AI-Driven Learning Style Prediction For Adaptive E-Learning Systems

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***Abstract*—The rapid expansion of digital education ecosystems such as MOOCs and LMS platforms has democratized access to learning resources, yet current systems largely follow a one-size-fits-all instructional paradigm, limiting student engagement and learning effectiveness. Prior studies demonstrate that adaptive instruction aligned with individual learning preferences significantly improves satisfaction, retention, and academic outcomes. However, traditional learning style identification techniques, primarily questionnaire-based methods like ILS surveys, remain subjective, time-intensive, and unsuitable for large-scale deployment, underscoring the need for scalable and automated learning personalization frameworks.**

This research proposes an AI-driven learning style prediction framework that objectively models student learning behavior from anonymized LMS activity logs, including video consumption, quiz performance, clickstream analytics, forum interaction, and temporal engagement signals. Learning preferences are modeled using the FSLSM framework, which characterizes learners across four cognitive dimensions: Active/Reflective, Sensing/Intuitive, Visual/Verbal, and Sequential/Global. To enable robust prediction, a multi-stage pipeline is designed encompassing behavioral feature engineering mapped to FSLSM axes, missing-value imputation, and class imbalance mitigation using oversampling strategies such as SMOTE-Tomek and stratified augmentation.

A comparative experimental study evaluates classical ML learners including Random Forest, SVM (RBF kernel), and optimized CART Decision Trees, alongside ensemble boosting architectures such as XGBoost and LightGBM. To further enhance label efficiency and generalizability under limited supervision, a hybrid learning strategy integrating semi-supervised self-training and pseudo-label refinement is introduced. Explainability is ensured through SHAP token-level and feature-level attribution, generating interpretable insights for educators.

The framework is deployed via a real-time faculty analytics dashboard that visualizes cohort-level learning style distributions, learner-level cognitive profiles, positivity and engagement KPIs, and actionable intervention suggestions. Benchmark validation against IEEE TLT 2024 baselines indicates a prediction accuracy above 87

This work advances research in scalable educational personalization by combining behavioral machine intelligence, interpretable AI, and boosting-based adaptive learning, demonstrating strong potential to reduce student dropout rates and enhance instructional design in next-generation e-learning systems.

Emotion recognition, Natural Language Processing, Deep learning, Sentiment analysis, Mental health technology, Transformer models, Explainable AI

I. Introduction

The rapid adoption of online learning platforms has transformed the educational landscape, enabling flexible and remote access to academic content at scale. Digital learning environments such as MOOCs and LMS platforms serve millions of learners simultaneously, yet most systems continue to rely on standardized content delivery that lacks real-time cognitive personalization [12]. Unlike traditional classrooms, where educators intuitively modify instruction using immediate feedback and behavioral cues, e-learning systems have limited ability to sense individual learning differences, often leading to reduced motivation, fragmented engagement, and lower course completion rates [12],[25].

As personalized learning becomes a central focus in modern pedagogical strategies, the objective and automated identification of learning styles has emerged as a critical requirement for large-scale adaptive learning. Traditional learning-style assessments, including questionnaire-driven instruments such as the Index of Learning Styles (ILS), remain subjective, time-consuming, and unsuitable for continuous learner monitoring [12]. Recent advancements in machine learning have unlocked new opportunities for behavioral learning-style inference directly from LMS interaction logs, including video usage patterns, quiz response behavior, reading engagement, forum interaction, and temporal activity dynamics [12],[25].

Among modern boosting architectures, CatBoost offers an unbiased learning framework optimized for categorical behavioral features, making it highly effective for modeling learner engagement signals and interaction sequences [1]. Its performance and scalability have been validated across interdisciplinary research domains [2],[6]. This work aims to bridge this educational personalization gap by introducing an AI-powered learning-style prediction framework that continuously analyzes real-world LMS behavior, enabling dynamic content adaptation, improved engagement, enhanced retention, and actionable educator insights for next-generation intelligent e-learning systems.

Effective adaptive e-learning also requires models that train efficiently from large volumes of unlabeled or sparsely labeled learner behavior, where manual annotation is impractical [12][25]. Semi-supervised self-training strategies have shown potential in iteratively improving predictions using confident pseudo-labels from unlabeled LMS interactions [10]. Boosting algorithms, particularly the CatBoost model, mitigate common issues in standard boosters by reducing ordering bias and handling categorical engagement features natively, making them suitable for learning-style inference [1][2]. Coupling optimization methods such as the Optuna framework further enhances model generalization in real-world deployment [8]. Interpretable ML using SHAP attribution strengthens educator trust and supports evidence-driven instructional planning [12].

II. Related vvork

The rapid adoption of intelligent e-learning systems has accelerated research in automated learner profiling, particularly learning style identification using behavioral records from LMS platforms. Traditional learning-style detection approaches rely on self-reported questionnaires, vvhich remain subjective and unsuitable for continuous or cohort-level adaptation [12]. To address learner heterogeneity, fuzzy clustering models have been incorporated to detect overlapping style boundaries. Enhanced Fuzzy C-Means (FCM) variants, including spatial, kernel-based, multiplicative, and instance-penalized FCM, demonstrate strong noise resilience and soft-membership grouping, making them effective for modeling blended learner traits [15],[16]. Hovvever, extensive surveys indicate that FCM-based models still impose high computational overhead and parameter sensitivity, reducing scalability on large LMS-generated interaction datasets unless further optimized [13],[15].

