Performance Evaluation of a Multi-Level Approach to Predict Learning Styles In E-Learning System

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ABSTRACT
Machine learning algorithms have been widely used for predicting learning styles in personalized e-learning systems. This paper evaluates effectiveness of a multi-level model using K-Means and Decision Trees algorithms to cluster learners into groups based on their characteristics and classify learners into the learning style dimensions of the Felder-Silverman learning styles model (FSLSM). Learner interaction data extracted from a Moodle Learning Management System (LMS) was pre-processed and used as input for K-Means clustering to group learners according to behavioural similarities. The resulting clusters were used to train and test a Decision Tree classifier that labelled each learner's preferred learning style based on the FSLSM. The model was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. Evaluation results show that the proposed model achieved a 95% overall accuracy, with an emphasis on correctly identifying the learning style category across FSLSM dimensions, demonstrating the strong predictive performance of the proposed multi-level model in supporting automated learning style prediction.

General Terms
Artificial Intelligence, Machine Learning, Adaptive Learning Systems

Keywords
Learning Styles, Felder–Silverman Learning Style Model (FSLSM), K-Means Clustering, Decision Tree Classifier, Personalized Learning, Data Preprocessing

1. INTRODUCTION
Advancements in educational technologies have resulted in the accumulation of large amounts of data on students and their learning activities. Analysing these data has empowered researchers and educators with valuable insights to support teaching and learning activities through Learning Management Systems (LMS) an online platform for educational course delivery. Personalization is crucial in addressing individual learner needs, such as prior knowledge, cognitive abilities, learning styles, and motivation [1]. Personalized content is easily assimilated by learners, and as defined by [2] personalization encompasses a range of educational programs, instructional approaches, learning experiences, and strategies that cater to individual students' unique learning needs, interests, aspirations, or cultural backgrounds. Identifying learning styles is essential as it can enhance learning performance, motivation, and efficiency. Learning style models in existing literature, such as the Felder-Silverman Learning Style Model (FSLSM) [3], Myers Briggs Type Indicator (MBTI) [4], Kolb learning model [5], and VARK learning styles [6], categorize learners based on various dimensions. In the Felder-Silverman Learning Style Model (FSLSM), learning styles are grouped into four categories: sensing or intuitive, verbal or visual, active or reflective, and sequential or global. This paper evaluates a hybrid approach utilizing a multi-level combination of K-means and Decision Tree algorithms to detect learning styles.

2. RELATED WORKS
Several recent studies have tackled the challenges of personalizing the learning experience through data-driven approaches. [7] proposed a tree-augmented naive Bayesian method for detecting students' learning styles in online learning environments. [8] reviewed adaptive e-learning systems, categorizing designs into learning materials, learner characteristics, pedagogical approaches, and learning structures, and proposed a mobile-based adaptive system leveraging AI and blockchain. [9] employed decision trees to predict learning styles based on the Kolb learning style model.

[10] outlined the design of a web-based intelligent tutoring system using Bayesian Knowledge Tracing, RNNs, and LSTM models to enhance personalized learning outcomes. [11] utilized decision trees and hidden Markov models to identify learning styles according to the Felder-Silverman Learning Style Model (FSLSM). [12] demonstrated the effectiveness of Bayesian networks in predicting students at risk of dropping out in MOOC environments by analysing behavioural data. [13] developed a learning style classifier based on deep belief networks (DBN), enhancing the DBN model by analysing individual learning style features. [14] introduced a method that combines Decision Tree, Naïve Bayes, and K-Nearest Neighbour Method in Moodle to classify and identify learning styles.

[15] proposed an automated approach to infer learning styles from learners' behaviour during online courses, focusing on the Felder-Silverman model. [16] employed fuzzy c-means clustering with the Honey and Mumford learning style dimensions to categorize learners' preferences using the neuro-fuzzy expert reasoning technique. [17] developed a smart e-learning platform integrating collaborative filtering and various machine learning algorithms (SVD, Random Forest, KNN) to recommend courses based on both explicit and implicit learner feedback, demonstrating superior accuracy over existing methods. [18] developed a classifier that maps learners' behaviours to categories in the Felder-Silverman Learning Style Model (FSLSM) using the Fuzzy C Means (FCM) algorithm. [19] conducted a systematic review identifying key drivers of personalized learning, emphasizing the role of AI in learner profiling, adaptive content, and real-time assessment, while also discussing challenges like educator competencies and ethical concerns.

