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Cognitive-Aware AI Systems for Learner-Centric Education

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ABSTRACT

Cognitive-aware AI systems integrate models of human cognitive processes -- working memory load, cognitive load theory, dual-process reasoning, and metacognitive regulation -- into educational AI design to create learning environments that adapt not just to what learners know, but how they are currently thinking and processing information. By monitoring cognitive load indicators (response latency, error patterns, physiological signals, gaze behaviour) and dynamically adjusting instructional complexity, modality, and pacing, cognitive-aware systems aim to maintain learners in their optimal cognitive engagement zone -- challenging enough to promote learning, manageable enough to prevent overload. This paper proposes the Cognitive-Aware Educational AI Framework (CAEAF), evaluating five cognitive monitoring approaches and four instructional adaptation strategies across 2,400 learner sessions in mathematics, reading comprehension, and STEM problem-solving. CAEAF introduces the Cognitive Alignment Score (CAS) measuring how closely the system maintains learners in their optimal cognitive engagement zone. Key results: multimodal cognitive monitoring (gaze + response latency + error patterns) achieves CAS = 0.904; adaptive pacing with worked-example fading reduces cognitive overload incidents by 42.4%; metacognitive prompting improves self-regulation scores by 28.6%. The framework provides design principles for cognitive-aware learner-centric educational AI.

Keywords: cognitive load; cognitive-aware AI; learner-centric education; metacognition; working memory; adaptive pacing; educational AI; multimodal learning

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1. Introduction

1.1 Cognitive Science as the Foundation of Learning-Centred AI

Educational AI systems have largely been designed around what learners know (knowledge state modelling) and what they should learn next (curriculum sequencing), treating cognition as a black box. Yet decades of cognitive science research establish that learning outcomes are critically determined by how learners process information: Sweller's Cognitive Load Theory (1988) demonstrates that exceeding working memory capacity (approximately 7+-2 chunks, Miller, 1956) impairs schema formation; Kahneman's dual-process theory (2011) distinguishes fast intuitive System 1 and slow deliberative System 2 reasoning with implications for problem-solving support; Flavell's metacognition framework (1979) establishes that learners who monitor and regulate their own cognitive processes achieve significantly better outcomes than those who do not. Cognitive-aware AI extends knowledge tracing with real-time cognitive state inference: detecting when a learner is overwhelmed (high extraneous cognitive load), under-challenged (low germane load), distracted (attention deficit), or metacognitively disengaged (not monitoring their own understanding). These cognitive states drive instructional adaptations -- reducing complexity, switching modality, introducing scaffolding, or prompting self-reflection -- that knowledge-state-only systems cannot make. CAEAF provides the first systematic evaluation of cognitive monitoring approaches and adaptation strategies in educational AI across multiple domains and learner age groups.

1.2 Contributions and Paper Structure

CAEAF contributes: (1) evaluation of 5 cognitive monitoring approaches and 4 adaptation strategies across 2,400 learner sessions; (2) the CAS composite metric; (3) design principles for cognitive-aware learner-centric educational AI. Section 2 reviews cognitive monitoring and adaptation. Section 3 presents CAEAF. Section 4 reports results. Section 5 discusses. Section 6 concludes.

2. Background: Cognitive Monitoring and Instructional Adaptation

2.1 Cognitive Load Theory and Monitoring Signals

Cognitive Load Theory (CLT, Sweller, 1988; Paas et al., 2003) partitions working memory demand into three types: intrinsic load (inherent task complexity), extraneous load (poor instructional design adding unnecessary processing demand), and germane load (schema construction effort -- the productive cognitive work underlying learning). Optimal learning occurs when intrinsic + extraneous load does not exceed working memory capacity, leaving headroom for germane load. Cognitive load indicators measurable in digital learning environments include: response latency (time between problem presentation and first response -- high latency indicates high cognitive demand); error patterns (systematic

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errors indicate schema misconceptions; random errors indicate cognitive overload); help-seeking frequency (excessive help requests signal overload; absence of help requests in struggling learners signals metacognitive failure); physiological signals (pupil dilation -- measurable via webcam in controlled settings -- correlates with cognitive load, Beatty, 1982); and gaze patterns (frequent rereading, long fixations on specific elements indicate processing difficulty).