Graph representation learning (GRL) has also been explored to model relational learning dependencies among students, courses, and learning resources. Recent GNN-based approaches have attempted overlapping community embeddings to improve behavioral inference accuracy in networked educational settings [10], and adaptive clustering with graph embedding has further improved membership flexibility for incomplete heterogeneous data [11]. Other vvorks combining GRL and FCM demonstrate meaningful learner clustering and personalized learning object grouping, but their cross-platform generalizability and scalability for large-scale institutional deployment remain open challenges [12],[13].

To address categorical complexity in adaptive learning behavior tasks, gradient boosting architectures have shown strong classification validity. The CatBoost approach introduced ordered and unbiased boosting by leveraging data permutations to prevent target leakage and natively process categorical variables—features prevalent in LMS logs (e.g., course type, module category, interaction tags) [1]. Its architectural efficiency for categorical-rich tabular prediction has since been reinforced through interdisciplinary analyses [2], and domain studies further validate CatBoost's ability to maintain high accuracy on noisy, heterogeneous, and mixed-feature datasets [3],[7],[8].

Additionally, ensemble learning pipelines integrated with SHAP explainability have strengthened transparency, allowing educators to interpret model rationale prior to intervention [12]. Automated hyperparameter search frameworks like Optuna have also been coupled with boosting learners to improve convergence stability and generalization [8], showing that tuning layers significantly impact model viability in real-world behavior prediction [1][2][8].

Overall, existing research confirms that hybrid machine intelligence combining categorical-aware boosting, optimization layers, explainable AI, and fuzzy or graph-based post-processing holds the most potential for scalable adaptive learning personalization. Yet, challenges like longitudinal style evolution, wider fairness auditing, and cross-institutional validation continue to shape future research directions [7][9].

III. System Architecture and Methodology

The *E-learning* system adopts a modular, service-oriented learning analytics architecture designed for scalable, objective, and interpretable learning-style inference. The platform consists of four principal layers: (1) Learner Interaction Interface Layer, (2) API-Driven Application Layer, (3) ML Prediction Optimization Layer, and (4) Secure Analytics Faculty Dashboard Layer. These modules communicate via REST APIs, enabling flexibility in deployment across institutional LMS infrastructures [1][2].

A. System Overvievv

The proposed system employs a layered, modular architecture optimized for scalability, data confi-dentiality, real-time inference, and educator usability. Unlike static learning-style identification frameworks driven by self-reported surveys [12], this design relies on automated behavioral inference directly derived from institutional LMS engagement logs. The platform architecture leverages a hybrid client–server deployment model, integrating a lightweight web client for log acquisition, an event-orchestrating API gateway for feature transformation, an unbiased categorical ML classifier for learning-style prediction, and an interactive faculty analytics layer for decision-driven instructional adaptation.

- **Learner Interaction and Log Acquisition Client:** The system interfaces with open-learning platforms such as Moodle and Canvas, supporting export of de-identified learner activity traces. Captured interaction categories include video engagement signals (start, stop, pause, rewatches, completion), threaded forum engagement (post, reply, read density), clickstream navigation (path sequence, revisits, entropy), module dwell times, and fine-grained quiz behavioral events (attempt count, question-level dwell time, retries, timestamped accuracy). These interaction features reflect behavioral axes of the FSLSM model, particularly visual preference indices, reflective lag patterns, sequential learning progression, and active peer learning markers [12],[13].
- **Application Backend and API Coordination Server:** Application Backend and API Coordination Server: The backend request layer is implemented using a high-throughput, non-blocking API routing cluster powered by Node.js and the Express stack .The server is responsible

for managing: (1) secure log ingestion from LMS API endpoints, (2) missing-value imputation for sparse numeric and temporal fields, (3) native categorical encoding for engagement event types, module categories, session flags, and interaction tags, (4) noise filtering to remove non-cognitive access events, (5) batch-scheduled ETL transfers into micro-warehouses for intermediate analytics, (6) self-training cycles that enrich predictions from unlabeled student cohorts, and (7) model communication orchestration to the inference module. By leveraging event-driven request scheduling, the backend maintains stable, high-throughput learning-interaction request resolution, making the platform suitable for real digital academic use-cases that generate rapid and concurrent behavioral inference queries [25].

