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Adaptive Hybrid Model for Academic Performance Prediction and Learning Strategy Recommendation

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Abstract: Academic performance prediction is important for helping lecturers identify student learning needs before academic problems become difficult to address. However, students differ in learning preferences, engagement, prior knowledge, and academic achievement, making uniform learning strategies less effective. This study proposes an adaptive hybrid model for academic performance prediction and learning strategy recommendation by integrating K-Means Clustering, Simple Additive Weighting, and an Artificial Neural Network. The dataset consists of 74 student samples containing VARK learning preferences, engagement scores, pretest scores, and GPA-like academic indicators. After data cleaning, median imputation, and standard scaling, K-Means was applied to segment students into five learning profiles. Cluster centroids were then transformed into three decision criteria, namely Engage, Retention, and Effort. Simple Additive Weighting was used to rank three learning strategies: Micro-video Learning, Quiz Drill Practice, and Peer Discussion. The resulting recommendation labels were used together with the academic features to train an Artificial Neural Network for performance prediction and strategy classification. The evaluation showed that both models achieved an unrounded accuracy of 99.63%, while the rounded classification report displayed nearly perfect precision, recall, and F1-score. These findings indicate that the proposed integration can support data-driven adaptive learning decisions. Nevertheless, the high performance should be interpreted carefully because the dataset is limited and comes from a single institutional context. Further validation with larger, more diverse datasets is required to confirm generalizability.

Keywords: Adaptive Learning; Artificial Neural Network; K-Means Clustering; Simple Additive Weighting; Student Performance.

INTRODUCTION

Higher education is expected to prepare students who are not only able to complete academic requirements but also capable of developing learning habits that match their personal characteristics. Academic performance is often used as a practical indicator of whether a learning process has been successful. In many academic settings, performance is represented by grades, grade point averages, or competency achievements (Cabero-Almenara et al., 2023; Geletu, 2022). Even so, academic achievement is rarely determined by cognitive ability alone. It is shaped by learning preferences, engagement, prior knowledge, learning environment, and the suitability of teaching strategies used in the classroom.

A persistent problem in higher education is that learning strategies are frequently delivered in a general manner (Donelan & Kear, 2024; Halabieh et al., 2022). The same material, learning media, and instructional approach are often applied to students with different learning profiles. Some students understand concepts more easily through diagrams and video-based explanations, whereas others benefit more from verbal discussion, reading activities, repeated exercises, or practice-oriented tasks. The VARK perspective, which represents visual, auditory, reading/writing, and kinesthetic preferences, offers a practical way to describe these differences (El-Saftawy et al., 2024; Mohd Noor & Amri Ramly, 2023). When such differences are not mapped systematically, lecturers may find it difficult to provide timely and appropriate academic support.

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Educational data mining and machine learning provide an opportunity to examine student data more objectively. Previous studies have shown that academic records, learning behavior, digital activity logs, and student engagement indicators can be used to predict student outcomes and identify students who may require intervention (Alhothali et al., 2022; Arizmendi et al., 2023). However, prediction alone is not enough. A useful decision support system in education should not only estimate future performance but also suggest learning actions that lecturers and students can understand and apply. Therefore, a model that connects student profiling, decision-making criteria, and predictive classification is needed.

Several methods have been used separately in educational decision support (Maniyan et al., 2024; Phan et al., 2023). K-Means Clustering has been applied to group students based on academic characteristics and learning styles. Simple Additive Weighting has been widely used in decision support systems because it can rank alternatives using transparent criteria and weights. Artificial Neural Networks have also been used to predict academic performance because they can learn non-linear relationships among input variables. Nevertheless, these methods are often discussed as separate components. A gap remains in how clustering results can be translated into strategy recommendations and then learned by a predictive model in one adaptive workflow.

To address this gap, this study proposes an adaptive hybrid model that integrates K-Means Clustering, Simple Additive Weighting, and Artificial Neural Network. K-Means is used to segment students based on VARK preferences, engagement, pretest score, and GPA-like indicators. Simple Additive Weighting converts cluster profiles into learning strategy recommendations. The Artificial Neural Network then learns academic performance patterns and strategy classes. The main contribution of this study is a data-driven decision support flow that is both diagnostic and prescriptive: it identifies student profiles, recommends learning strategies, and predicts academic performance within a single framework.