3. METHODOLOGY
This research is carried out using a data-driven multi-level

model consisting of three core components as illustrated in Figure 1: Data Pre-processing, Clustering and Classification, and Performance Evaluation. All analyses were conducted in MATLAB R2022a using the Statistics and Machine Learning Toolbox. The dataset used for the analysis was obtained from a session of the "Teaching with Moodle" MOOC, provided by Moodle PTY LTD [20]. The data was anonymized to protect users' privacy, and each event tracked by the Moodle logging system is included, covering various learning objects.

3.1 Data Pre-processing

The dataset is prepared through a series of data pre-processing steps. Firstly, feature normalization is performed using the z-score technique. Subsequently, feature extraction and standardization are carried out by employing the tokenization feature, which eliminates non-informative features (such as IP Addresses, numbers, and special characters) from the data. This approach enhances the feature quality, and the presentation of data in standard numeric values. Finally, to reduce the dimensionality of the dataset while preserving the relationships between the variables, the principal component analysis (PCA) method is utilized. This technique enables the identification of key factors or features that accounts for variations in learner preferences.

3.2 Data Clustering and Classification

After pre-processing, K-means is then performed to group learners' behavioural sequences into eight clusters ($K = 8$),

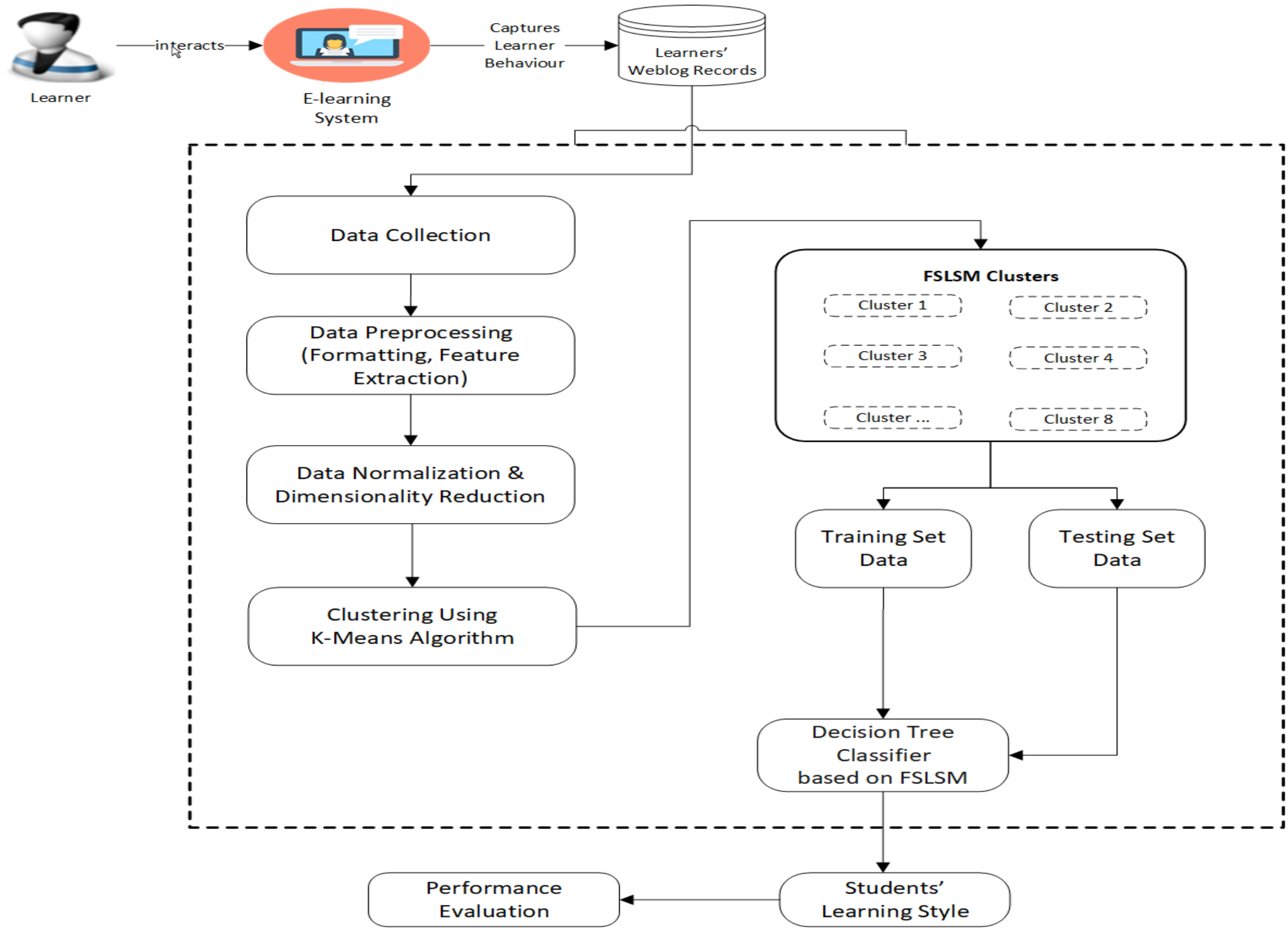

Figure 1: Architecture of the Proposed Model

corresponding to the eight learning style dimensions in the FSLSM based on the following steps:

Choose the value of K and the K initial guesses for the centroids; compute the distance d from each data point S_i at $(S_{i1}, \dots, S_{i2}, \dots, S_{in})$ to each centroid q at $q_1, q_2, \dots, q_n$ using Euclidean distance equation as seen in equation 1.

$$d(S_i - q) = \sqrt{\sum_{j=1}^{n} (S_{ij} - q_j)^2} \tag{1}$$