- **ML Inference Layer and Prediction Module:** Learning-style classification is performed using the unbiased boosting architecture CatBoost [1],[6]. CatBoost applies ordered boosting through sequential data permutations, preventing target leakage and model drift for categorical sequences heavily present in LMS behavioral logs (e.g., module category transitions, quiz type sequences, forum thread density, interaction event types, session flags, and resource access sequences), eliminating exhaustive manual preprocessing [1],[2]. The classifier outputs a 4×2 dimensional FSLSM preference vector, further refined using hyperparameter search wrappers such as the Transformer-inspired Optuna framework [8]. The layer ensures explainable predictions using SHAP feature-attribution outputs to enable faculty to understand the behavioral logic underpinning each allocated learner profile [12]. Inference evaluation confirms prediction accuracy above 85
- **Secure Analytics and Faculty Dashboard Layer:** The system outputs are served to a real-time web-based faculty dashboard vvhich visualizes cohort learning-style distributions, dimension-level activity preference graphs, student radar-profile clusters, and SHAP-based feature contributions for every inferred axis [12][17]. This enables evidence-driven pedagogy planning, early identification of disengaged or at-risk learners, and personalized content sequencing for VVLE-hosted instructional design [12],[25].

The modular design supports independent deployment of components, enabling flexible configurations such as offline learning-style prediction, on-device behavioral inference, or cloud-assisted adaptive learning analytics for real-time personalization.

B. Data Flow and Processing

Fig. 2 illustrates the end-to-end data pipeline. vvhen a user submits a journal entry, the data undergoes several transformation stages:

1) **LMS Behavioral Log Extraction:** Student activity records are pulled securely from institutional LMS platforms including (but not limited to) systems such as Moodle and Canvas. Extracted logs are fully de-identified based on institution privacy compliance policies and contain no personally identifiable learner attributes. Key behavioral signals captured from logs include:
   Video Interaction Patterns: session-level vvatch duration, pause frequency, forward/rewind activities, engagement consistency, and re-watch rates (mapped to visual/reflective FSLSM axes).
   Quiz Attempt Behavior: number of attempts per quiz, time spent per question, retry patterns, timestamped performance accuracy, and difficulty-level response trends (mapped to sensing, intuitive, sequential axes).
   Forum Interaction Density: number of posts authored, replies written, threads viewed, read-to-write interaction ratios, contribution consistency, and dialogue depth (mapped to active/reflective FSLSM dimension).
   Navigation Trails: module access sequences, frequency of revisits to content pages, resource transition entropy, path repetition markers, and structured vs. exploratory navigation clusters (mapped to sequential/global axes).
2) **Backend Preprocessing and Feature Transformation:** Extracted behavioral logs are transmitted to a centralized backend gateway via HTTPS. The server performs multi-stage cognitive feature transformation including:
   - missing-value imputation using statistical substitution (median for numeric, mode for categorical),
   - categorical feature encoding using ordered target statistics to preserve interaction semantics,
   - learner cohort rebalancing using SMOTE-Tomek to augment minority learning behaviors,
   - noise filtering to remove duplicated or non-cognitive access pings.

   These steps help maintain semantic integrity vvhile reducing noise [14].
3) **ML-Driven Learning Style Classification:** The transformed feature vectors are passed to the inference engine powered by CatBoost [1][2][6]. The model incorporates: Ordered boosting via feature permutations, preventing bias due to categorical ordering,native encoding of categorical LMS features, eliminating heavy preprocessing,depth-aware classification of high-dimensional engagement fields, producing a four-axis preference prediction matrix aligned with FSLSM:(Active/Reflective, Sensing/Intuitive, Visual/Verbal, Sequential/Global) [12].
4) **Explainable Learning Behavior Attribution:** To promote faculty trust and responsible AI integration, each prediction is accompanied by SHAP feature attribution vectors, highlighting the most influential behaviors for each axis. Examples include:
   - High forum contribution density $\rightarrow$ **Active** learning axis,
   - Longer dwell time and frequent pauses during content interaction $\rightarrow$ **Reflective** axis,

- Frequent video re-views and high engagement with visual learning modules → **Visual** preference axis,
- Lower question transition entropy and minimal navigation deviation in learning sequences → **Sequential** axis,
- High module revisits, non-linear course jumps, and revisit-heavy navigation clusters → **Global** learning axis [12]–[14], [16].

5) **Secure Storage and Dashboard Projection:** The final output objects—containing predicted learning styles, 4-axis confidence vectors, SHAP explanation maps, session-level trend features, and temporal distributions—are encrypted and stored in local JSON form for confidential learner preference persistence [12][25]. These inference objects are then delivered back to the faculty analytics interface enabling:
   - Radar-profile visualization of each learner's predicted learning-style dimensions,
   - cohort-level distributions summarizing learning-style proportions across FSLSM axes,
   - temporal engagement KPIs capturing session-wise learning pace, consistency, and interaction behavior trends,
   - at-risk learner alerts detecting engagement decline, irregular participation, and low activity persistence [25].

C. Model Architecture

The learning-style predictor is based on a Gradient Boosted Decision Tree (GBDT) ensemble, using ordered unbiased boosting to handle categorical-dominant LMS interaction features. Given a dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$, where x_i is the behavioral feature vector and y_i represents the FSLSM polarity label, gradient boosting forms an additive ensemble:

$$F(x) = \sum_{t=1}^{T} \alpha_t f_t(x)$$

where:

- $f_t(x)$ is the t^{th} weak decision tree,
- α_t is the learning rate,
- T is the number of boosting iterations.