LITERATURE REVIEW

Educational Data Mining and Academic Prediction

Educational data mining focuses on extracting meaningful patterns from educational data to support teaching, learning evaluation, and institutional decision-making. In higher education, the analyzed data may include grades, attendance, pretest scores, learning management system activity, and engagement indicators. Chaka explains that academic performance prediction has become one of the dominant themes in educational data mining because it can help institutions detect at-risk students and design earlier interventions (Chaka, 2022).

Al-Din and Al Abdulqader reported that academic prediction models commonly use academic variables, behavioral data, demographic information, and digital learning interactions (Al-Din & Abdulqader, 2024). Angeioplastis et al also showed that learning management system data can be used to predict student performance and improve learning outcomes (Angeioplastis et al., 2025). These studies indicate that prediction becomes more valuable when it is connected to learning support actions rather than used only as a final classification result.

K-Means Clustering for Student Segmentation

K-Means Clustering is an unsupervised learning method that partitions data into groups based on distance to cluster centroids. In educational contexts, K-Means can group students according to learning style, academic achievement, reading patterns, or participation levels. Handayani used K-Means to group students based on learning styles (Handayani, 2022), while Ariawan et al used a clustering approach for final grade prediction (Ariawan et al., 2023). Fatkhudin et al also demonstrated the use of K-Means for student grouping (Fatkhudin et al., 2023). The strength of K-Means lies in its simplicity, computational efficiency, and interpretable centroid representation.

However, clustering does not automatically provide learning recommendations. A centroid only describes the dominant characteristics of a group, whereas lecturers still need an operational decision about which learning strategy should be applied. In addition, educational data often contains overlapping characteristics because student behavior is not always clearly separated. Therefore, clustering results need to be followed by a decision-making method that can translate group profiles into practical recommendations.

SAW and Artificial Neural Network in Decision Support

Simple Additive Weighting is a multi-criteria decision-making method that ranks alternatives by combining normalized criterion values with their respective weights. The method is widely used because the calculation process is transparent and easy to communicate to decision makers. Previous research such as Suwarno and Muhtarom (Suwarno & Muhtarom, 2021), Amalia (Amalia, 2022) and Pranoto (Pranoto et al., 2022) showed that SAW can support educational decision-making when criteria and alternative options are clearly defined.

Artificial Neural Networks are useful for learning complex relationships between input features and target classes. Chavez et al showed that neural network models can be used to predict student performance using non-personal information (Chavez et al., 2023). This approach is relevant to the present study because the selected

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features focus on academic and learning behavior indicators rather than sensitive personal attributes. Integrating K-Means, SAW, and Artificial Neural Network provides a more complete framework: segmentation, criteria-based recommendation, and predictive classification.

METHOD

This study used a quantitative computational experiment to develop and evaluate an adaptive decision support model. The research flow consisted of literature study and problem identification, data collection and preparation, clustering, learning strategy assessment using SAW, ANN model training, and evaluation. Each stage was designed to produce an interpretable output that could be carried forward to the next stage.

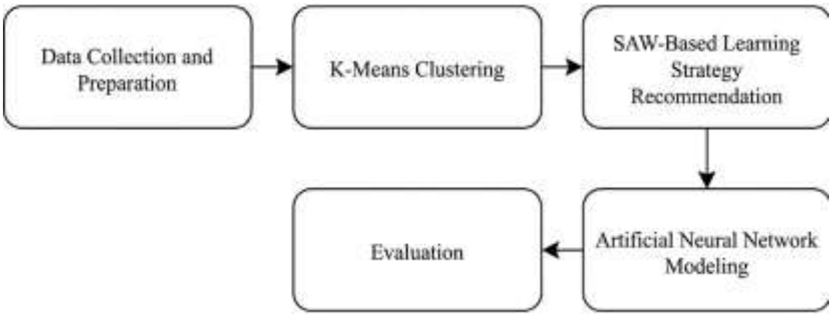

Fig. 1 Research stages of the proposed adaptive decision support model

Data Collection and Preparation

The dataset consisted of 74 student samples from the 2024/2025 academic year. The data were collected from academic records and adaptive learning support instruments. Administrative fields such as student identity, student number, gender, and cohort were used only for data management. They were not used as predictive features in the model. The main modeling variables were VARK learning preferences, engagement, pretest score, and GPA-like score.

