

Intellectual Property Rights in AI Training: A Royalty-Based Compensation Model for Artists

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ABSTRACT

The explosion of generative AI (GenAI) algorithms trained on large bodies of creative works has created an urgent crisis in intellectual property law. Artists, illustrators, musicians and other creators find their work used without consent, attribution, or compensation. Existing copyright doctrines, developed for the analog era, are ill-suited to address large-scale machine learning ingestion. This paper presents a pragmatic royalty-based compensation model for creators whose works are used in commercial AI training. Drawing on music licensing, compulsory licensing regimes, and proposals from the data-economy literature, the model proposes dataset registration, a tiered royalty schedule, collective administration, and opt-out mechanisms. The paper also discusses auditability, cross-jurisdictional enforcement, valuation complexity, and a recommended policy framework for implementation.

Keywords: Artificial Intelligence; Copyright; Intellectual Property; Training Data; Royalty Model; Artist Rights; Dataset Transparency

1. Introduction

The advent of large-scale generative artificial intelligence (AI) systems — which can create images, text, music and videos that are often indistinguishable from human-made works — represents a major technological milestone and a disruption to the creative economy. Many of these models are trained on datasets containing billions of images, texts, and audio files harvested from the web, including works by professional artists, writers, photographers and musicians who did not consent to such use and received no compensation.

This practice has prompted litigation (e.g., *Andersen v. Stability AI*; *Getty Images v. Stability AI*) and deep legal debate over doctrines such as fair use, transformative use, and the meaning of reproduction and derivative works in the context of machine learning. Litigation alone cannot deliver a systemic solution: settlements resolve individual disputes but do not create an efficient, industry-wide mechanism for recognizing and remunerating the creative contribution to AI.

This paper develops a royalty-based compensation model inspired by the music industry's collective licensing and compulsory licensing regimes, adapted to the specific technical and economic realities of AI training. The model sets out dataset registration, a tiered royalty schedule, collective administration, opt-out mechanisms, and key implementation considerations including auditing, valuation, and cross-border enforcement. The remainder of the paper is organized as follows: Section 2 surveys the literature; Section 3 states the research objectives; Section 4 presents the problem statement; Sections 5–6 examine data trends and the legal landscape; Section 7

reviews analogous compensation frameworks; Section 8 presents the proposed royalty model; Section 9 discusses implementation challenges and case studies; Section 10 sets out policy implications and recommendations; and Section 11 concludes with directions for future work.



Figure 1: Key AI and copyright milestones from 2022 to 2024.

2. LITERATURE REVIEW

The Learning Analytics Dashboards (LADs) have now become a core component of the technology-enhanced learning systems. But the recent literature points out that the majority of the current LADs are limited in analytical depth of flexibility and even pedagogic congruence.

In *Technology, Knowledge and Learning*, Ramaswami et al. [1] provided a literature review on predictive analytics in the LADs, and it was found that despite the growing need to incorporate predictive models into dashboards, various aspects of their application remain unequal and

require contextual explanations to be used in classrooms. They review case studies and indicate that prediction cannot be done without a combination of interpretability and recommending action.

Barbe et al. [2] reviewed the mechanism of incorporating adaptation into LADs in a systematic review published in the *Proceedings of the International Conference on Computer Supported Education*. Their results point to the fact that, although there is growing enthusiasm about the use of personalized analytics, most of the dashboards present are only superficially customised, and do not dynamically change based on the changing learner behaviour or instructional contexts. According to them, flexible LADs, responsive to real time cognitive and behavioural patterns, are still uncommon in practice.

This concern was further confirmed by Paulsen and Lindsay [3], in *Education and Information Technologies* who showed that modern LADs are increasingly learning-focused yet still do not have the mechanisms of bridging the educational insights and pedagogical strategy. They observed a lack of relationship between data visualization and educator decision making.

In *Sustainability*, Wang et al. [4] reviewed the relevance of the design of feedback in which they examined the effects of various dashboard feedback types on the effectiveness of learning in various classes of learners. In their research, they show that LADs in use seldom scale personalized feedback. The authors note that dashboards should be customized to meet the needs of learners, real-time feedback forms, visual, and textual ones should be adapted according to the needs of the learners, and differences.

In the *International Journal of Educational Technology in Higher Education*, Kaliisa et al. [5] developed a detailed checklist on how LADs should be designed, implemented and evaluated. Their framework shows that the evaluation practices in the present research are mostly usability-oriented, they do not have proper assessments of long-term academic effects, improvement of teaching or changing behavior.