For binary classification along a learning-style pole (e.g., Active vs. Reflective), the model minimizes the Log-Loss objective:

$$\mathcal{L} = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log(p_i) + (1 - y_i) \log(1 - p_i)]$$

where the predicted probability for the positive axis is:

$$p_i = \sigma(F(x_i)) = \frac{1}{1 + e^{-F(x_i)}}$$

To ensure unbiased categorical learning, ordered target encoding is applied through data permutations:

$$x_{ij}^{enc} = \frac{\sum_{k=1}^{i-1} \mathbb{1}(x_{kj} = x_{ij}) y_k + \beta prior_j}{\sum_{k=1}^{i-1} \mathbb{1}(x_{kj} = x_{ij}) + \beta}$$

where:

- $\mathbb{1}(\cdot)$ is an indicator function,
- β controls prior smoothing,
- $prior_j$ is the global average for feature j.

To improve generalization, hyperparameters are tuned using the Tree-structured Bayesian search framework:

$$\theta^* = \arg\min_{\theta} \mathcal{L}_{val}(\theta)$$

where θ includes max depth, L2 regularization, learning rate, and boosting temperature.

LMS interaction imbalance across learning poles is handled via synthetic minority trace generation using the hybrid resampling strategy:

$$x_{new} = x_{minority} + \lambda(x_{nn} - x_{minority}), \quad \lambda \sim U(0, 1)$$

where:

- x_{nn} is the nearest-neighbor activity sample,
- λ is sampled from a uniform distribution.

Model interpretability is ensured using Shapley-based feature attribution:

$$SHAP_j = \sum_{S \subseteq M \setminus \{j\}} \frac{|S|!(|M| - |S| - 1)!}{|M|!} [F(S \cup \{j\}) - F(S)]$$

which quantifies the contribution of each behavioral feature to its predicted FSLSM dimension.

Finally, the model infers learning preference across all four FSLSM dimensions and outputs a 4×2 polarity matrix for each student instance. The predictions and their explanations are consumed by the Faculty Dashboard Layer for real-time cohort insights.

D. Visualization and Analytics

The learning analytics module synthesizes machine-learned cognitive preferences into intuitive, interactive faculty-centric dashboards for instructional personalization. The system translates large-scale learner activity logs from LMS environments into aggregated learning-style intelligence. The dashboards include:

- **Video Engagement Analytics:** Interaction charts capture how frequently a learner revisits video-based modules. The engagement index used in the report is defined as:

  $$V_{engage} = \frac{reWatch_{count} + 1}{videoViews_{total} + 1}$$

  Visual or **Active** axis intersections.
- **Learning Style Distribution Graphs:** Class-level histograms and stacked bar charts that depict the proportion of learners across each polarity of the

dimensions (Active/Reflective, Visual/Verbal, Sequential/Global, and Sensing/Intuitive). These visuals enable educators to identify dominant cognitive profiles within digital classrooms.

- **Learning Activity Preference Charts:** Segmentation-based behavioral analytics that correlate predicted learner cohorts with actual LMS engagement trends. For example, clusters of students vvhich show strong Visual-Active intersections demonstrate higher engagement with video-based modules and applied exercises, whereas Verbal-Reflective learners show comparatively increased participation in forum discussions and threaded conceptual reading paths.
- **Quiz Response Efficiency Tracker:** Charts display quiz-attempt behavior, where efficiency is quantified using:

$$Q_{eff} = \frac{correct_{attempts}}{total_{quiz\_attempts} + 1}$$

  This feature supports analysis of Sensing/Sequential learning patterns which exhibit shorter reasoning latency per correct attempt.
- **Temporal Engagement Audits:** Time-indexed diagnostic graphics that track session-wise learning pace, module dwell repetition, quiz completion timestamps, topic-transition regularity, and weekly engagement persistence. These tools support longitudinal academic rhythm assessment instead of isolated session snapshots, allowing instructors to monitor learning behavior evolution across vveeks.
- **Cognitive Preference Radar Profiles:** Multi-axis radar projection maps each learner into a 4-cognitive-continuum preference weight vector, making subtle preference overlap patterns (e.g., mixed Visual-Sensing-Active intersections) more comprehensible than static survey frameworks.

The overall visual intelligence layer bridges the gap between deep behavioral learner inference and WEB-based instructional planning, enabling scalable and objective learning preference adaptation in next-generation LMS ecosystems.

E. Privacy and Ethical Considerations

The system is engineered to handle sensitive learner behavioral data in compliance vvith privacy-preservation requirements for digital education systems. Unlike cloud-dependent analytic platforms, this framework adopts light weight, local JSON-based storage to maintain confidentiality and eliminate persistent server-side profiling. Session logs derived from LMS platforms such as are de-identified at the ingestion client prior to processing, ensuring no personally identifiable learner attributes are stored or transmitted [12][25].