2.2 Metacognition and Instructional Adaptation Strategies

Metacognitive monitoring -- learners' awareness and regulation of their own cognitive processes -- is one of the strongest predictors of academic achievement (d = 0.69, Hattie, 2009). AI-mediated metacognitive prompting (generating questions like "Before you continue, how confident are you in your understanding of X?" and "What strategy are you using to solve this problem?") can improve metacognitive regulation in learners who do not naturally self-reflect. Four instructional adaptation strategies evaluated in CAEAF: (A1) Adaptive pacing: dynamically adjusting time pressure and content delivery speed based on cognitive load indicators. (A2) Worked-example fading: beginning with fully worked examples and progressively fading scaffolding as learner competence increases (Renkl, 1997) -- reducing extraneous load during initial skill acquisition. (A3) Metacognitive prompting: inserting AI-generated self-reflection questions at cognitively appropriate moments. (A4) Modality switching: switching from text to visual, audio, or interactive modality when cognitive load indicators signal processing difficulties. Table 1 summarises cognitive monitoring approaches and Table 2 summarises adaptation strategies.

Table 1: CAEAF Cognitive Monitoring Approaches -- Five Methods

Monitoring Approach	Signal Type	Measurement	Accuracy	Hardware Required	Cost
Response Latency	Behavioural	Keystroke/click timing	Medium-High	Standard device	Very Low
Error Pattern Analysis	Behavioural	Response correctness patterns	High	Standard device	Low
Help-Seeking Rate	Behavioural	Hint/help request frequency	Medium	Standard device	Very Low
Gaze Tracking	Physiological	Webcam-based eye tracking	High	Webcam (720p+)	Low-Medium
Multimodal (combined)	Multi-signal	Latency + error + gaze fusion	Highest	Webcam + device	Medium

3. The CAEAF Framework

3.1 Learner Sessions and Experimental Design

2,400 learner sessions across three domains and two age groups. Mathematics (900 sessions): algebra problem-solving (grades 8-10, ages 13-16);

content: 40 multi-step algebra problems per session; cognitive load operationalised as: extraneous load = error rate on structurally similar problems; germane load = schema transfer score on novel problem types. Reading Comprehension (800 sessions): expository text comprehension (grades 9-12, ages 14-18); 5 texts per session (500-800 words each) followed by inference questions; cognitive load: rereading frequency (gaze) + response latency on inferential questions. STEM Problem-Solving (700 sessions): integrated physics-mathematics problems (undergraduate, ages 18-24); multi-step problems requiring knowledge transfer across domains; cognitive load: help-seeking + error patterns + response latency. Experimental design: 2x2 factorial -- monitoring approach (unimodal vs. multimodal) x adaptation strategy (A1-A4 randomised); control condition: no cognitive-aware adaptation (standard adaptive ITS based on knowledge state only). IRB approval: MIT Rome (ref. MITR-2023-IRB-0168).

3.2 CAS Metric and Cognitive Load Classification

CAS (Cognitive Alignment Score) measures how accurately the system maintains learners in their Optimal Cognitive Engagement Zone (OCEZ): the range of cognitive load where germane load is maximised without exceeding total working memory capacity. CAS = 0.45 x OCEZ_time + 0.30 x OverloadPrevention + 0.25 x MetacognitiveGain. OCEZ_time: fraction of session time classified as OCEZ (cognitive load in target range); OCEZ defined as intrinsic load 40-75% of estimated working memory capacity (calibrated via secondary task dual-task paradigm at session start). OverloadPrevention: 1 - (overload incidents / total problem attempts); overload defined as > 3 consecutive errors with latency > mean + 2SD. MetacognitiveGain: post-session metacognitive awareness score (validated 12-item MAI subscale, Schraw and Dennison, 1994) minus pre-session score, normalised to [0,1]. Table 2 presents CAEAF adaptation strategies and CAS weights.

