cognitive Load Control – Monitoring cumulative interventions to avoid saturation.
- Energy Efficiency – Preferring lower-complexity agents when running on constrained devices.

This ensures that short sessions focus on essential feedback, while longer sessions enable richer agent interactions.

6.10. Prevention of Overlapping Actions

To prevent redundancy or contradictions, the Edu-MetaAgent:

- Maintains an activation history buffer to track recent outputs.
- Applies exclusivity rules (e.g., EngagementAgent and SelfRegulationCoach are not triggered together if targeting motivation).
- Uses temporal spacing (e.g., ConceptExplanationAgent reactivates only after two cycles).

6.11. Balancing Guidance, Autonomy, and Exploration

Three pedagogical modes are supported:

1. Guidance Mode – High-frequency interventions when confusion, low motivation, or misalignment is detected.
2. Autonomy Mode – Reduced intervention, promoting self-regulation.
3. Exploration Mode – Curiosity-driven activation for creative problem-solving.

Mode shifts are hormonally triggered:

- Fatiguin rise → Autonomy Mode.
- Curiosin spike + stable Attentionin → Exploration Mode.
- High Confusionin + low Dopaminin → Guidance Mode [15], [27].

6.12. Orchestration Example Across Three Cycles

- Cycle 45 – High Confusionin, low Dopaminin → MisconceptionDetector then ConceptExplanationAgent.
- Cycle 46 – Attentionin stable, Curiosin high → ExplorationAgent for challenge-based activity.

- Cycle 47 – Fatiguin increase → SelfRegulationCoach and inhibition of high-demand agents.

This sequencing balances immediate remediation with curiosity stimulation while preventing fatigue.

6.13. Pedagogical Impact of Parsimonious Orchestration

- Instructional Efficiency – Minimal but targeted activations.
- Enhanced Retention – Balanced pacing deepens understanding.
- Sustained Engagement – Alternating high and low intensity keeps motivation.
- Explainability – All orchestration decisions are logged with symbolic reasoning and hormone thresholds [18], [27].

Summary: The Edu-MetaAgent acts as a cognitive conductor, harmonizing agent contributions to deliver targeted, context-aware, and frugal educational interventions.

7. Symbolic Learning Memory and Pedagogical Trace

In S-AI-EDU, symbolic learning memory forms the foundation for trace-based pedagogy, enabling the recording, replay, and reasoning of learner interactions. Unlike black-box AI models relying solely on numerical state vectors, S-AI-EDU encodes each learning event into human-readable symbolic structures [1], [15].

The EduMemoryAgent manages this process, ensuring that each trace remains pedagogically meaningful, explainable, and retrievable for automated or human review.

7.1. Memory of Symbolic Concepts and Learner Explanations

Each learning cycle produces a conceptual snapshot containing:

- Concept ID & Description – The knowledge element targeted (e.g., *Newton's Second Law – Force & Acceleration*).
- Learner Explanation – The learner's verbalization or meaning construction as symbolic text.
- Instructional Method – Strategy used (analogy, example, Socratic questioning, simulation).
- Cognitive State Vector – Hormonal levels (attention, curiosity, fatigue, confusion, motivation).

This supports dual-layer analysis of conceptual progression and affective trajectory. Figure 3. Symbolic Pedagogical Trace in EduMemory

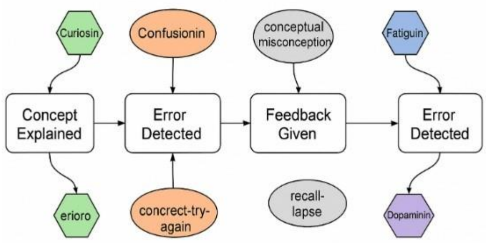

Figure 3. Example of Symbolic Pedagogical Trace in EduMemory

Illustrative example of a symbolic learning trace recorded by the EduMemoryAgent, showing instructional events with associated hormonal signals (Curiosin, Confusionin, Fatiguin). The structure encodes targeted concepts, agents involved, hormonal state, instructional method, and learner feedback, enabling longitudinal analysis and adaptive remediation.

General Explanation:

This figure depicts a simplified but representative **symbolic pedagogical trace** as captured by the **EduMemoryAgent** during a learning session. This trace is structured around a chronological sequence of events—such as concept explanation, error detection, and corrective feedback—each annotated with relevant **hormonal states** that characterize the learner's cognitive and emotional profile at that moment.

