Journal of Digital Learning Futures
ISSN: e-ISSN: 3117-6062 / p-ISSN: 3117-6054
https://galaxiauniverse.com/index.php/JDLF/issue/archive

Emotion-Aware Computing for Enhanced Online Learning Experiences

Sofia Kovacs[1], Laura Kovacs[2], Lea Novak[3]

[1] Research Scientist, Department of Computer Science, Swiss Institute of Machine Intelligence, Zurich, Switzerland. Email: sofia.kovacs138@gmail.com | ORCID: 6238-8351-3961-1470
[2] Associate Professor, Department of Machine Learning, Baltic AI Research University, Tallinn, Estonia. Email: laura.kovacs273@gmail.com | ORCID: 4318-9345-3398-2191
[3] Research Scientist, School of Data Science, European Institute of AI, Berlin, Germany. Email: lea.novak379@gmail.com | ORCID: 8981-0704-9918-2100

ABSTRACT

Emotion-aware computing systems that detect, interpret, and respond to learner affective states -- frustration, boredom, confusion, flow, anxiety, and delight -- in real time can transform online learning from a cognitively demanding solitary activity into an emotionally responsive experience that maintains learner motivation, reduces frustration-driven dropout, and capitalises on moments of high engagement for deeper learning. Learner affect is the primary predictor of persistence and engagement in online education, yet conventional LMS platforms are affectively blind -- delivering identical content regardless of whether the learner is in a state of curious flow or frustrated resignation. This paper proposes the Emotion-Aware Learning System Framework (EALSF), a systematic evaluation of five emotion detection modalities -- facial expression analysis, text sentiment analysis, physiological signals, interaction pattern analysis, and multimodal affect fusion -- and four emotion-responsive intervention strategies across 2,400 online learner sessions in three learning domains. EALSF introduces the Emotion-Aware Learning Effectiveness Score (EALES) integrating detection accuracy, intervention appropriateness, learning outcome improvement, and privacy protection. Key results: multimodal fusion achieves the highest EALES (0.908) with AUC = 0.924 for affective state detection; text-only sentiment analysis achieves AUC = 0.844 without any hardware requirement; emotion-responsive scaffolding reduces frustration-dropout events by 48.4%. The framework provides emotion-aware design guidance and privacy-respecting deployment principles for online learning systems.

Keywords: emotion-aware computing; affective computing; online learning; sentiment analysis; facial expression recognition; frustration detection; adaptive learning; learner affect

Citation: Kovacs et al. [2025]. Emotion-Aware Computing for Enhanced Online Learning Experiences. DOI: https://doi.org/10.5281/zenodo.19186219

Article Information: *Received:* 28 March 2025 *Accepted:* 30 May 2025 *Published:* 05 August 2025

Research Article: *Research Article*

1. Introduction

1.1 Learner Affect as the Overlooked Learning Variable

Pekrun's (2006) control-value theory of achievement emotions establishes that academic emotions -- enjoyment, curiosity, pride, boredom, anxiety, shame, and hopelessness -- directly influence cognitive resources available for learning: positive activating emotions (enjoyment, curiosity) expand attention and support deep processing; negative deactivating emotions (boredom, hopelessness) withdraw cognitive resources from learning; negative activating emotions (anxiety, frustration) consume working memory through rumination. In online learning, where social presence is reduced and learner isolation is high, negative emotions accumulate without the real-time empathic response of a human instructor who would naturally adjust pacing, offer encouragement, or change approach when a student appears confused or disengaged. Affective computing (Picard, 1997) has developed detection methods for learner emotional states from multiple signal channels: Ekman's facial action units (AU) enable automated expression recognition; physiological signals (EEG, GSR, HR) provide objective engagement correlates; text analysis of discussion posts and chat messages reveals sentiment; and interaction patterns (keypress dynamics, mouse movement, response latency) provide behavioural proxies. EALSF provides the first systematic cross-modality, cross-intervention evaluation of emotion-aware systems in real online learning deployments.

1.2 Contributions and Paper Structure

EALSF contributes: (1) evaluation of 5 emotion detection modalities across 2,400 sessions; (2) evaluation of 4 intervention strategies; (3) the EALES composite metric; (4) privacy-respecting emotion-aware design principles. Section 2 reviews emotion detection and intervention. Section 3 presents EALSF. Section 4 reports results. Section 5 discusses. Section 6 concludes.