Before modeling, the dataset was cleaned by checking duplicate and irrelevant records, standardizing numeric formats, and validating missing values. Median imputation was used to handle incomplete numeric values. Feature selection was then performed to retain variables that were relevant to academic performance prediction and learning strategy recommendation. Because the variables had different numeric scales, standard scaling was applied before the clustering process so that no single variable dominated the Euclidean distance calculation.

Table 1. Variables Used in the Dataset

Variable	Description	Role
vark_v	Visual learning preference score	Feature
vark_a	Auditory learning preference score	Feature
vark_r	Reading/writing learning preference score	Feature
vark_k	Kinesthetic learning preference score	Feature
engagement	Student engagement in academic activities	Feature
pretest_score	Initial knowledge or academic readiness score	Feature
gpa_like	Academic achievement indicator similar to GPA	Feature and target basis
strategy_label	Learning strategy generated from SAW	Target for strategy model

K-Means Clustering

K-Means Clustering was used to segment students based on similarity in their learning and academic characteristics. The selected features were vark_v, vark_a, vark_r, vark_k, engagement, pretest_score, and gpa_like. The number of clusters was set to five to obtain several student profile groups that could later be mapped into adaptive learning strategies.

The model used k = 5, random_state = 42, n_init = 10, max_iter = 300, and tolerance = 0.0001. Inertia and silhouette score were used to describe the clustering quality. Inertia measures the total squared distance between samples and their nearest centroids, while the silhouette score indicates how well each sample fits within its assigned cluster compared with other clusters.

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Table 2. K-Means Clustering Parameters and Output

Parameter	Value
Number of clusters	5
Random state	42
Initialization	n_init = 10
Maximum iteration	300
Tolerance	0.0001
Scaler	Standard scaler
Imputer	Median
Inertia	225.743677
Silhouette score	0.221
Fitting time	3.217 seconds

SAW-Based Learning Strategy Recommendation

The cluster centroids were converted into decision criteria to make the clustering output more actionable. Three criteria were used: Engage, Retention, and Effort. Engage represents the expected level of student involvement, Retention represents the potential to retain learning material, and Effort represents the learning burden required by a strategy. Engage and Retention were treated as benefit criteria, while Effort was treated as a cost criterion.

Three alternative strategies were evaluated: Micro-video Learning, Quiz Drill Practice, and Peer Discussion. Micro-video Learning emphasizes short and focused content delivery, Quiz Drill Practice emphasizes repeated practice and recall, while Peer Discussion emphasizes interaction and collaborative understanding. SAW was applied by normalizing the decision matrix and multiplying each normalized criterion value by its cluster-specific weight. The alternative with the highest score was selected as the recommended strategy for each cluster.

Table 3. SAW Criteria Weights for Each Cluster

Cluster	Engage	Retention	Effort	Dominant emphasis
0	0.2500	0.2500	0.5000	Reduced learning burden
1	0.3277	0.4723	0.2000	Retention and engagement
2	0.3477	0.3061	0.3462	Balanced criteria
3	0.3334	0.3333	0.3333	Balanced criteria
4	0.3333	0.3333	0.3334	Unique/outlier profile

Artificial Neural Network Modeling

Two ANN models were developed. The first model predicted academic performance classes derived from GPA-like values. The second model classified learning strategies generated by the SAW process. Both models used the same input features: VARK scores, engagement, and pretest score. The use of two models allowed the system to support both academic performance estimation and automatic strategy recommendation.

The network architecture consisted of an input layer, two hidden layers, and a softmax output layer. The hidden layers used ReLU activation with 64 and 32 neurons. Adam optimizer was used with a learning rate of 0.001 and alpha regularization of 0.0001. The performance prediction model was trained for 100 epochs, while the strategy recommendation model was trained for 300 epochs because the strategy labels were generated from multi-criteria decision patterns.