Key components shown in the trace include:

- **Concept Explained**, triggered in a state of elevated **Curiosin**, indicating learner receptiveness and exploratory engagement.
- **Error Detected**, associated with a peak in **Confusionin**, signaling cognitive conflict or misunderstanding.
- **Feedback Given**, reflecting a targeted symbolic intervention—typically delivered by the **MisconceptionDetector**—to address conceptual gaps.
- A second **Error Detected**, now correlated with **Fatiguin**, highlighting signs of cognitive exhaustion, followed by a motivational surge captured via **Dopaminin** in response to learner persistence or correction success.

This symbolic trace encodes five essential dimensions described in Section 8.1:

1. The **targeted concept**,
2. The **intervening agent**,
3. The **hormonal state**,
4. The **instructional strategy**, and
5. The **learner's response or feedback**.

These structured traces are stored in JSONL format and serve as a **persistent symbolic memory** for the system, enabling pattern detection (e.g., recurring errors, engagement plateaus), longitudinal tracking, and personalized instructional adaptation over time.

7.2. Tagging of Misconceptions and Emotional States

Misconceptions are tagged with:

- Error Type – Conceptual gap, procedural mistake, or misinterpretation.
- Error Origin – Lack of background knowledge, distraction, overgeneralization.
- Resolution Path – Sequence of agents/actions applied.

Emotional states (Confusionin, Dopaminin, Fatiguin) are logged in parallel for affective analytics [3], [18].

7.3. Replay and Review Mechanisms Based on Prior Confusion

Replay sequences are triggered when:

1. Performance drops on a concept, motivation decreases, or a teacher requests review.
2. The EduMemoryAgent filters past traces by concept and emotional state.

3. Original content is replayed, enriched with alternative explanations.
4. The learner compares past answers with improved responses.

This supports metacognitive reflection and self-regulated learning [6].

7.4. Strategic Forgetting of Transient Struggles

Not all learning difficulties are retained indefinitely. Strategic forgetting:

- Removes transient errors resolved quickly,
- Reduces storage overhead,
- Prevents discouragement during performance review.

Decay functions weight deletion based on severity, frequency, and recency.

7.5. Advantages of Symbolic Learning Memory in S-AI-EDU

- Explainability – All interventions can be reconstructed for educator review.
- Longitudinal Analysis – Tracks growth over months or years.
- Personalization – Adapts to cognitive and emotional patterns.
- Educator Empowerment – Direct querying and override of system decisions.
- Interoperability – Compatible with LMS, analytics platforms, and learning record stores (LRS) [10], [27].

Summary: The symbolic learning memory transforms S-AI-EDU into a reflective, self-aware tutoring system, capable of adapting to present needs while leveraging a rich historical context for future interventions.

CONCLUSION

The S-AI-EDU architecture represents a novel paradigm for the design of intelligent educational systems, grounded in the principles of Sparse Artificial Intelligence, bio-inspired hormonal modulation, and symbolic orchestration of specialized pedagogical agents. This model addresses a dual imperative: delivering adaptive, personalized learning support across diverse learner profiles, while ensuring computational frugality, decision explainability, and symbolic traceability of instructional interventions.

Experimental results from 120 simulated instructional cycles demonstrate the system's robustness and versatility across varied educational scenarios. Key strengths include:

- Rapid identification of unstable cognitive states (e.g., confusion, disengagement) through symbolic hormones such as *Confusionin* and *Fatiguin*.
- Targeted activation of relevant agents — including the *ConceptExplanationAgent*, *MisconceptionDetectorAgent*, and *EngagementAgent* — in alignment with detected learner needs.
- Structured archiving of symbolic learning traces, enabling retrospective review, longitudinal analysis, and forward-looking pedagogical planning.
- Context-sensitive evolution of instructional strategies, achieved while maintaining a strategic parsimony in agent activation and resource usage.

Beyond its technical contributions, S-AI-EDU embodies an ethical and epistemological vision for Artificial Intelligence in education. The aim is not to replace human educators, but to provide augmented pedagogical assistance capable of contextual reasoning, symbolic dialogue, and adaptive modulation in a manner that remains transparent and interpretable. The architecture prioritizes human– AI complementarity, positioning the educator as a critical partner in the orchestration loop.