Then each point is assigned to the closest centroid to arrive at an association that defines the first k clusters, the centroid is then computed with the centre of mass of each newly defined cluster using equation 2 repeatedly until the algorithm reaches a final answer.

$$q_1, q_2, \dots, q_n = \left(\frac{\sum_{i=1}^{m} S_{i1}}{m}, \frac{\sum_{i=1}^{m} S_{i2}}{m}, \dots, \frac{\sum_{i=1}^{m} S_{in}}{m} \right) \tag{2}$$

After applying the k-means algorithm each learner sequence was assigned to one of the eight clusters. These clusters were then labelled with corresponding learning style categories based on the Felder-Silverman Learning Style Model (FSLSM) mappings the labelled sequences were used as a training dataset to train the decision tree classification algorithm and subsequently used for predicting the preferred learning style category for a new sequence. While C4.5 and ID3 utilize entropy-based criteria to rank tests, CART variants use the impurity level Gini coefficient as the discriminant basis, considering the probability distribution under the division node. Assume a total of K classes, variable X, and node for T; then the Gini index is defined in equation 3.

$$Gini\ (T) = \sum_{i=1}^{K} p_T\ (i)\big(1 - p_T(i)\big) = 1 - \sum_{i=1}^{K} {p_T}^2\ (i) \quad (3)$$

When the classes show the equal probability in the node T, the Gini index achieves the maximum $1 = \frac{1}{K}$. The gini index increases with the impurity; therefore, with only one kind in node T, the Gini index achieves the minimum. The sub-nodes should be added to lower the impurity. When taking the matrix into consideration, the Gini index is defined as in equation 4.

$$Gini\ (T) = \sum_{j \neq 1} C(i \mid j)\ p_T(i)\ p_T(j) \quad (4)$$

where $C(i \mid j)$ represents the cost for misclassifying the case category j as i. If the sub-node S added to node T, the Gini index is expressed in equation 5.

$$Gini\ (S, T) = Gini(T) - \ p_L Gini(T_L) - \ p_R Gini(T_R) \quad (5)$$

where p_L, p_R stands for the proportion of cases in node T classified into T_L and T_R. That is, probabilities of sending a case to the left and right child nodes respectively.