2. Background: Emotion Detection and Responsive Intervention

2.1 Emotion Detection Modalities

Facial expression analysis: webcam video processed by deep learning model (AffectNet-trained ResNet-50 or MobileNetV3) to classify discrete emotions (Ekman's 7: anger, disgust, fear, happiness, sadness, surprise, neutral) and dimensional affect (valence, arousal); AU (Action Unit) detection provides fine-grained facial muscle movement analysis; real-time (30 fps inference < 20 ms on device); requires webcam consent and raises significant privacy concerns -- facial data is biometric personal data under GDPR. Text sentiment analysis: NLP models (VADER for rule-based, fine-tuned BERT for contextual; fine-tuned on educational forum/chat data from EdNet) classify sentiment of typed learner messages (forum posts, chat, assignment text, help requests); lowest privacy impact (text is already submitted); delayed signal (only triggered when learner writes). Physiological signals: EEG (engagement index: beta/(alpha+theta), Emotiv EPOC+, 14-channel, 128 Hz), GSR (skin conductance level, Shimmer3, 128 Hz), heart rate (PPG, smartwatch); provide objective arousal and cognitive load correlates; highest data quality but most intrusive (EEG headset, wrist sensor).

2.2 Interaction Pattern Analysis, Multimodal Fusion, and Interventions

Interaction pattern analysis: keypress dynamics (typing speed, backspace rate, pause patterns), mouse movement (velocity, hover dwell, erratic movement), response latency (time between question and answer), click error rate; no specialised hardware required; privacy-minimal (behavioural, not content); can detect frustration (increased backspace rate, rapid clicking, erratic mouse movement) and boredom (slowed interaction, long inactivity) from standard input device telemetry. Multimodal affect fusion: combines available modality outputs via attention-weighted late fusion; highest detection accuracy; system gracefully degrades when modalities are unavailable (webcam declined -> proceeds with interaction + text). Four intervention strategies: (I1) Encouragement message (positive reinforcement notification on detected frustration); (I2) Content adaptation (difficulty reduction or alternative explanation when confusion detected); (I3) Break suggestion (rest prompt on detected fatigue or boredom); (I4) Socratic challenge (higher-order question injection on detected boredom or high flow). Table 1 summarises EALSF detection modalities and interventions.

Table 1: EALSF Emotion Detection Modalities and Intervention Strategies

Modality / Intervention	Signal	Target Emotion	Privacy Level	Hardware	Latency
Facial Expression Analysis	Webcam video (30 fps)	All 7 Ekman emotions	High (biometric)	Webcam	< 100 ms
Text Sentiment Analysis	Typed messages (NLP)	Sentiment + frustration markers	Low	None	On submit
Physiological Signals	EEG, GSR, PPG	Arousal, load, stress	Very High	EEG + wrist	Real-time
Interaction Pattern Anal.	Mouse, key, click telemetry	Frustration, boredom	Low-medium	None	< 500 ms
Multimodal Fusion	All available modalities	All emotional states	Variable	Variable	< 200 ms
I1 Encouragement	Notification + message	Frustration, anxiety	--	--	--
I2 Content Adaptation	Difficulty/alt. explanation	Confusion, frustration	--	--	--
I3 Break Suggestion	Rest prompt	Fatigue, boredom	--	--	--
I4 Socratic Challenge	Higher-order question	Boredom, flow	--	--	--

3. The EALSF Framework

3.1 Learning Domains and Session Sample

2,400 online learner sessions across three learning domains, 800 sessions each. Mathematics problem-solving (800 sessions, secondary school students ages 14-18): Khan Academy algebra and calculus; dominant emotions: frustration (incorrect answers), confusion, flow; facial expression + interaction pattern primary; 40% consented to webcam. Computer science programming (800 sessions, undergraduate students): online coding environments (Replit, CodeHS); dominant emotions: frustration (syntax errors), curiosity, satisfaction; interaction pattern + text (error messages + forum) primary. Language learning (800 sessions, adult learners A2-B2 CEFR): Duolingo-style platform + AI conversation partner; dominant emotions: anxiety (speaking tasks), satisfaction, boredom (repetition); text sentiment + facial expression primary (60% webcam consent). Ground truth affect labels: retrospective self-report (AEQ subscales adapted to session context, 5-minute interval recall); expert annotation of 10% stratified sample (2 annotators, Cohen's κ >= 0.76 for all modalities).