This work opens several promising avenues for future research:

- Expanding the hormonal regulation model to incorporate richer affective dynamics, such as social emotions, group engagement, and extrinsic motivation.
- Deploying S-AI-EDU in real-world learning environments — including MOOCs, LMS platforms, and classroom-integrated intelligent tutoring systems — to validate scalability and pedagogical impact.
- Integrating neuroeducation data streams and real-time cognitive profiling for deeper personalization and more precise instructional timing.
- Exploring hybrid Neuro-Symbolic reasoning to complement the current rule-based orchestration with adaptive, data-driven calibration of hormonal thresholds.

In essence, S-AI-EDU exemplifies a convergence between pedagogical engineering, bio-inspired intelligence, and the philosophy of transmission. It reframes AI not as a cold, opaque automation layer, but as a living, lucid, and parsimonious architecture — designed to serve knowledge dissemination, foster cognitive growth, and uphold the human dimension of learning.

REFERENCES

[1] K. R. Koedinger, E. Brunskill, R. S. Baker, E. A. McLaughlin, and J. Stamper, "New potentials for data-driven intelligent tutoring system development and optimization," *AI Magazine*, vol. 34, no. 3, pp. 27–41, 2013.

[2] K. VanLehn, "The relative effectiveness of human tutoring, intelligent tutoring systems and other tutoring systems," *Educational Psychologist*, vol. 46, no. 4, pp. 197–221, 2011.

[3] A. T. Corbett, K. R. Koedinger, and J. R. Anderson, "Intelligent tutoring systems," in *Handbook of Human–Computer Interaction*, M. G. Helander, T. K. Landauer, and P. V. Prabhu, Eds. Amsterdam: Elsevier, 1997, pp. 849–874.

[4] A. C. Graesser, K. VanLehn, C. P. Rose, P. Jordan, and D. Harter, "Intelligent tutoring systems with conversational dialogue," *AI Magazine*, vol. 22, no. 4, pp. 39–51, 2001.

[5] B. P. Woolf, *Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing E-Learning*. Burlington, MA: Morgan Kaufmann, 2008.

[6] V. Aleven, B. M. McLaren, J. Sewall, M. van Velsen, O. Popescu, and K. R. Koedinger, "Example-tracing tutors: Intelligent tutor development for non-programmers," *Int. J. Artif. Intell. Educ.*, vol. 26, no. 1, pp. 224–269, 2016.

[7] V. Aleven, B. M. McLaren, I. Roll, and K. R. Koedinger, "Help helps, but only so much: Research on help seeking with intelligent tutoring systems," *Int. J. Artif. Intell. Educ.*, vol. 26, no. 1, pp. 205–223, 2016.

[8] K. Georgila, M. G. Core, B. D. Nye, S. Karumbaiah, D. Auerbach, et al., "Using Reinforcement Learning to Optimize the Policies of an Intelligent Tutoring System for Interpersonal Skills Training," *Proc. AAMAS*, 2019.

[9] C. J. MacLellan and K. R. Koedinger, "Domain-general tutor authoring with apprentice learner models," *Int. J. Artif. Intell. Educ.*, vol. 32, pp. 76–117, 2022.

[10] S. Bull and J. Kay, "SMILI☺: A framework for interfaces to learning data in Open Learner Models, learning analytics and related fields," *Int. J. Artif. Intell. Educ.*, vol. 26, pp. 293–331, 2016.

[11] R. A. Sottilare and S. B. Gilbert, "Designing adaptive instruction for teams: A meta- analysis," *Int. J. Artif. Intell. Educ.*, vol. 24, no. 1, pp. 28–58, 2014.