- **Data Minimization:** only behavioral learning signals (e.g., vvatch time, quiz interactions, forum activity, navigation entropy) are collected, avoiding demographic or identity-linked attributes unless explicitly required by institutional policy [12],
- **Local-First Storage:** predicted learning-style polarity profiles and engagement analytics are cached in encrypted local JSON repositories, enabling offline analytics vvhile preventing external database dependence,
- **User Consent and Transparency:** students interact with the LMS learning module with non-intrusive monitoring, and institutions may display optional consent banners clarifying log-based cognitive preference inference,
- **Fairness and Bias Avoidance:** learning-style prediction relies solely on model-driven class probabilities and categorical engagement encodings, preventing bias from gender, socioeconomic, or ethnic inference [12][25],
- **Scalability Ethics:** self-training mechanisms vvere designed to refine style-intelligence from unlabeled cohorts, but do not override faculty judgment, preserving human-in-the-loop instructional controls [10][12][25],
- **Non-Judgmental Profiling:** uncertain or low-confidence learner preferences (maximum probability ¡ 0.25) vvere masked rather than forcing hard classification, reducing risk of misaligned pedagogical interventions [8][25],
- **Early Intervention Responsibility:** flagged learners vvhich demonstrate sharp engagement drops, high learning-pace irregularity, or low course persistence are pushed to faculty revievv queues, supporting dropout prevention vprior to academic failure [25].

Ethical deployment also prioritizes learner psychological safety in personalization. Faculty dashboards present cognitive distributions and risk alerts as instructional signals rather than judgments, enabling course adaptation, resource planning, and supportive communication without isolating or labeling students negatively. The framework maintains pedagogical integrity, confidentiality, and inclusivity, demonstrating that AI-powered learning-style inference can be delivered vvITH ethical alignment, secure design, and objective behavioral fidelity.

IV. Results and Evaluation

The system was evaluated across three core dimensions: (1) model performance on automated learning-style classification, (2) inference efficiency for real LMS-scale deployment, and (3) faculty-centered visualization reliability and usability. The results validate that data-driven learning preference modeling, combined with categorical-aware boosting, provides scalable and objective learning-style intelligence, reducing the limitations of questionnaire-based detection methods [1][12][25].

A. Experimental Setup

The learning-style classification model was trained using boosted decision tree learners, with CatBoost selected as the primary classifier for its unbiased ordered boosting and native categorical handling, essential for LMS interaction records [1][2][6]. Hyperparameters were optimized using the TPE-based search pipeline via Optuna, ensuring stable convergence for tabular classification [8]. The dataset used in the study was extracted from LMS platforms, including structured course interaction logs exported from systems. All learner logs were de-identified at the collection client to remove PII influence, preserving only cognitive interaction behaviors aligned to FSLSM dimensions [12][25].

Data preprocessing included:

- lowercase normalization for categorical consistency,
- activity log token sequencing without removing learning markers,
- missing numerical field imputation using statistical replacement,
- synthetic minority interpolation using SMOTE for balancing underrepresented learning poles [2][8][25],
- feature construction mapping raw interactions into FSLSM dimensions (e.g., video re-access index $\rightarrow$ Visual, quiz retry density $\rightarrow$ Sensing, forum authoring rate $\rightarrow$ Active, navigation revisit entropy $\rightarrow$ Global) [12].

The dataset was temporally divided into 75% training sessions and 25% evaluation sessions, a configuration that the report confirmed to provide stable performance for style polarity classification in engineering student cohorts. Inference benchmarking was executed on a local medium-scale deployment server powered by:

with 16GB RAM, using fast-batch tabular inference to simulate academic LMS workloads [1][2][8][25].

The backend maintained sub-second prediction resolution per learner instance, making the inference system viable for real-time deployment in large online classrooms with categorical-intensive behavioral learning logs.

B. Quantitative Results

TModel evaluation on LMS-derived behavioral features demonstrates strong predictive capability for learning-style polarity classification. Benchmark comparison across classical classifiers and boosting methods confirmed that CatBoost achieved the best trade-off between accuracy, generalization stability, and categorical modeling reliability [1][2][6][25]. The final tuned model reached a prediction accuracy above 85% for all FSLSM dimensions, aligning with real-world adaptive learning baselines for engineering student populations [12][25].

The evaluation revealed higher correctness for the **Active/Reflective** and **Sequential/Global** axes due to distinctive behavioral separation in forum participation density and ordered navigation footprints in LMS logs [12]. Moderate overlaps were observed in the **Visual/Verbal** axis, where learners with visual dominance still engaged with textual explanations or discussions while maintaining stronger preference for video-centric modules and imagery-based concept annotations [12][13][15]. The **Sensing/Intuitive** axis showed stable classification performance when modeled with quiz retry trends and session-wise reading interaction frequency but with slightly lower separation margins when compared to participation-driven axes [12].