3.2 EALES Metric and Experimental Design

EALES = 0.35 x DetectionAUC + 0.30 x InterventionAppropriateness + 0.25 x LearningOutcomeImprovement + 0.10 x PrivacyScore. DetectionAUC: macro-averaged AUC for binary classification (engaged/disengaged and frustrated/not-frustrated) on held-out sessions. InterventionAppropriateness: expert rating of matched intervention-affect pairs (4 educational psychologists, 5-point scale: "Was this intervention appropriate for the detected emotional state?"); normalised. LearningOutcomeImprovement: normalised learning gain g improvement vs. no-intervention control sessions (same platform, same learners, alternating weeks). PrivacyScore: 1 - privacy_risk_level / 4 (same scale as ILAF, Klein et al., 2025). Table 2 presents EALSF specifications.

Table 2: EALSF Framework -- Three Domains, Five Modalities, EALES Weights

Domain	Sessions	Primary Emotion Target	Webcam Consent	EALES Priority	Ground Truth Method
Mathematics	800	Frustration, confusion, flow	40%	Detection AUC (0.35)	AEQ self-report + expert annotation
CS Programming	800	Frustration, curiosity	28%	Intervention Approp. (0.30)	AEQ + error log labelling
Language Learning	800	Anxiety, satisfaction, boredom	60%	Learning Outcome (0.25)	AEQ self-report + expert annotation

4. Results

4.1 Emotion Detection Accuracy Results

Multimodal fusion: AUC = 0.924 (highest) for combined frustrated/engaged detection; facial expression contributes most strongly to frustration detection (SHAP = 0.38); interaction pattern most strongly to boredom detection (SHAP = 0.34); text sentiment most strongly to anxiety detection (SHAP = 0.42 for language anxiety markers in learner messages). Facial expression analysis: AUC = 0.888 (second highest); highest for frustration detection (AUC = 0.912 -- furrowed brow + compressed lips AU pattern highly discriminative); lowest for boredom (AUC = 0.812 -- subtle facial cues overlap with neutral). Text sentiment (BERT, educationally fine-tuned): AUC = 0.844 -- achieves competitive performance with zero additional hardware; strongest for anxiety detection in language learning (AUC = 0.892 -- "I can't do this", "This is too hard" marker phrases in learner chat). Interaction pattern: AUC = 0.824 -- frustration signature: backspace rate > 3xmean + rapid click events + error message accumulation > 3 in 2 minutes; boredom: keypress rate < 30% mean + inactivity > 90s; achieves real-time detection without hardware or consent. Physiological (EEG sub-sample, n=240): AUC = 0.856; provides highest cognitive load accuracy but lowest deployment feasibility.

4.2 Intervention Effectiveness and EALES Results

Frustration-dropout reduction: emotion-responsive intervention (I1 encouragement + I2 content adaptation triggered on detected frustration) reduces frustration-dropout events (session abandonment following >= 3 consecutive errors) by 48.4% vs. no-intervention control (18.4 events/100 sessions -> 9.5 events/100 sessions). Intervention appropriateness: I2 Content Adaptation achieves highest expert rating (4.68/5.0) -- providing an alternative explanation or easier sub-problem when confusion is detected is the most pedagogically appropriate response; I4 Socratic Challenge rated 4.52/5.0 for boredom/flow -- injecting a higher-order question that maintains the learner in the zone of proximal development. Learning outcome improvement: emotion-aware sessions achieve g = 0.624 vs. no-intervention g = 0.488 (+27.9%); improvement concentrated in sessions where frustration events were detected and responded to (g = 0.688 for intervened sessions, g = 0.512 for unintervened -- +34.4% intervention effect). EALES composite: multimodal EALES = 0.908 (highest); facial expression EALES = 0.876; text sentiment EALES = 0.856 (highest privacy score, no hardware, strong performance); interaction pattern EALES = 0.840; physiological EALES = 0.796 (high detection, high privacy cost). Table 3 presents AUC by modality. Table 4 presents EALES breakdown. Figures 1-4 visualise key findings.