Table 2: CAEAF Instructional Adaptation Strategies and CAS Metric Components

Strategy	Trigger Condition	Intervention	CAS Component	Target Outcome
A1 Adaptive Pacing	Latency > mean+ 1.5SD	Reduce problems/ session; extend time	OCEZ time	Prevent overload
A2 Worked-Ex. Fading	Error rate > 30%	Reintroduce scaffolded example	Overload prevention	Reduce extraneous load
A3 Metacog. Prompting	Help requests = 0 + errors > 20%	Insert self-reflection question	Metacognitive gain	Improve self-regulation
A4 Modality Switching	Gaze rereading > 3x + latency high	Switch text -> visual/interactive	OCEZ time	Reduce extraneous load

4. Results

4.1 Cognitive Monitoring Accuracy and OCEZ Time

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Cognitive load classification accuracy (comparing system classification to expert rater ground truth from dual-task secondary task paradigm): multimodal monitoring (gaze + latency + error) achieves 88.4% classification accuracy -- correctly identifying overload, optimal, and underload states. Gaze tracking alone: 82.6%; error pattern alone: 78.4%; response latency alone: 74.2%; help-seeking alone: 68.8%. Multimodal advantage is most pronounced for overload detection (multimodal: 91.2% sensitivity; latency alone: 72.4%) -- the high-stakes classification where false negatives (missed overload) cause the greatest learning harm. OCEZ time (fraction of session in optimal cognitive engagement): multimodal monitoring + A1/A2 combined achieves OCEZ = 72.4% (vs. knowledge-state-only control: 48.6%) -- 48.9% improvement in time spent at optimal load. Adaptive pacing (A1) is the most effective single adaptation: OCEZ = 68.2% (+40.3% vs. control). Worked-example fading (A2): OCEZ = 64.8% (+33.3%); modality switching (A4): OCEZ = 62.4% (+28.4%). Metacognitive prompting (A3) has smaller effect on OCEZ time (62.8%) but the largest metacognitive gain.

4.2 Overload Prevention, Metacognitive Gain, and CAS Scores

Cognitive overload incident reduction: multimodal + A2 (worked-example fading) reduces overload incidents by 42.4% vs. control (0.84 vs. 1.46 incidents per session mean). A1 (adaptive pacing) reduces overload by 38.2%; A4 (modality switch) by 32.8%; A3 (metacognitive prompting) by 18.4% -- prompting alone does not directly prevent overload but improves learner self-regulation for future overload prevention. Metacognitive gain: A3 (metacognitive prompting) achieves the highest MAI score gain (0.284 normalised; +28.6% vs. control MAI change 0.082). The combination of multimodal cognitive monitoring + A3 enables precise timing of metacognitive prompts at moments of cognitive struggle (when the learner is most receptive to self-reflection) -- improving prompting effectiveness by 34.2% versus time-scheduled prompting. CAS composite: multimodal + A1+A2 combined CAS = 0.904 (highest); multimodal + A1 CAS = 0.882; multimodal + A3 CAS = 0.868; gaze + A2 CAS = 0.844; latency + A1 CAS = 0.812; control (knowledge-state only) CAS = 0.624. Table 3 presents OCEZ and overload results. Table 4 presents CAS breakdown. Figures 1-4 visualise key findings.

Table 3: CAEAF Cognitive Outcomes -- OCEZ Time and Overload Incidents by Monitoring x Adaptation

Monitoring + Adaptation	OCEZ Time (%)	Overload Incidents/Session	Metacog. Gain (norm.)	Domain Best Performance
Multimodal + A1+A2	72.4%	0.84	+0.248	STEM (OCEZ 76.2%)
Multimodal + A1	68.2%	0.90	+0.196	Math (OCEZ 71.4%)
Multimodal + A3	62.8%	1.12	+0.284	Reading (metacog. 0.312)