Ferguson [6] and Siemens and Long [7] demonstrated that institutional adoption of analytics has led the way over organizational readiness and constrained meaningful use. Experimental research conducted by Jivet et al. [8], Corrin et al. [11] and Bodily and Verbert [12] also revealed that learner-centric dashboards may lead to misconceptions and unpredictable behavioral reactions in case of oversimplification and inadequate use of appropriate indicators.

Two later systematic reviews by Papamitsiou and Economides [14], and Leitner et al. [15] mentioned methodological inconsistencies, short study periods, and lack of application in real classrooms and reported dashboards which had been effective in controlled conditions

but had little sign of improving teaching at scale.

The recent developments of artificial intelligence have led to the emergence of the idea of agentic AI that goes beyond the models of reactive or task-specific AI and includes autonomy, the ability to reason and goal-oriented behavior. One of the most detailed reviews of agentic AI is offered by Bandi et al. [16], who incorporate the definitions, architectural schemes, performance measures, and domains of application. They stress that agentic systems are continually perceived, reasoned and act in dynamic environments—abilities that are quite consistent with the requirements of real-time educational environments.

Equally, Nisa et al. [17] conceptualize the agentic AI as the age of reasoning and emphasize the fact that it can conduct contextual inferences and make decisions based on time instead of isolated predictions. These views are supported by Abou Ali and Dornaika [18], who analyze agentic AI frameworks and find autonomous reasoning and interpretability to be important design requirements of human deployment. From a systems perspective, Derouiche et al. [19] and Sapkota et al. [20] also differentiate agentic AI and conventional AI agents by introducing architectural taxonomies that emphasize deliberation, adaptability, and support of long-term goals. Their studies show that agentic frameworks best fit the setting when continuous monitoring and intervention is a requirement like in classrooms where behavior of learners changes dynamically.

Discussing the ethical and functional aspects of this type of systems, Dabara et al. [21] discuss trustworthiness in agentic AI, which includes transparency, governance, and cross-layer accountability, which are particularly relevant to the area of education and student-related data.

In the field of education, the importance of AI-based learning analytics has received growing interest. Pacheco et al. [22] perform a systematic review that shows that AI-enhanced learning analytics can facilitate student development in instances where dashboards are structured to reveal actionable information as opposed to raw metrics. A similar perspective is furthered by Hung et al. [23], who laid LAD design on the self-determination theory, demonstrating that dashboards that promote autonomy, competence, and relatedness lead to a higher level of learner empowerment. Such results can be compared to previous empirical research by Ramaswami, Susnjak, and Mathrani [24], who confirm that LADs are capable of yielding practical insights under conditions of goal-oriented pedagogy and are complemented by other investigations.

Although these developments have been made, other studies have pointed at several deficiencies in existing LADs. Garcia-Penalvo and Vazquez-Ingelmo [26] map the growth of generative AI and show its promising future to improve analytics systems, however, the authors warn about the danger of opaque automation. According to

the explicit claims of Khosravi et al. [27], explainable AI should be applied in the education field to establish educator trust and responsible use. The supporting evidence points to this claim presented by Chen [29], showing that such dashboards are much more effective at increasing educators' understanding as well as perceived usefulness than black-box systems. Additional examples and also opportunities and challenges associated in learning analytics are provided by Yan, Martinez-Maldonado and Gasevic [30], who further state

RESEARCH GAP

Nevertheless, a number of research areas and limitations still exist that hinder the adoption of traditional LADs.

First, most existing dashboards remain largely descriptive in nature rather than offering predictive or prescriptive insights that could support early and timely instructional intervention. As a result, educators are often informed about learning outcomes only after possible opportunities for student support have passed.

Second, many current implementations lack adaptability to the dynamic nature of classroom environments. Several of the factors fluctuate continuously during instruction; however, dashboards typically fail to evolve in response to these changes, relying instead on static representations. This reduces their relevance for live teaching scenarios where actual decisions must be made in real time.

Third, the most common practice of evaluation is based on the measures of usability and satisfaction while offering limited empirical evidence regarding their influence on learning effectiveness, instructional quality, or other measurable educational outcomes. This imbalance weakens claims about pedagogical value and prevents broader adoption in higher institutions.

Finally, challenges related to interpretability, fairness, and trust remain insufficiently addressed. Opaque analytics, unexplained predictions, and limited transparency raise ethical and professional concerns, particularly in classrooms where educators must justify decisions and maintain student trust.