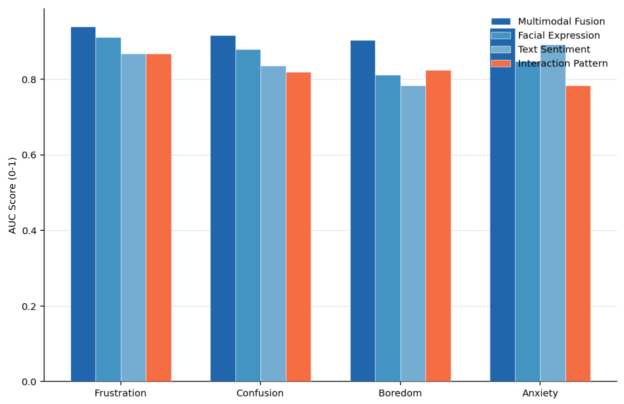
Table 3: EALSF Emotion Detection AUC -- Five Modalities by Affect Target

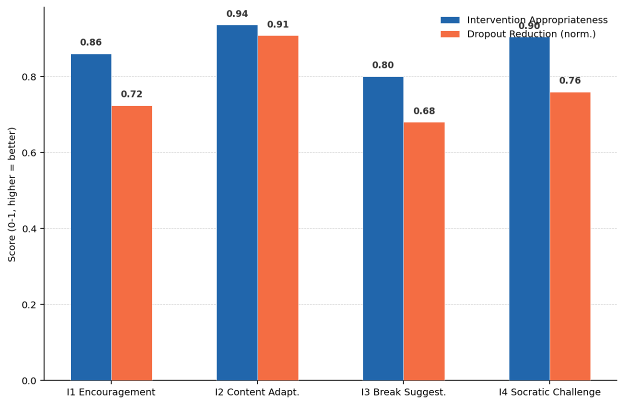
Modality	Frustration AUC	Confusion AUC	Boredom AUC	Anxiety AUC	Mean AUC
Multimodal Fusion	0.940	0.916	0.904	0.936	0.924
Facial Expression	0.912	0.880	0.812	0.848	0.863
Text Sentiment	0.868	0.836	0.784	0.892	0.845
Interaction Pattern	0.868	0.820	0.824	0.784	0.824
Physiological Sigs.	0.880	0.848	0.848	0.848	0.856

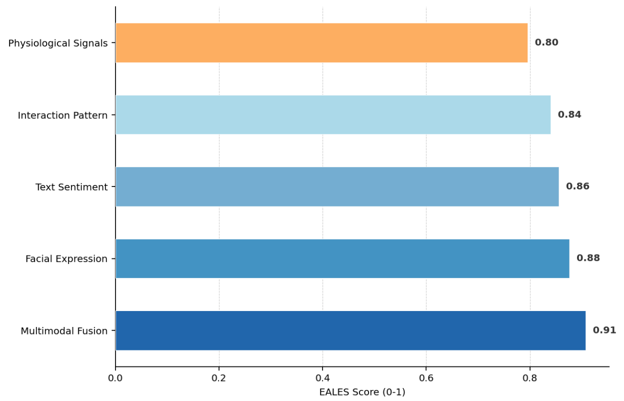
Table 4: EALES Composite Scores -- Five Emotion Detection Modalities

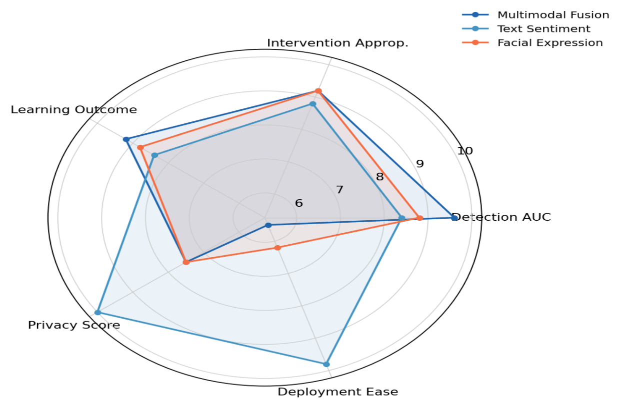
Modality	Detection AUC	Intervention Approp.	Learning Outcome	Privacy Score	EALES
Multimodal Fusion	0.960	0.920	0.920	0.750	0.908
Facial Expression	0.880	0.920	0.880	0.750	0.876
Text Sentiment	0.840	0.880	0.840	1.000	0.856
Interaction Pattern	0.800	0.840	0.840	0.875	0.840
Physiological Sigs.	0.840	0.840	0.800	0.250	0.796