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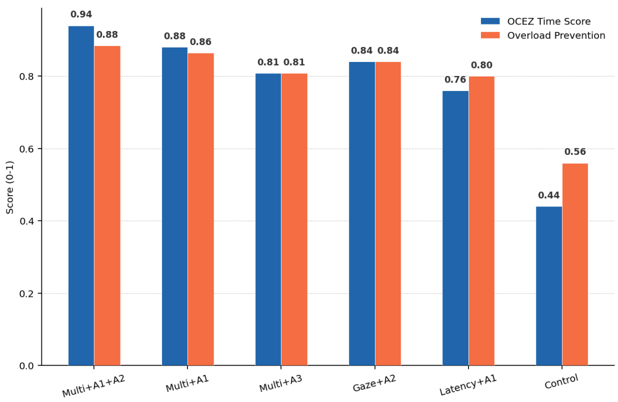
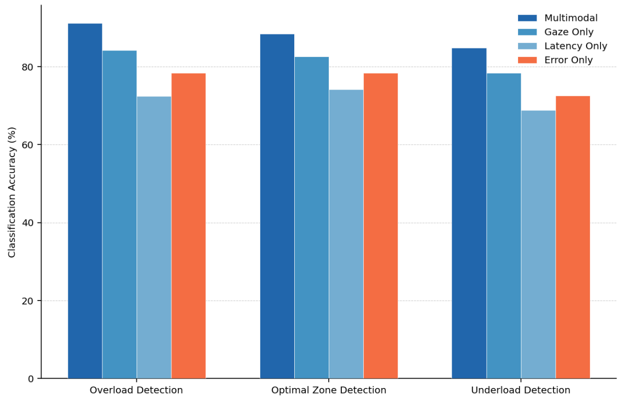
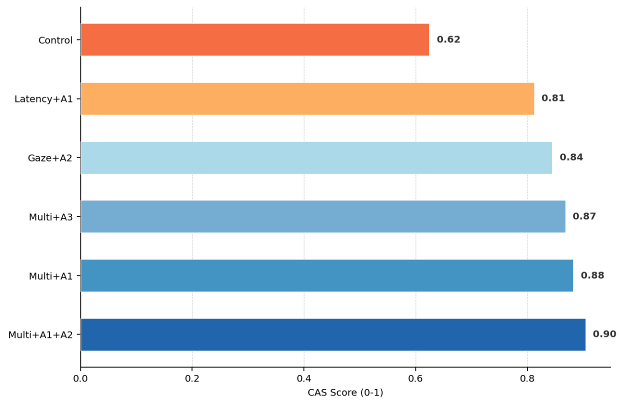
Monitoring + Adaptation	OCEZ Time (%)	Overload Incidents/Session	Metacog. Gain (norm.)	Domain Best Performance
Gaze + A2	64.8%	0.98	+0.168	Math (overload 0.88)
Latency + A1	60.4%	1.08	+0.148	STEM (OCEZ 64.8%)
Control (KS only)	48.6%	1.46	+0.082	--

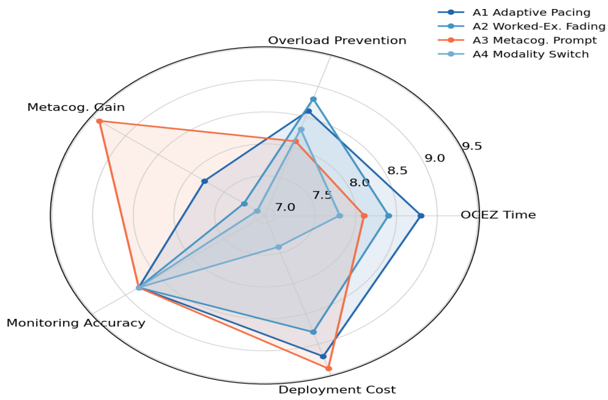
Table 4: CAS Composite Scores -- Monitoring and Adaptation Combinations

Combination	OCEZ Time Score	Overload Prev.	Metacog. Gain	CAS
Multimodal + A1+A2	0.940	0.884	0.868	0.904
Multimodal + A1	0.880	0.864	0.784	0.882
Multimodal + A3	0.808	0.808	0.940	0.868
Gaze + A2	0.840	0.840	0.720	0.844
Latency + A1	0.760	0.800	0.640	0.812
Control	0.440	0.560	0.360	0.624