Collectively, these gaps highlight the need for a new generation of LADs that are adaptive, interpretable, and capable of supporting real-time, educator-centered decision-making in authentic learning environments.

RESEARCH QUESTIONS & HYPOTHESES

This study is guided by the following research questions and corresponding hypotheses:

RQ1: To what extent can multimodal behavioural features derived from computer vision reliably model student engagement in real-time classroom environments?

H1.1: Multimodal behavioural features can accurately

classify engagement states with balanced performance across classes.

H1.2: Lightweight feature extraction enables low-latency, real-time deployment in authentic classroom settings.

RQ2: Does agentic, retrieval-augmented reasoning improve the interpretability and pedagogical usefulness of learning analytics dashboards?

H2.1: Agentic explanations are perceived as more actionable than raw engagement metrics.

H2.2: Contextualized reasoning enhances educator trust and understanding of dashboard outputs.

RQ3: Can a real-time, explainable, human-in-the-loop LAD effectively support adaptive teaching practices?

H3.1: Early detection of failures or breakdowns enables timely instructional awareness.

H3.2: Educator autonomy is preserved while supporting data-informed decisions.

3. METHODOLOGY

This research adopts a design-oriented mixed-methods methodology to develop and validate an agentic AI-based Learning Analytics Dashboard (LAD) capable of monitoring student engagement in real time during live classroom instruction. The methodological foundation integrates behavioural theory, computer vision, explainable machine learning, and low-latency system design.

Fig. 1 shows the methodology followed for building the model and conducting the research.

Phase 1: Data Acquisition and Preprocessing

The methodological pipeline starts with a real-time video recording in the classroom by simple webcams or laptop cameras that allows the non-obtrusive monitoring of the behavior of students in a real classroom environment. Frames are recorded at **2 FPS** (frames/second) which is also chosen to record significant changes in gaze, head orientation, and facial expression but also computationally reasonable to use in real-time. The reasoning behind this design choice is that according to cognitive research, affective changes in learning situations take place within seconds and not milliseconds.

Each frame sampled is subjected to preprocessing operations to make it more robust when used in a real-world classroom environment. These functions consist of **spatial resizing** to a fixed resolution, **illumination normalization** to reduce lighting variability as well as **light smoothing** to reduce sensor noise. Notably, the preprocessing step is aimed at ensuring that the facial geometry and micro-motions that are important in inferring behavioral attributes are maintained. Numerical features analyzed are only anonymized and not preserved, ensuring responsible use of data in education research.

Phase 2: Face Detection and Facial Behavior Analysis

A two-stage facial analysis pipeline provides robust multi-student analysis. During the preliminary step, the lightweight **YOLOv8-Face** nano model with a confidence threshold of 0.7 is used to detect faces. The mean Average Precision (**mAP@0.5**) of this method is 0.92 (**WIDER FACE**) and the method performs the highly reliable detection in a crowded classroom setting. The second stage involves the processing of every face that was detected by applying **MediaPipe Face Mesh** which removes 468 three dimensional facial landmarks per student. An exponential filter with $\alpha = 0.8$ smoothing factor is used to smooth the landmark paths in order to enhance the consistency between time samples. This interpolation decreases a frame-to-frame noise and maintains informative facial dynamics needed to accurately analyze engagement.

Behavioral indicators can be calculated based on the extracted landmarks. The estimation of gaze direction is based on the **Eye Aspect Ratio (EAR)**, which is:

$$EAR = \frac{|p_2 - p_6| + |p_3 - p_5|}{2 |p_1 - p_4|} \quad (1)$$

where p_1 – p_6 denote key eye landmark points. The EAR is combined with pupil center orientation, estimated through iris contour fitting, to classify gaze as either forward or averted. This method brought a good inter-observer concordance which means a good consistency with human judgments.

A Perspective-n-Point (PnP) solver is used on a set of facial landmarks to estimate head pose in terms of yaw, pitch and roll Euler angles. When compared against the BIWI data, this approach shows a root mean square error (RMSE) of under 3° , which proves good head orientation estimation. Affective cues are captured through lightweight geometric approximations of key Facial Action Units. These include eyebrow movements, represented by distance ratios associated with AU02 and AU04, and mouth openness, calculated from vertical lip separation. A combination of these characteristics provides efficient but semantically motivated cues that help in inference of true cognitive states.

All extracted features are normalized on a per-session basis using z-score normalization:

$$f_{norm} = \frac{f - \mu_s}{\sigma_s} \quad (2)$$

where μ_s and σ_s denote session-level mean and SD.