Table 4. ANN Training Configuration

Component	Academic performance model	Learning strategy model
Input features	VARK, engagement, pretest score	VARK, engagement, pretest score
Hidden layers	64 and 32 neurons	64 and 32 neurons
Activation	ReLU	ReLU
Output classes	Academic performance categories	Microvideo, Peer Discussion, Quiz Drill
Optimizer	Adam	Adam
Learning rate	0.001	0.001
Alpha regularization	0.0001	0.0001
Epochs	100	300
Validation size	0.20	0.20

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Evaluation Metrics

Model performance was evaluated using accuracy, precision, recall, and F1-score. These metrics were selected because the proposed model performs a classification task, both for academic performance prediction and learning strategy recommendation. Accuracy was used to provide a general overview of how many predictions were correctly classified by the model. However, accuracy alone is not always sufficient, especially when the distribution of classes is not fully balanced. Therefore, precision, recall, and F1-score were also included to provide a more comprehensive evaluation.

Precision indicates the proportion of predicted class members that were correctly classified, while recall measures the ability of the model to identify actual members of each class. F1-score was used as a balanced metric because it combines precision and recall into a single value, making it useful when the evaluation needs to consider both false positive and false negative predictions. In this study, the combination of these four metrics is considered sufficient to evaluate the classification performance because it covers the overall correctness of the model, the reliability of class predictions, the completeness of class detection, and the balance between precision and recall. The evaluation results were reported using class-based scores as well as overall performance to ensure that the model was not only accurate in general, but also consistent across different target classes.

RESULT

This section reports the experimental results of the proposed hybrid model, starting from student grouping using K-Means Clustering, learning strategy recommendation using Simple Additive Weighting, and model evaluation using Artificial Neural Network. The results are presented according to the research workflow to show how the student profile data were transformed into cluster patterns, recommendation decisions, and classification outcomes. Through this structure, the analysis highlights not only the numerical performance of the model, but also the practical meaning of each result in supporting adaptive learning strategy recommendation.

The K-Means process grouped the 74 student samples into five clusters with different learning and academic characteristics. The silhouette score of 0.221 indicates that the separation between clusters was low to moderate. This result is reasonable for educational data because students may share overlapping learning characteristics. However, the resulting clusters were still useful as a basis for adaptive learning strategy recommendation. Cluster 3 was the largest group with 34 students, representing 45.90% of the dataset. Cluster 2 contained 20 students or 27.00%, while cluster 1 contained 12 students or 16.20%. Cluster 0 consisted of 7 students or 9.50%. Cluster 4 contained only one student, indicating an outlier profile with characteristics that differed substantially from the other groups.

Table 5. Cluster Distribution and Recommended Learning Strategy

Cluster	Students	Percentage	Main characteristic	SAW recommendation
0	7	9.50%	Lower engagement and achievement; specific learning pattern	Quiz Drill Practice
1	12	16.20%	Lower engagement with stronger retention need	Micro-video Learning
2	20	27.00%	Better academic readiness and positive engagement	Quiz Drill Practice
3	34	45.90%	Largest group; moderate and overlapping profile	Peer Discussion
4	1	1.40%	Outlier with unique VARK profile	Micro-video Learning

The SAW calculation produced different recommendations for the five clusters. Cluster 0 was recommended Quiz Drill Practice because the dominant weight was placed on Effort, and repeated exercises provided a structured way to improve learning without requiring a high level of new learning burden. Cluster 1 was recommended Micro-video Learning because the strategy offered short, accessible, and focused learning content that could support retention and engagement. Cluster 2 was recommended Quiz Drill Practice because this cluster already had a relatively strong academic profile and could benefit from reinforcement through practice. Cluster 3 was recommended Peer Discussion. This recommendation fits the cluster because collaborative discussion may increase active participation and reduce individual learning burden. Cluster 4 was recommended Micro-video Learning because the cluster contained an outlier profile that required a flexible and individualized strategy. These recommendations were then assigned to each student based on cluster membership and used as class labels for the ANN learning strategy model.