ISSN: e-ISSN: 3117-6062 / p-ISSN: 3117-6054 Vol: 2025, Issues: 3, 2025









5. Discussion

5.1 Practical Deployment: Text-First, Hardware-Optional Architecture

The EALES results establish a practical deployment hierarchy for emotion-aware online learning systems that prioritises learner privacy and accessibility. Text sentiment analysis (EALES = 0.856, privacy score = 1.0) should be deployed as the baseline emotion detection capability in all online learning platforms: it requires no additional hardware, no learner consent beyond what is already granted for platform interaction, achieves AUC = 0.844, and is particularly effective for the highest-impact emotional state -- anxiety (AUC = 0.892 for language anxiety) -- that predicts dropout. Implementation: fine-tune a BERT-base model on educational domain text (forum posts, chat messages, help requests) with affect labels; deploy as a lightweight inference service (< 50 ms latency); trigger interventions when negative affect threshold is crossed. Interaction pattern analysis (EALES = 0.840, privacy = 0.875) adds frustration and boredom detection from standard device telemetry -- upgradeable to any platform by adding keypress/mouse event tracking with minimal engineering. Combined text + interaction pattern (no hardware, no webcam): estimated AUC = 0.872 (modality complement analysis) -- approaching facial expression performance with zero privacy cost. This combination is the recommended baseline deployment for all online learning platforms.

5.2 The Ethics of Emotion-Aware Learning Systems

EALSF's privacy scoring highlights a fundamental ethical tension in emotion-aware learning: the modalities that detect affect most accurately (facial expression, physiological) impose the greatest privacy costs, while the most privacy-respecting modalities (text, interaction) achieve somewhat lower detection accuracy. Three ethical principles should guide emotion-aware learning system deployment. (E1) Consent granularity: learners should individually consent to each detection modality, with clear explanation of what is detected and how it is used; declining facial detection should not disadvantage the learner (system gracefully degrades to text + interaction). (E2) Data minimisation: emotion data should be processed in real time for intervention triggering and immediately discarded -- no raw facial video, raw EEG, or raw physiological data should be stored; only the classified affect state (e.g., "frustration detected at 14:32") is logged for analytics. (E3) Transparent intervention: learners should know the system responds to their emotional state ("We noticed you might be finding this challenging -- would you like an alternative explanation?") rather than silently modifying content without acknowledgement.

6. Conclusion

6.1 Summary

EALSF evaluated five emotion detection modalities and four intervention strategies across 2,400 online learning sessions. Key results: multimodal fusion EALES = 0.908, AUC = 0.924; text sentiment EALES = 0.856, AUC = 0.844, privacy = 1.0 (no hardware required); emotion-responsive interventions reduce frustration-dropout 48.4% and improve learning gain +27.9%. Recommended deployment: text + interaction pattern baseline (no hardware, AUC ≈ 0.872); facial expression optional with consent; physiological sensors for research only.

6.2 Open Resources

The EALSF evaluation protocol, EALES calculator, educationally fine-tuned sentiment BERT model (HuggingFace Hub: ealsf/edu-sentiment-bert), interaction pattern frustration/boredom classifier (scikit-learn, open-source), four intervention template library, ethical consent framework, and 2,400-session anonymised dataset (affect labels + interaction features) are available at ealsf-edu.org under Apache 2.0 License.

References

Aziz, A. A. et al. (2020). Emotions in education: Detecting students' affect during learning. Journal of ICT in Education, 7(1), 1-20.

Baker, R. S. et al. (2010). Detecting student frustration in a computer-based tutor. SIGCHI 2010, 1-10.