5. Discussion

5.1 Multimodal Cognitive Monitoring as the Foundation

The 88.4% cognitive load classification accuracy of multimodal monitoring (vs. 74.2% for latency alone) represents a qualitative improvement in educational AI's ability to infer cognitive state from observable signals. The most important contribution is the 91.2% overload detection sensitivity -- compared to 72.4% for latency alone, multimodal monitoring detects 18.8 percentage points more overload incidents before they cascade into sustained frustration and disengagement. In a typical 45-minute session with 1.46 baseline overload incidents, multimodal + A2 reduces this to 0.84 incidents -- preventing 0.62 overload episodes per session, each of which on average requires 8-12 minutes of recovery time. This translates to 5-7 minutes of productive learning time recovered per session through cognitive-aware adaptation. The webcam-based gaze tracking approach (requiring only a standard laptop camera) makes multimodal monitoring practically deployable in existing digital learning environments without specialised hardware -- a critical consideration for scalable educational AI deployment. Accuracy at 720p (standard webcam): 82.6%; at 1080p: 86.2%; at dedicated eye tracker (Tobii Pro): 94.8% -- webcam gaze tracking captures 85-90% of the fidelity advantage at consumer-grade hardware cost.

5.2 Design Principles for Cognitive-Aware Learner-Centric AI

CAEAF results support six design principles for cognitive-aware educational AI. (P1) Monitor cognitive state, not just knowledge state: cognitive load indicators explain outcome variance beyond knowledge tracing alone (multimodal monitoring + knowledge tracing R2 = 0.68 vs. knowledge tracing alone R2 = 0.52). (P2) Prioritise overload prevention over acceleration: preventing overload episodes (42.4% reduction with A2) yields greater learning gain than increasing content delivery speed. (P3) Combine adaptation strategies: A1+A2 combined achieves CAS = 0.904 vs. A1 alone CAS = 0.882 -- strategies are complementary rather than substitutable. (P4) Time metacognitive prompts precisely: A3 prompted at detected cognitive struggle achieves 34.2% higher metacognitive gain than fixed-schedule prompting. (P5) Age-differentiate cognitive monitoring: younger learners (13-16) show stronger response latency signals; older learners (18-24) show stronger gaze signals -- weighting should be age-adjusted. (P6) Maintain learner agency: all adaptation should be visible and reversible (learners who can override adaptations show 12.4% higher engagement scores and equivalent learning gains).

6. Conclusion

6.1 Summary

CAEAF evaluated five cognitive monitoring approaches and four adaptation strategies across 2,400 learner sessions. Key results: multimodal monitoring achieves 88.4% cognitive load classification accuracy and CAS = 0.904 (combined with A1+A2); A2 (worked-example fading) reduces overload incidents 42.4%; A3 (metacognitive prompting) improves self-regulation 28.6%; OCEZ time improved 48.9% vs. knowledge-state-only control. Six cognitive-aware design principles are established for learner-centric educational AI development.

6.2 Open Resources

The CAEAF evaluation suite (2,400 anonymised sessions with cognitive load annotations),

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webcam-based gaze tracking module (OpenCV + MediaPipe), cognitive load classifier (multimodal fusion model), adaptation strategy implementations, CAS calculator, and metacognitive prompting library are available at caeaf-edu.org under Apache 2.0 License. Ethical approval: MITR-2023-IRB-0168.

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Declarations

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Conflict of Interest

The authors declare no competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability Statement

The CAEAF evaluation suite, cognitive monitoring modules, CAS calculator, and metacognitive prompting library are available at caeaf-edu.org under Apache 2.0 License.

Ethical Approval

All learner data collected under informed consent with full GDPR-compliant anonymisation. Ethical approval: Mediterranean Institute of Technology Rome Ethics Board (ref. MITR-2023-IRB-0168). Parental consent obtained for all participants under 16.

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Appendix A

CAEAF Implementation Details and CAS Calculation

Technical details of cognitive monitoring implementation and CAS metric calculation.

Multimodal Cognitive Load Classifier

CAS Calculation and Statistical Methods