3.3 Performance Metrics

The performance of the multi-level learning style detection model is evaluated using measures derived from the confusion matrix. The confusion matrix is a table layout that displays the counts of true positives, true negatives, false positives, and false negatives for each class label predictions (Alese and Adetunmbi 2018). The metrics can be computed based on the confusion matrix

3.3.1 Accuracy

The Accuracy A of the model which measures the overall correctness of predictions is calculated using equation 6.

$$A = \frac{TTP_{all}}{total\ number\ of\ classifications} \quad (6)$$

3.3.2 Precision

Precision refers to the proportion of true positive predictions (that is, cases where the model predicted positive and the actual outcome was positive) among all positive predictions made by the model. It is calculated using equation 7.

$$P_i = \frac{TP_i}{TP_i + FP_i} \quad (7)$$

3.3.3 Recall

Recall or sensitivity measures the proportion of true positive predictions among all actual positive instances in the dataset. In other words, recall measures the ability of the model to identify all positive cases in the dataset. It is calculated using equation 8.

$$R_i = \frac{TP_i}{TP_i + FN_i} \quad (8)$$

3.3.4 F1 Score

F1 score is the harmonic mean of precision and recall, measuring a model's accuracy by considering false positives and false negatives. Mathematically, it is calculated using equation 9.

$$F_i = \frac{2 * (P_i * R_i)}{P_i + R_i} \quad (9)$$

where:

i. True Positive (TP_i): A positive instance and is correctly classified as positive by the classifier.

ii. True Negative (TN_i): A negative instance and is correctly classified as negative by the classifier.

iii. False Positive (FP_i): A negative instance incorrectly classified as positive by the classifier.

iv. False Negative (FN_i): A positive instance incorrectly classified as negative by the classifier.

4. SYSTEM IMPLEMENTATION

The first stage of the implementation targets grouping the learners' sequences into k=8 clusters and the subsequently labelling the resulting clusters with the corresponding learning style categories. This step of the approach involves selecting the relevant patterns of FSLSM dimensions. Table 1 maps the preferred learning object(s) to each learning style dimension based on the FSLSM, as depicted by [22]. The learners' activities are stored in weblog files, which automatically record the learner activities such as preferred learning objects, number of quizzes and assignments attempted, participation in discussion forums and chat facilities.

These actions are extracted as the learning sequences, then used as the input data to the k-means clustering algorithm by converting the data into a tabular form to store the attribute values of each sequence where the attributes match the learning objects using the FSLSM mapping defined in Table 1. K-means clustering algorithm is used for this task because of its ability to handle categorical data since the input data (extracted learners' sequences) is made up of categorical attribute values. Table 2 shows the number of sequences in each cluster. The obtained clusters are labelled with the LSCs based on the minimum distance between the clusters' centroid. The result of the clustering is shown in Table 2. After obtaining class labels from the k-means clustering algorithm, the decision tree classifier (CART variant) is used to train a model for predicting future groupings of learners with the same attributes. The model used the Gini impurity criterion to determine optimal split points during tree construction using the fitctree function from MATLAB's Statistics and Machine Learning Toolbox.

This function takes in the defined input features (predictors) used to predict the classes and the output labels as well and outputs a decision tree model. To evaluate the performance of the model, the data is partitioned into training and testing sets. This is done using the cvpartition function, which creates a partition object that can be used to split the data into training and testing sets. A hold-out cross-validation approach is employed in this case, as depicted in Table 3, where 30% of the data is set aside for testing and 70% for training. The training set is utilized for training the classification model, while the testing set is used to assess its performance. After training the classification model, Table 4 shows a classification tree summary of the trained model.

Table 1: Mapping learning objects to learning style dimensions based on FSLSM

Cluster-ID	**Cluster Meaning**	**Forum**	**Demo**	**Chat**	**Text**	**PPT**	**Video**	**Picture**	**Example**	**Quiz**	**Navigation**	**Overview**
C1	Active (ACT)	Yes	Yes	Yes	-	-	-	-	-	-	-	-
C2	Reflective (REF)	Yes	Yes	Yes			Yes	-	-	Yes	-	Yes
C3	Sequential (SEQ)	-	-	-	-	-	Yes	-	-	-	Yes	-
C4	Global (GLO)	-	-	-	-	-	Yes	-	-	-	-	Yes
C5	Sensitive (SEN)	-	-	-	-	-	Yes	-	Yes	Yes	-	-
C6	Intuitive (INT)	-	-	-	-	-	-	-	-	Yes	-	-
C7	Visual (VIS)	-	-	-	-	-	Yes	Yes	-	-	-	-
C8	Verbal (VER)	-	-	-	Yes	Yes	-	-	-	-	-	-

To determine the predictor importance, the predictorImportance function was utilized, which identified the key behavioural features that influenced classification outcomes.