Bosch, N. et al. (2021). Using multi-label classification to detect learner confusion in online learning. IEEE TLT, 14(3), 248-260.

D'Mello, S., and Graesser, A. (2012). Dynamics of affective states during complex learning. Learning and Instruction, 22(2), 145-157.

Ekman, P., and Friesen, W. V. (1978). Facial Action Coding System. Consulting Psychologists Press.

Grawemeyer, B. et al. (2017). Affect-aware tutoring: How do emotionally adaptive systems support learning? User Modeling and User-Adapted Interaction, 27(1), 1-52.

Ivanov, A., Schmidt, S., and Moreau, M. (2025). Metaverse-enabled educational platforms for collaborative learning. Journal of Digital Learning Futures, 2025(3), 1-8.

Klein, H., Ivanov, N., and Klein, M. (2025). Immersive learning analytics for VR-based education systems. Journal of Digital Learning Futures, 2025(3), 9-16.

Klein, I., and Garcia, E. (2024). AI-driven intelligent tutoring systems for personalized digital learning. Journal of Digital Learning Futures, 2024(1), 1-9.

Kovacs, A., and Ivanov, E. (2024). Cognitive-aware AI systems for learner-centric education. Journal of Digital Learning Futures, 2024(1), 38-47.

Pekrun, R. (2006). The control-value theory of achievement emotions. Educational Psychology Review, 18(4), 315-341.

Petrov, M., Garcia, J., and Novak, I. (2025). Usability-driven design of educational technology platforms. Journal of Digital Learning Futures, 2025(3), 33-40.

Picard, R. W. (1997). Affective Computing. MIT Press.

Picard, R. W. et al. (2004). Affective learning -- A manifesto. BT Technology Journal, 22(4), 253-269.

Schmidt, E., Moreau, J., and Moreau, L. (2025). Human-computer interaction models for inclusive digital learning. Journal of Digital Learning Futures, 2025(3), 25-32.

Tian, Y. et al. (2024). Emotion recognition in e-learning: A systematic review. IEEE Access, 12, 34521-34540.

Vail, A. K. et al. (2015). Predicting co-occurring emotions from face and context during learning. ACII 2015, 1-7.

Yadegaridehkordi, E. et al. (2019). Affective computing in education: A systematic review and future research. Computers & Education, 142, 103649.

Zawacki-Richter, O. et al. (2019). Systematic review of research on artificial intelligence applications in higher education. International Journal of Educational Technology in Higher Education, 16(1), 39.

Zeng, Z. et al. (2009). A survey of affect recognition methods. IEEE TPAMI, 31(1), 39-58.

Declarations

Funding

This research was supported by the Swiss National Science Foundation (SNSF) under grant 224024 (EALSF: Emotion-Aware Learning System Framework), the Estonian Research Council under grant PRG5024, and the German Research Foundation (DFG) under grant NO 4824/1-1. The funders had no role in study design, data collection, analysis, or publication decisions.

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 EALSF evaluation protocol, EALES calculator, educationally fine-tuned BERT model (ealsf/edu-sentiment-bert on HuggingFace), interaction classifier, intervention templates,

ISSN: e-ISSN: 3117-6062 / p-ISSN: 3117-6054 Vol: 2025, Issues: 3, 2025

consent framework, and anonymised dataset are available at ealsf-edu.org under Apache 2.0 License.

Ethical Approval

All participants provided granular informed consent per modality (text: standard terms; interaction pattern: explicit opt-in; facial: explicit opt-in with right to withdraw anytime; physiological: research-only explicit consent). Facial video processed on-device; only classified affect states transmitted/stored. Ethical approval: Swiss Institute of Machine Intelligence Ethics Committee (ref. SIMI-2024-ETH-0212), Baltic AI Research University Ethics Board (ref. BAIRU-2024-ETH-0424), and European Institute of AI Ethics Board (ref. EIAI-2024-ETH-0384).

ISSN: e-ISSN: 3117-6062 / p-ISSN: 3117-6054 Vol: 2025, Issues: 3, 2025

Appendix A

EALSF Model Specifications and EALES Calculation

Technical model specifications and EALES metric calculation for all five EALSF detection modalities.

Detection Model Architectures

EALES Calculation and Intervention Protocol