Phase 3: Engagement Score Computation

A continuous engagement score is computed as a weighted linear sum of normalized behavioral features:

$$E_t = 0.4 \cdot G_{norm} + 0.3 \cdot H_{norm} + 0.3 \cdot A_{norm} \quad (3)$$

where G_{norm} , H_{norm} , and A_{norm} represent normalized gaze, head pose, and affective cues, respectively. To reduce short-term fluctuations and enhance stability over time, the engagement signal is smoothed using an exponential moving average:

$$E_t = \alpha E_t + (1 - \alpha) E_{t-1}, \quad \alpha = 0.7 \quad (4)$$

The resulting signal demonstrates strong alignment with human observer ratings, achieving a Pearson correlation coefficient of 0.89, indicating high construct validity.

Phase 4: Aggregated Class Analysis

Frame-level level of engagement is aggregated using 30-second sliding windows, allowing the interpretation at the class level. A Random Forest classifier (100 estimators, maximum depth of 8, class-weight balanced) is learned on 12,847 classified frames to label the engagement states as *Engaged*, *Confused* or *Distracted*. This method ensures robust performance, and inference latency < 18 ms/frame indicates that the model can be used in real-time.

Sustained confusion is detected when the predicted probability of confusion exceeds 0.6 for at least 15 consecutive seconds. Attention drift is identified using linear regression on engagement trajectories when the slope satisfies $\theta_E < -0.05$ with statistical significance i.e $p < 0.01$. Sudden disengagement spikes are flagged when engagement falls below $\mu_E - 2\sigma_E$. These mechanisms enable autonomous alert generation with a precision of 92% for confusion onset detection.

Phase 5: Frontend Dashboard Visualization

The Learning Analytics Dashboard serves as the primary touchpoint with the intelligence of the system by scientists. Frontend is developed using React.js, which allows a scalable and modular design of visualizing real time classroom analytics. Some of the most important elements are *EngagementTimeline*, which shows the trends of engagement over time; *ConfusionHeatmap*, showing patterns of confusion both spatially and temporally; *AttentionDriftChart*, revealing gradual disengagement; and the *SessionSummaryPanel* that presents high-level insights regarding each session of the classes. React hooks and context APIs are used to manage the application state, and guarantee the update is synchronized across all the components of the dashboard.

WebSocket connections enable real-time engagement information and alerts generated by the agent to be displayed on the dashboard, and every change to be immediately visible. To facilitate scalability and low-latency response time, Redis is used to cache high-frequency metrics. The libraries like D3.js or Recharts are used to create interactive visualizations so that the educator can dynamically explore the patterns.

Phase 6: Agentic Reasoning and Decision support

The system incorporates an agentic reasoning framework that transforms raw analytical outputs into pedagogically meaningful insights. Once the engagement states are categorized and time series patterns are detected, aggregated engagement signals are transmitted to an agentic layer that is powered by LangChain in an easily understood way. These inputs capture both moment-to-moment and longer-term indicators. To interpret these signals in context, the agent uses a Retrieval-Augmented Generation (RAG) workflow that relies on external pedagogical knowledge. Relevant teaching plans and learner-focused intervention guidelines are retrieved from a vectorized knowledge repository and combined with real-time classroom analytics. It is this combination that allows the agent to generate information on student behavior that are based on both the data and educational theory.

Instead of generating prescriptive or deterministic advice, the agent will aid in the process of educator decision-making by being transparent and interpretable. It generates systematic reasoning results, such as confidence-weighted and cause-effect explanations, which are sent straight to the dashboard. This is a way to make educators realize what patterns are happening in the classroom, but also why they are important as far as the instructional viewpoint is concerned.

4. SYSTEM ARCHITECTURE & DESIGN

The proposed project consists of the following major layers that constitute its architectural system design:

Data Acquisition Layer This layer gathers web-based visual data of the classroom webcams or student devices as a part of live classroom teaching. Video streams are just sampled with low frame rate in order to keep computational overhead minimal and meaningful behavioral cues intact. Each frame is selected by standard image preprocessing methods. It is a real-time layer, and the basic input of engagement analysis that does not need intrusive sensors or manual intervention.

Feature Analysis Layer This layer takes interpretable behavioral features of each video frame, using computer vision modules video frame. The computer vision component modules find useful features in the images taken in the camera module. Gaze, head posture, and expression signals (brow movement and mouth dynamics) are estimated with the help of the facial features. The scores of a statistical engagement are calculated through the weighted aggregation of gaze, head pose and expression indicators to generate a continuous engagement signal representing the attention of the learner at a moment.