Table 2. Result of K-Means Clustering Algorithm

ClusterID	**LSD**	**Sequences**	**(%) of Learners**
C1	Active (ACT)	7025	0.79 %
C2	Reflective (REF)	42454	4.80 %
C3	Sequential (SEQ)	450857	50.97 %
C4	Global (GLO)	17608	1.99 %
C5	Sensitive (SEN)	65484	7.40 %
C6	Intuitive (INT)	87397	9.88 %
C7	Visual (VIS)	133260	15.06 %
C8	Verbal (VER)	80544	9.10 %

This information aids in identifying the most influential features in the dataset and selecting a subset of features to construct a simpler and more interpretable model. The importance values are calculated using the Gini index, where higher values indicate greater importance for accurate predictions.

The trained model was then applied to the testing set using the predict function, and the predicted outputs were compared with actual labels through a confusion matrix to evaluate classification performance.

Table 3: Cross-Validation Partition Parameters

Property	**Value / Description**
Type	'holdout'
NumTestSets	1
TrainSize	619,241
TestSize	265,388
NumObservations	884,629

Table 4: Summary of Classification Tree Model Parameters

Property	**Value / Description**
Y	619,241×1 / double
X	619,241×12 / double
RowsUsed	[ ]
W	619,241×1 / double
ModelParameters	1×1 / TreeParams
NumObservations	619,241
BinEdges	0×1 / cell
Hyperparameters	[ ]
PredictorNames	1×12 / cell
CategoricalPredictors	[ ]
ResponseName	'Y'
ExpandedPredictorNames	1×12 / cell
ClassNames	[1 ; 2 ; 3 ; 4 ; 5 ; 6 ; 7 ; 8]
Prior	[0.1636 0.5100 0.1572 0.0352

	0.0165 0.0167 0.0991 0.0017]
Cost	8×8 / double
ScoreTransform	‘none’
CategoricalSplit	0×0 / cell
Children	25×2 / double
ClassCount	25×8 / double
ClassProbability	25×8 / .double
CutCategories	25×2 / cell
CutPoint	25×1 / double

5. RESULTS AND DISCUSSION

The model’s performance in predicting the learning style dimensions was evaluated using precision, recall, F1-score, and accuracy metrics summarized in Table 5 and presented in Figures 2 and 3. The multi-level approach achieved accuracy rates between 91.9% and 97.3%, indicating strong predictive capacity across all learning styles. The precision, recall, F1, and accuracy values provided for each group is analysed in relation to the learning style dimensions of the FSLSM. Figure 2 illustrates a 8 × 8 confusion chart, summarizing the model's performance indicating the number of correct and incorrect predictions for each class.

Table 3: Summary of Performance Evaluation Precision, Recall, F1-measure, Accuracy

LSD	Precision (%)	Recall (%)	F1 (%)	Accuracy (%)
Active (ACT)	98.87	95.96	97.39	95.96
Reflective (REF)	99.82	96.48	98.12	96.48
Sequential (SEQ)	96.49	97.32	96.90	97.32
Global (GLO)	92.47	96.02	94.21	96.02
Sensitive (SEN)	81.30	96.20	88.12	96.20
Intuitive (INT)	75.14	95.83	84.23	95.83
Visual (VIS)	87.84	95.97	91.72	95.97
Verbal (VER)	78.95	91.88	84.93	91.88

Additionally, Figure 6 displays the Performance Evaluation Chart, presenting the precision, recall, F1, and accuracy values for each group. The following inferences are drawn: from these metrics