The academic performance prediction model was trained for 100 epochs. The accuracy curve shows that both training and validation accuracy increased steadily during training. In the early epochs, accuracy was still around the lower range, but it quickly improved as the model learned the relationship between VARK, engagement, pretest

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score, and academic performance. Near the end of training, the rounded classification report showed nearly perfect results, while the unrounded accuracy was 99.63%.

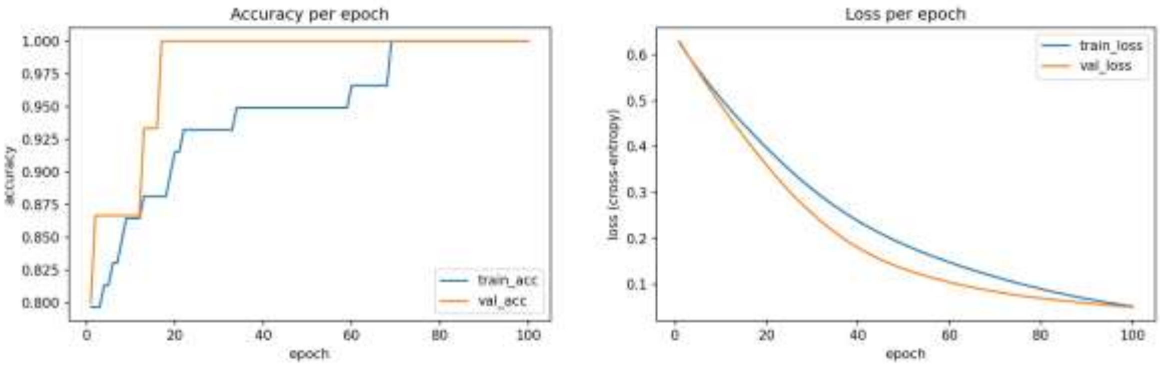

Fig. 2 Training accuracy and loss of the academic performance prediction model

The loss curve also decreased consistently. The validation loss remained close to the training loss, indicating stable convergence. This pattern suggests that the model was able to reduce prediction errors without a strong visible divergence between training and validation loss in the performance prediction task.

The learning strategy recommendation model was trained for 300 epochs. The training accuracy increased rapidly and eventually approached a rounded value of 1.00. The validation accuracy also improved sharply during the early training phase and then stabilized. This result indicates that the model learned the SAW-generated strategy labels effectively, although the validation curve suggests that additional regularization may be needed in future work.

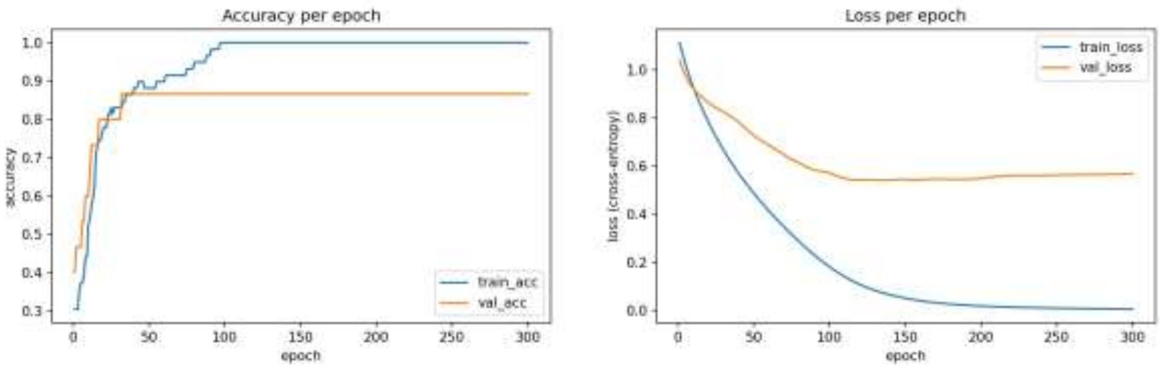

Fig. 3 Training accuracy and loss of the learning strategy recommendation model

The loss curve of the strategy model shows a clearer indication of possible overfitting. Training loss continued to decrease, while validation loss flattened after the early training phase. This result does not invalidate the model, but it shows that the high performance should be understood as an initial computational result that still requires wider validation. The rounded classification report displayed values close to 1.00 for precision, recall, and F1-score. However, the unrounded evaluation value was 99.63%. Therefore, the results are reported as 99.63% to avoid presenting the model as absolutely perfect. Both the academic performance model and the learning strategy recommendation model achieved the same unrounded accuracy, indicating that the hybrid pipeline was able to capture the patterns in the dataset effectively.