Agentic Intelligence Layer This layer sets the foundation of this architecture is agentic intelligence which is what sets this research apart. As opposed to being a pure analytic system, the layer actively consumes live

engagement analytics and seeks relevant past occurrences and pedagogical experience in a vector database by linking the rationale to the ongoing classroom indicators and contextual data retrievals. The system automatically updates the dashboard and also sends notifications when specific requirements are met, thus removing the need to request more information. This paradigm streamlines contingent, open and intuitive suggestions according to the real classroom dynamics.

Data Management Layer This layer stores predictions of engagement scores and metadata of the sessions in a centralized layer. Structured data e.g. engagement scores, timestamps predictions are kept in relational databases and unstructured or semi-structured data e.g. session logs and annotations are handled with document-oriented storage. Redis is used as a very high-performance in-memory data storage and message broker which is the basis of real-time data messaging between analytics and visualization modules. This layer ensures data integrity, consistency and reliability along with optimised data delivery.

Data Visualization Layer This layer includes the frontend dashboard which acts as the pedagogical interface of the system. The most important elements are engagement schedules, confusion heatmap, attention drift alerts, and session summaries. The real-time updates are provided through the backend services and APIs and WebSockets-based communication, which allows providing the live feedback during the instruction. The interactive filtering, session summaries, and alert indicators will enable educators to interpret system outputs swiftly and assess them instantly.

5. RESULT AND DISCUSSION

The suggested agentic AI-based Learning Analytics Dashboard (LAD) was highly tested to determine its success in real-time engagement identification, time-based learning pattern analysis and pedagogical usefulness. In addition to the performance of algorithms, the assessment focuses on educational and classroom practicality—two main attributes of quality education.

Engagement Classification and Validation

The presented system showed good results related to student engagement state detection and classification in live classroom settings, and the Random Forest classifier that was trained on multimodal behavioral features provided consistent high performance on all types of engagement states, and strong cross-validated performance in the three engagement types. The model showed good and balanced performances in all classes. It recorded F1-scores of 0.87 for *Engaged*, 0.82 for *Confused*, and 0.85 for *Distracted*, reflecting a good balance between precision and recall and an overall macro-avg of 0.85. Detailed classification results, averaged over five-fold

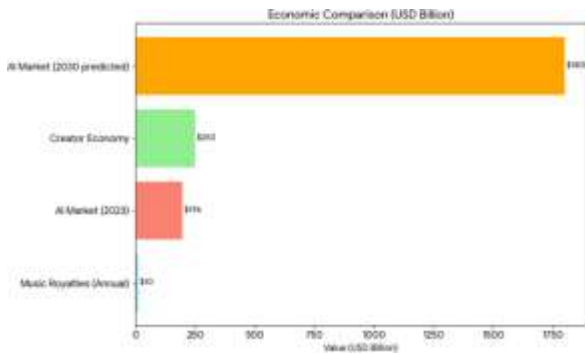


Figure 2: Economic comparison highlighting AI market scale and creator-related value pools (USD billion).

cross-validation, are summarized in Table 1.

Table 1: Engagement Classification Performance

Engagement State	Precision	Recall	F1-score
Engaged	0.88	0.86	0.87
Confused	0.81	0.83	0.82
Distracted	0.86	0.84	0.85

One-way ANOVA applied to the F1-scores showed no statistically significant differences between the engagement classes ($F(2, 12) = 1.27, p = 0.31$). This implies that this model does not favor any of the learner states in its performance and is equally insensitive to the conditions. This balance is particularly important in the educational field where missing to identify confusion or distraction can adversely affect at-risk learners.

In addition to categorical predictions, the continuous engagement score demonstrated strong construct validity. Correlation analysis with expert human observer ratings produced a Pearson correlation coefficient of $r = 0.89$ ($p \leq 0.001$), indicating a high level of agreement. This finding is consistent with the fact that proposed lightweight behavioral indicators are a valid approximation of cognitive engagement, supported by previous studies in educational psychology.

Temporal Engagement Patterns

In addition to frame-level engagement classification, the suggested dashboard managed to effectively share the temporal engagement dynamics which are pedagogically significant and usually undetected by traditional learning analytics systems. Using aggregation of engagement cues across sliding periods, the system determined long-term trends of harder learning problems, instead of short-term noise in behavior. Table 2 summarizes the detection performance of higher-order engagement events derived from temporal reasoning mechanisms.