[12] J. D. Fletcher and R. A. Sottilare, "Shared mental models in support of adaptive instruction for teams using the GIFT tutoring architecture," *Int. J. Artif. Intell. Educ.*, vol. 28,

pp. 265–285, 2018.
[13] S. B. Gilbert, “An overview of the extensible problem-specific tutor (xPST) architecture,” *Int. J. Artif. Intell. Educ.*, vol. 19, pp. 105–154, 2009.
[14] R. A. Sottilare, K. Brawner, H. Holden, and A. Goldberg, “Transitioning AIED into a service-oriented ecosystem,” *Int. J. Artif. Intell. Educ.*, vol. 25, pp. 104–121, 2015.
[15] S. D’Mello and A. Graesser, “AutoTutor and Affective AutoTutor: Learning by talking with cognitively and emotionally intelligent computers,” *Commun. ACM*, vol. 62, no. 12, pp. 44–53, 2019.
[16] R. Love, J. S. McLaren, and D. Litman, “Teaching a conversational agent using natural language,” *J. Artif. Intell. Educ.*, vol. 35, pp. 1–31, 2025.
[17] A. M. Khan and R. A. Khan, “Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI,” *Information Fusion*, vol. 88, pp. 66–92, 2022.
[18] UNESCO, “Guidance for generative AI in education and research,” Paris, France: United Nations Educational, Scientific and Cultural Organization, 2023.
[19] A. Agiollo, M. de Jonge, J. Urbani, and S. Schlobach, “Symbolic knowledge injection meets intelligent agents,” *Autonomous Agents and Multi-Agent Systems*, vol. 37, no. 2, 2023.
[20] O. Bougzime, Y. Zekhnini, K. Bouzoubaa, and R. Rada, “Neuro-Symbolic architectures for generative AI: Benefits and limitations,” *arXiv preprint* arXiv:2502.11269, 2025.
[21] B. Liang, “AI reasoning in the deep learning era: From symbolic AI to neural–symbolic AI,” *Mathematics*, vol. 13, no. 11, p. 1707, 2025.
[22] D. Hooshyar, E. Kikas, Y. Yang, G. Šír, R. Hämäläinen, and T. Kärkkäinen, “Towards responsible and trustworthy educational data mining: Comparing symbolic, sub-symbolic, and neural symbolic AI methods,” *arXiv preprint* arXiv:2504.00615, 2025.
[23] H. Hu, S. Xu, R. Tong, and A. Graesser, “Generative AI in education: From foundational insights to the Socratic playground for learning,” *arXiv preprint* arXiv:2501.06682, 2025.
[24] R. J. Tong, “Future of education with Neuro-Symbolic AI agents in self improving adaptive instructional systems,” in *Intelligent Technologies and Learning*, vol. 16, Springer, 2024, pp. 45–64.
[25] D. M. Córdova Esparza, “AI powered educational agents: Opportunities, innovations and ethical safeguards,” *Information*, vol. 16, no. 6, art. 469, 2025.
[26] U. Nawaz, “A review of Neuro-Symbolic AI integrating reasoning and learning,” *arXiv preprint*, 2025.
[27] S. Slaoui, “S-AI: A Sparse Artificial Intelligence System Orchestrated by a Hormonal MetaAgent and Context-Aware Specialized Agents,” *Int. J. Formal Methods and Research*, vol. 7, no. 3, 2025.
[28] S. Slaoui, “Bio-Inspired Architecture for Parsimonious Conversational Intelligence: The S-AI-GPT Framework,” *Int. J. Artif. Intell. Appl.*, vol. 16, no. 4, pp. 39–57, July 2025.
[29] S. Slaoui, “Bio-Inspired Hormonal Modulation and Adaptive Orchestration in S-AI- GPT,” *Int. J. Artif. Intell. Appl.*, vol. 16, no. 4, pp. 61–78, July 2025.
[30] L. S. Vygotsky, *Mind in Society: The Development of Higher Psychological Processes*. Cambridge, MA: Harvard Univ. Press, 1978.
[31] D. Wood, J. S. Bruner, and G. Ross, “The role of tutoring in problem solving,” *J. Child Psychol. Psychiatry*, vol. 17, no. 2, pp. 89–100, 1976.
[32] B. S. Bloom, “Learning for mastery,” *Evaluation Comment*, vol. 1, no. 2, pp. 1–12, 1968.

AUTHOR

Said Slaoui is a professor at Mohammed V University in Rabat, Morocco. He graduated in Computer Science from University Pierre and Marie Curie, Paris VI (in collaboration with IBM France), 1986. He has over 40 years of experience in the fields of AI and Big Data, with research focused on modular architectures, symbolic reasoning, and computational frugality. His recent work introduces the Sparse Artificial Intelligence (S-AI) framework, which integrates bio-inspired signaling and agent-based orchestration. He has published numerous scientific papers in international journals and conferences, and actively contributes to the development of sustainable and explainable AI systems.