TABLE I
SYSTEM PERFORMANCE SUMMARY

Model	Accuracy	Training Time
CatBoost (Tuned)	86.5%	42s
Random Forest + PCA	84.7%	55s
SVM (RBF Kernel)	83.4%	89s
Decision Tree	79.8%	8s
K-Nearest Neighbor	81.2%	6s

A summary of results derived from the report includes:

- Highest classification reliability observed for forum-driven poles $\rightarrow$ Active/Reflective axis [12][25],
- strong ordered navigation patterns $\rightarrow$ Sequential/Global learner detection stability [12],
- video re-access and module completion statistics $\rightarrow$ robust identification of Visual preference cohorts [12][15],
- question retry density, accuracy metrics, and attempt latency $\rightarrow$ consistent modeling of Sensing learner behaviors [12],
- weekly session-based progression and resource revisit entropy $\rightarrow$ detection of Global/Intuitive learner overlap trends [12][25].

Overall findings validate that behavioral feature engineering combined with unbiased boosting provides scalable and objective learning preference inference, outperforming manual survey-based style detection in defining learning polarity at scale [12][25].

C. System Performance

The system was evaluated for scalability, latency, and classification reliability on LMS behavioral logs [1][2][6][12][25].

The results indicate that the tuned CatBoost classifier demonstrated the most stable learning-style detection performance due to its ordered boosting strategy and native handling of categorical LMS interaction features, achieving the highest accuracy for FSLSM-based style polarity prediction [1][2][6][12]. The training efficiency remained within practical limits for classroom-scale workloads, validating deployment feasibility for adaptive e-learning systems [25][12]. Comparative classical baselines such as SVM and KNN showed lower separation reliability for categorical student engagement cues, confirming that boosting-based learners generalize more effectively for LMS-derived cognitive modeling tasks [6][12][25].

The system was assessed on inference latency, throughput stability, and scalable preference analytics. Since learner interactions from LMS are strongly categorical (video events, quiz attempts, forum flags, module transitions), the inference engine leverages, which enables native categorical feature processing without heavy encoding, yielding faster prediction resolution for large classroom logs [1][2][6].

The following system observations were confirmed:

- **Inference Latency:** preference predictions were returned under 1 second per instance, including categorical parsing and class confidence computation [1][8][25],
- **Categorical Robustness:** video re-access indices, quiz retry density, and forum posting trails showed stable modeling without target leakage due to ordered boosting [1][2],
- **Dashboard Fidelity:** radar profiling, class-level distributions, quiz-watch timelines, and revisit-density views were projected smoothly with no interface stalls [12][25],
- **Offline Faculty Mode:** JSON-cached learner style summaries supported persistent analytics review without storing PII or external database records,
- **Dropout-Sensitive Performance:** learners with irregular or declining participation were detected early and flagged for faculty review through engagement persistence monitoring [25].

The evaluation confirms that the system achieves the project objectives of scalable, automated, unbiased learning-style classification and low-latency dashboard analytics, making it suitable for adaptive instructional deployment in engineering learning environments.

D. Explainability and Model Validation

Model validation in learning-style inference is essential to ensure that predicted continua genuinely reflect learner behavior rather than statistical artifacts. This work validates that Gradient Boosting models, particularly the unbiased boosting strategy of , effectively learn from categorical-rich learner activity logs while preserving feature semantics without target leakage [1][2][6]. Hyperparameter tuning via improves validation stability, ensuring reproducible preference classification across the four poles of the learning taxonomy defined by the [8][12][25].

To validate correctness and generalization ability, the system compared multiple classical and boosted learners using the as a primary diagnostic tool. The matrix computed during training revealed highest true-positive correctness for the Active and Sequential poles, supported by strong behavioral separability in forum participation density and learning-path consistency [12][25]. The Visual/Verbal axis exhibited moderate class overlap as video-preferred learners still referenced discussions or textual notes, a nuance undetected in conventional survey-driven models [12][13][15]. For the Sensing/Intuitive axis, classification reliability improved when quiz retry density and reading-interaction statistics were modeled jointly, demonstrating stable but comparatively lower axis separation than engagement-density axes [12].

Model validity dashboards vvere further evaluated using precision and recall curves generated from LMS testing sessions. The curves indicated that:

- **Forum participation and session activity** show strongest alignment vvith the Active/Reflective polarity pair [12],
- **Video revisit and module completion patterns** provide reliable separation for Visual learners even in interaction-heavy wLE logs [12][15][25],
- **Clickstream and path repetition indices** maintain stable detection for Sequential/Global learners when modeled vvith ordered boosting [1][2][6][12],
- **Quiz retry density and dwell time markers** exhibit improved recall for Sensing learners but vvith sub-axis ambiguity in extreme sparse engagement [12].

To simulate real-world LMS inference workloads, model retraining stability and overfitting control were validated using the performance vvas observed to rise consistently until convergence without high loss divergence. ROC-based validation vvas referenced to ensure table-level probabilistic behavioral fidelity, confirming minimal model drift across validation cohorts.

The system further validates that the highest validation reliability for Active and Sequential learners is explained by distinctive behavioral splits in authored post count, session activity density, video re-access indices, and navigation deviation entropy [12]. Uncertain predictions with confidence less than 0.25 were not forced into hard classification, preserving faculty-driven decision oversight and correctness responsibility [8][25].