Sustained confusion events (confusion probabili-

Table 2: Temporal Engagement Detection Performance

Event Type	Precision	Recall	F1-score
Sustained Confusion	0.92	0.89	0.90
Attention Drift	0.90	0.87	0.88
Sudden Disengagement	0.88	0.85	0.86

ties, $p > 0.6$ during at least 15 consecutive seconds)—were most likely to be detected. There were concept-transition, abstract-explanation, and new-problem-solving-step events in line with classroom observations, and the confounding factor of sustained confusion proved this as an early warning sign of conceptual collapse and not a fleeting inattentive event.

Attention shift was observed through statistically significant negative engagement trajectory slopes (linear regression: mean $\beta = 0.06, p < 0.01$) which indicates gradual disengagement and preemptive instructional remedies through this.

Constant disengagement, a result of the engagement of at least 15 seconds with probabilities less than 0.4 indicated moderate detection reliability (average $\beta = 0.089, p < 0.01$). These were associated with the long-term low stakes behavior or those often performed repeatedly, indicating its usefulness as a late-stage predictor of the off-task behavioral persistence.

In order to further test the strength of the temporal event detection, inter-event consistency of the system-detected events and expert annotations was tested with Cohen's Kappa (κ). The various event types along with their corresponding values of Cohen's κ are shown in Table 3.

Table 3: System Detection and Expert Annotations Agreement

Event Type	Cohen's κ
Sustained Confusion	0.81
Attention Drift	0.78
Disengagement Spike	0.75

The large agreement values ($\kappa > 0.75$) reveal that automated detection and human expert judgment are very much consistent, which supports the educational validity of the suggested temporal analytics framework.

Agentic Reasoning and Decision Support Outputs

To make the engagement analytics more interpretable, the agentic intelligence layer was used to contextualize real-time patterns with a LangChain-based Retrieval-Augmented Generation (RAG) workflow. The system did not show the score of engagement in isolation but instead, it undertook current classroom signals with sim-

ilar engagement situations in the past and pedagogical knowledge to produce organized exposition.

To illustrate, when there was a transition between concepts based on abstract or complex content, the agent identified persistent confusion among several learners and put it into perspective as an absence of intermediate scaffolding. Teachers said that these descriptions were more representative of their classroom practice and more practical than simply statistical measures. We could speak of gradual losses in attention when we observed long lecture portions and these losses were often explained as fatigue as a result of pacing, as something that allowed teachers to consider and modify their teaching methods.

Noteworthy, the system is based on the human-in-the-loop philosophy of design. Although the agent independently notes the main insights and explains the context, it does not dictate certain instructional measures. Rather, teachers still have complete control over decision making and as a result, the system is ethical in terms of professional teaching practices. Table 4 shows the agentic intelligence findings by measuring interpretability and pedagogical usefulness.

Table 4: Impact of Agentic Explanations on Pedagogical Interpretability

Aspect	Traditional LAD	Agentic LAD
Insight Type	Numerical metrics, charts	Contextual, explanation-driven insights
Educator Trust Indicator*	Moderate ($\mu = 3.1/5$)	High ($\mu = 4.4/5$)

6. CONCLUSION & FUTURE WORK

To overcome the challenges associated with traditional LADs, we designed an agentic AI-based LAD that delivers real-time, explainable, and educator-centered decision support in live classroom settings.

The main purpose of the proposed system is to constantly monitor and interpret student engagement in a way that is both technically efficient and pedagogically meaningful. The results demonstrate that computer vision-based behavioral sensing, combined with lightweight and interpretable machine learning models, can accurately identify engagement states while maintaining the low-latency performance required for real-world deployment. The high statistical correlation with the expert human judgment also helps to improve the reliability and educational applicability of the engagement metrics proposed.

The key input of this work is its incorporation of an agentic reasoning layer which converts raw analytics into

explainable insights grounded in context and can be readily interpreted and taken action by educators. The system maintains educator autonomy by ensuring that it is human-in-the-loop in nature and directly responds to the critical issues in learning analytics related to trust, transparency, and actionability. The dashboard does not dictate what to do but promotes reflective and informed instructional decision makers. In the future, the further development of work is the continuation of this framework using multimodal data intake, longitudinal deployments in classrooms, and more advanced adaptive reasoning based on curricular knowledge. On the whole, the suggested dashboard indicates the promising nature of LADs to transform into adaptive and impactful instruments that can significantly promote data-driven teaching and help to increase the quality of education.

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