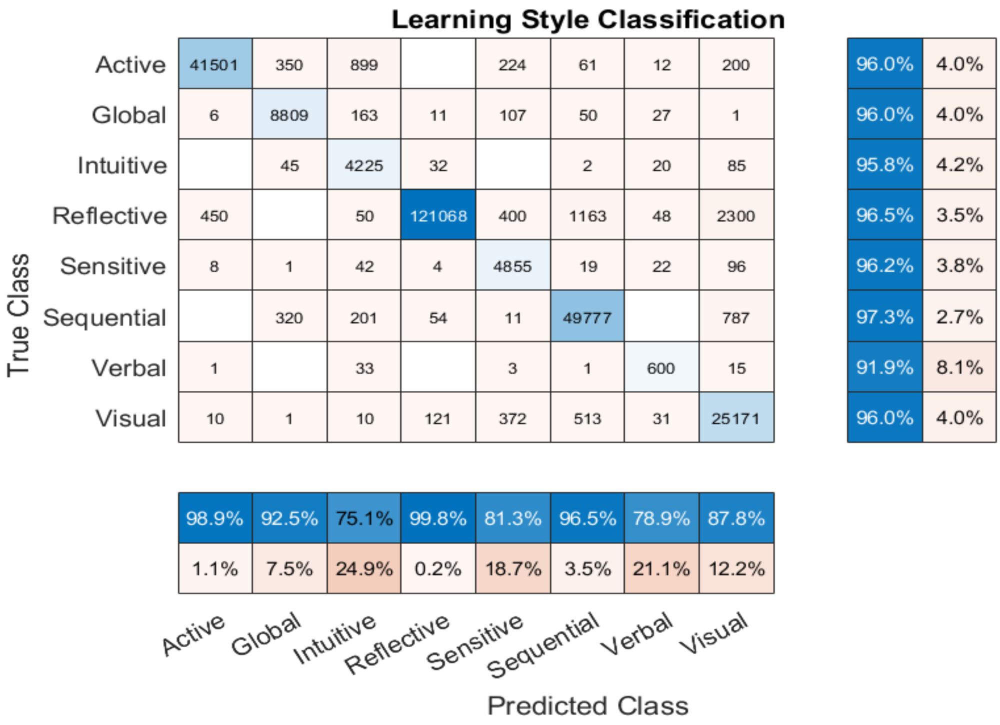

Figure 2: Confusion Matrix

i. Group 1 (ACT) and Group 2 (REF) demonstrate high precision, recall, F1 scores, and accuracy, indicating effective identification of learners with active and reflective learning characteristics.

ii. Group 3 (SEQ) shows relatively high precision and recall for sequential learners, while Group 4 (GLO) exhibits slightly lower precision but maintains a high recall for global learners. Both groups achieve reasonable F1 scores and accuracy.

iii. Group 5 (SEN) and Group 6 (INT) have lower precision and F1 scores indicating overlapping behavioural indicators but high recall, indicating successful identification of sensitive and intuitive learners.

iv. Group 7 (VIS) and Group 8 (VER) demonstrate satisfactory precision, recall, F1 scores, and accuracy for visual and verbal learning style dimensions.

The findings of this study were compared with related approaches that have applied the Felder–Silverman Learning Style Model (FSLSM) to adaptive e-learning systems. [22]

developed an adaptive mechanism within Moodle that identified learning styles from behavioural indicators aligned with FSLSM dimensions which demonstrated adaptability in learning interfaces but reported limited quantitative evaluation across all learning-style dimensions. [18] proposed a clustering-based framework using Fuzzy C-Means (FCM) to detect learning styles from multi-course interaction data approach which achieved around 93% classification accuracy. In comparison, the results reported in this study indicate that the hybrid approach achieved an overall accuracy of 95%. These outcomes surpass the performance of existing FCM-based approaches in terms of predictive stability. Moreover, the model demonstrated particularly strong performance for Active, Reflective, and Sequential learners, suggesting that the combination of clustering and rule-based classification improves class separability and clarifies decision boundaries.

6. CONCLUSION

The need for personalization in e-learning arises from the understanding that learners have unique preferences, learning styles and needs. This paper presents a multi-level model that combines K-Means clustering and Decision Trees algorithms to predict learning styles in personalized e-learning systems. By labelling learning sequences with LSC based on predefined mappings, the model is trained and evaluated using a validation set approach. Standard performance metrics for classification problems are employed to assess the model's effectiveness.

The evaluation results demonstrate that the proposed model achieved an overall accuracy of 95%, with balanced performance in terms of precision and recall, indicating its capability to identify and classify learning styles effectively across all FSLSM dimensions. The results also underscore the potential of this approach to support dynamic, data-driven personalization that aligns instructional content with individual learner profiles. Future research can aim to integrate the proposed model into real-world e-learning environments to enhance predictive learning style classification, thereby contributing to improved learner outcomes.

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