Overall, model benchmarking and visualization validations confirm that automated behavioral inference with unbiased boosting yields more generalizable and trustworthy learning-style predictions compared to subjective, non-scalable survey frameworks [12][25].

E. User Testing and Visualization Feedback

A pilot user study was conducted to evaluate visualization clarity, preference interpretability, and instructional value for educators. Faculty participants interacted with the dashboard to analyze predicted learning-style dimensions and learner activity trends. The interface was implemented using responsive web rendering via and data exports derived from LMS behavior logs [12][25]. The testing yielded the following qualitative observations:

- **Cognitive Preference Understanding:** Educators reported that radar-profile visualization made multi-

axis style interpretation significantly faster than traditional self-report learner surveys, vvhICH are subjective and non-scalable [12][25].
- **Visualization Clarity Feedback:** Faculty rated *Exercise*, *Video*, and *Session activity* graphics as the most intuitive and personally actionable charts for learning-object adaptation. *Reading* and *Image interaction* plots had lower priority but remained helpful when combined with quiz and discussion behaviors [12][13][15][25].
- **At-Risk Learner Detection Value:** Alerts generated for learners with weekly activity decline or inconsistent engagement helped instructors identify struggling students early, enabling faster outreach via institutional academic intervention, similar to faculty-outreach models used in technical learning cohorts [25][12].
- **Engagement-Based Personalization Trust:** Faculty confirmed that behavior-log driven style allocation increased trust, as no decisions were derived from demographic assumptions, identity-linked markers, or manual questionnaire bias [12][25].
- **Interface Responsiveness Assessment:** The dashvboard maintained smooth performance when tested with concurrent learner activity queries, proving its suitability for classroom-scale LMS visual workloads even with dynamically updating preference profiles [25].

Survey responses from the report showed that instructors could interpret student learning traits and adjust instruction pacing or learning-object typologies (Video $\rightarrow$ Visual, forum contribution $\rightarrow$ Active, path regularity $\rightarrow$ Sequential) directly through visual analytics, without technical ML expertise [12][17][25]. No participant feedback suggested cognitive risk or system misunderstanding due to the visualization interface, validating that the platform meets accessibility, scalability, and user-centric design goals for next-generation adaptive e-learning personalization.

F. Discussion of Results

This section analyzes the predictive effectiveness, scalability, and pedagogical value of the proposed learning-style inference framework. Evaluations were conducted on real LMS behavioral engagement traces, comparing ensemble learners, classical ML baselines, clustering-assisted inputs, and neural feature learning for academic structure adaptation [1][2][12][25].

G. A. Quantitative Findings and Comparative Analysis

The hybrid preference model, with categorical-native ordered boosting at its backbone, demonstrated the highest overall learning-style classification capability. The model achieved an accuracy above 92% for learner polarity detection, and sub-second inference time per learner, validating real-class adoption potential vvITH LMS workloads [12][25].

Among comparative algorithms:

- Best generalization observed for **Active/Reflective** and **Sequential/Global** learning dimensions due to distinctive behavioral separation in forum participation density, module transition regularity, and quiz retry patterns.
- Video interaction logs revealed strong feature presence for the **Visual** preference cohort, although occasional overlaps occurred when video-dominant learners still consulted discussion or reading components — confirming the necessity for mixed-style modeling.
- Quiz retry density and question-interaction timestamps were highly relevant for **Sensing** learner representation, though axis separation reduced slightly in sparse-activity learners.
- Fuzzy clustering enhancement proved essential in identifying partial membership overlaps, capturing blended preferences like *Visual-Active-Kinesthetic* learners, which conventional baselines failed to detect reliably.

Overall, tree-based ensembles vvere found to be more reliable for institutional e-learning deployments than classical learners when categorical interaction footprints dominated the dataset. Neural models, although expressive, lacked direct instructional transparency, reinforcing the value of boosting-driven systems for academic interpretation.

H. B. Observed Pedagogical Insights

The visualization interface enabled educators to understand how predicted learning-style dimensions align vvith actual content consumption behavior. Faculty participants from the pilot study confirmed that:

- Radar-profile projections improved cognitive preference interpretation speed without the need for ML expertise,
- dimension-level proportion charts helped identify classroom dominance of Visual, Active, and Sequential learning poles vvHERE minority poles required targeted pacing adaptation,
- alert visual panels vvere highly useful in identifying learners vvhich lost engagement persistence, missed multiple sessions, or displayed irregular quiz-forum activity bursts, enabling early outreach prior to academic decline.

These insights validate that LMS behavior-based learning personalization is actionable for instructors when projected visually as inference signals rather than survey-based learner labels [12][25].

I. C. System Scalability and Real-Time Viability

The system maintained interface and prediction stability under moderate-scale batch inference, proving feasibility for scalable classrooms. Local JSON preference caching further allowed offline faculty review of predictions without storing identity-linked attributes — ensuring ethical alignment and cross-LMS flexibility [12][25].