Table 6. Evaluation Result of the Proposed Models

Model	Accuracy	Precision	Recall	F1-score	Interpretation
Academic performance prediction	99.63%	99.63%	99.63%	99.63%	Very high performance; rounded report appears as 1.00
Learning strategy recommendation	99.63%	99.63%	99.63%	99.63%	Very high performance; rounded report appears as 1.00

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DISCUSSIONS

The results show that integrating K-Means, SAW, and Artificial Neural Network can produce a coherent adaptive learning decision support flow. K-Means provides the first layer of analysis by grouping students based on learning preferences and academic indicators. The clustering result shows that students do not form perfectly separated groups. Instead, some characteristics overlap, which is common in real educational data. This finding is important because adaptive learning systems should be able to handle variation rather than assume that student profiles are always cleanly separated. The use of SAW adds an interpretable decision-making layer. Instead of directly assigning strategies based on intuition, the model translates cluster characteristics into Engage, Retention, and Effort criteria. This makes the recommendation process more transparent. Lecturers can understand why a cluster receives Quiz Drill Practice, Micro-video Learning, or Peer Discussion. This transparency is especially important in educational decision support systems because recommendations must be explainable and acceptable to users. The ANN models produced very high performance, with an unrounded accuracy of 99.63%. This result supports previous work showing that neural networks can model complex relationships in student performance data. However, the performance should not be interpreted as evidence that the model is universally generalizable. The dataset consisted of 74 samples from one academic context. In addition, the strategy recommendation labels were generated from SAW, meaning that the ANN strategy model learned a structured decision pattern rather than labels obtained from long-term behavioral outcomes. This condition explains why performance can be very high while still requiring external validation.

Compared with studies that only use clustering for student segmentation, this study extends the process by converting clusters into learning strategy recommendations. Compared with studies that only use SAW for educational decision-making, this study adds an ANN layer to automate prediction and strategy classification. Compared with studies that only predict academic performance, this study also provides a prescriptive recommendation component. Thus, the novelty of this work lies in the integration of segmentation, multi-criteria recommendation, and predictive learning within one adaptive framework. Several threats to validity should be acknowledged. First, the dataset size is limited, and the samples come from a single institutional context. Second, GPA-like values may not represent all dimensions of academic achievement. Third, the recommended strategies have not yet been tested through a longitudinal intervention to measure whether students who receive the recommendations actually improve their performance. Fourth, the high model score may be influenced by the structured nature of the generated labels and the limited variability of the dataset. Future research should include larger datasets, cross-validation, comparisons with other algorithms, and empirical testing of recommendation impact in real learning activities.

CONCLUSION

This study developed an adaptive hybrid model for academic performance prediction and learning strategy recommendation by integrating K-Means Clustering, Simple Additive Weighting, and Artificial Neural Network. K-Means successfully segmented 74 student samples into five profiles based on VARK learning preferences, engagement, pretest score, and GPA-like indicators. SAW translated the cluster profiles into learning strategy recommendations, including Micro-video Learning, Quiz Drill Practice, and Peer Discussion. The ANN models then learned academic performance patterns and SAW-generated strategy labels.

The evaluation showed that both the academic performance prediction model and the learning strategy recommendation model achieved an unrounded accuracy of 99.63%. These findings indicate that the proposed hybrid model has strong potential as a data-driven adaptive learning decision support system. The contribution of this study is the combination of student segmentation, transparent multi-criteria recommendation, and predictive classification in a single workflow. Nevertheless, the study is limited by dataset size, single-context data, and the absence of longitudinal impact evaluation. Future research should validate the model using larger and more diverse datasets, apply cross-validation, add digital learning behavior features, and evaluate whether the recommended strategies improve student learning outcomes in practice.

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