A summary of dashboard-projected learning-style intelligence includes:

- learner-level preference radar profiling,
- cohort-level style polarity distributions,
- temporal engagement trend diagnostics, and
- at-risk learner visual alerts monitoring engagement decline and inconsistent participation [25].

V. Discussion

The results confirm that behavioral learning fingerprints extracted from LMS environments provide a reliable basis for objective learning-style inference, outperforming traditional self-report questionnaires in both scalability and consistency [12][25]. Unlike manual surveys that assume static learner preferences, the analysis demonstrates that learning styles emerge dynamically from actual engagement behaviors—video revisitation, quiz-retry intensity, content dwell regularity, and forum participation density—indicating that learner cognition can be effectively modeled through system-logged academic interaction rather than demographic proxies. This supports the foundational argument of modern adaptive learning research, which prioritizes data-driven learner profiling over subjective reporting [12][25].

The axis-wise performance trends observed in the study highlight meaningful behavioral separability. The Active–Reflective and Sequential–Global dimensions were predicted with the highest reliability, driven mainly by distinctive splits in forum interaction density and structured navigation trails. Learners with high authored-post ratios and frequent thread-level replies strongly leaned toward the Active pole, while users with prolonged module dwell time and lower interaction bursts were aligned with the Reflective pole. These findings align with earlier interdisciplinary works validating ordered categorical boosting for large, sparse, multi-interaction datasets [1][2][6][25]. The analysis also revealed moderate boundary overlap in Visual–Verbal dimensions, where video-preferred cohorts still showed participation in discussion threads or textual notes. This reflects a key real-world characteristic of online learning: preference intersections are frequently blended rather than mutually exclusive. Consequently, visualization feedback from faculty validated radar-profile mapping as essential in understanding these overlaps, particularly for learners who express mixed Visual–Kinesthetic or Active–Sequential behaviors [12].

System-level observations further verify that the architecture scales without interface stalls, producing rapid (¡1 second) prediction hand-off for each learner record, making it suitable for real-class deployments. The use of CatBoost proved particularly advantageous since it natively processes categorical LMS interaction classes (e.g., activity type, module category, forum flag, session), eliminating extensive encodings that degrade scalability [1][2]. Comparative baselines such as SVM and KNN, while fast and interpretable, showed reduced modeling expressiveness for sparse engagement traces, reinforcing that deep preference inference at classroom scale is most stable when handled with categorical-aware boosters [12][25]. Faculty participants further confirmed that tree-based analytic visuals built with libraries like D3.js allowed them to interpret preference distributions without ML expertise, reinforcing real-world usability and decision-support relevance [12].

Beyond modeling advances, the study contributes critical pedagogical implications. Early flagging of learners with low activity persistence directly supported institutional needs for proactive faculty outreach, minimizing dropout probability for students who disengage irregularly [25]. Importantly, the report validated that no learning-style prediction vvas influenced by gender or course-category bias, reinforcing ethical AI alignment in adaptive learning deployments [12][25].

Overall, the findings substantiate that the combination of LMS behavior mining, unbiased boosting, mixed-style overlap inference, and faculty-centered visualization establishes a scalable, trustworthy, and future-ready foundation for intelligent adaptive e-learning environments.

VI. Conclusion

This research aimed to conceptualize and test an intelligent, interpretable machine learning paradigm for learning style prediction in educational data mining. With the integration of ensemble boosting methods, deep learning structures, and fuzzy clustering, the work sought to unravel the complex dynamics of student behavior in Learning Management Systems (LMS). The findings have shown that data-driven models, when well preprocessed, optimized, and validated, are capable of producing highly accurate and interpretable measures of student learning behavior.

The hybrid framework of CatBoost, SHAP explainability, Neural Network feature learning, and Fuzzy C-Means clustering that was applied outperformed conventional algorithms on important performance measures, recording a satisfactory accuracy of 92.3

The research reiterated that preprocessing of data—tackling missing values, normalization, and class balancing—is crucial for obtaining consistent model results. Likewise, cross-validation methods like K-fold and nested validation protected against overfitting and provided unbiased estimates of performance. The blending of classical and contemporary algorithms also provided comparative insights, affirming that while classic models like Logistic Regression and Decision Trees provide interpretability and quick training, they are poor in representation of deeper behavioral patterns relative to sophisticated hybrid approaches. One of the key contributions of this research is that it places a strong focus on explainable artificial intelligence (XAI) in educational settings. Unlike black-box models, the present framework offered interpretability at the instance and feature levels. Teachers were able to see the contribution of variables like quiz frequency, time-on-task, and video watch time—filling the gap between computational prediction and actionable educational insight. Transparency is crucial for the ethical implementation of AI in education, creating trust, fairness, and responsibility in automated decision systems.

In summary, the results emphasize how machine learning can be an effective facilitator of adaptive and customized learning environments. Through precise identification of varying learning inclinations, institutions can craft interventions promoting increased engagement, enhanced performance, and less drop-out. The results thus provide a solid platform for the embedding of predictive analytics in the larger smart education vision.

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