RESEARCH PAPER

Predicting Student Learning Behavior Through Learning Analytics: An Empirical Study on Feature Validity and the Target-Leakage Pitfall in VARK-Based Prediction

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Abstract: The growing adoption of digital technologies in education generates large volumes of learner data that can be used to support personalized instruction. This study analyses a large-scale multilingual survey of 5,000 students in Grades 6–10 across CBSE, ICSE and State Board schools in India, with 4,996 responses validated for analysis [1]. Learning preference was assessed using the Visual, Auditory, Reading/Writing and Kinesthetic (VARK) framework [3], and a dominant learning style was derived for each respondent from sixteen diagnostic items. An initial modeling attempt that used VARK item responses and VARK category scores as predictive features produced apparent accuracies of 86–99.5%; this study demonstrates analytically and empirically that this performance is an artifact of target leakage, since those features are deterministic transformations of the label itself and encode no independent predictive signal [2]. The task is then re-evaluated using only demographic and contextual features — gender, age, grade, school board, area of residence and father's education — that are genuinely independent of the VARK instrument. Logistic Regression, Support Vector Machine, Random Forest and Artificial Neural Network classifiers were trained and evaluated with stratified 80/20 splits and 5-fold cross-validation. The leakage-free models achieve 28.9–33.6% test accuracy against a 30.4% majority-class baseline, indicating that demographic variables alone carry only weak, largely non-significant association with self-reported VARK learning style. This study discusses the methodological implications of this finding for learning-analytics research and presents a personalized learning-recommendation framework that maps predicted or self-reported learning style to instructional strategies, independent of the identified modeling limitation.

Keywords: Learning Analytics, Educational Data Mining, Data Leakage, Machine Learning, VARK, Support Vector Machine, Artificial Neural Network, Personalized Learning

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1. Introduction

The digital transformation of education has increased the volume of learner-related data generated through classroom activities, assessments and surveys [1], [14]. Traditional instruction often assumes that students learn in broadly similar ways, whereas educational research has documented substantial variation in learning preferences and behaviour across individuals. Learning Analytics (LA) has emerged as an interdisciplinary field that combines educational theory, data science and machine learning to analyse these patterns and support instructional decision-making [1], [18], [19]. Previous studies by Kabra and Kumar have highlighted the role of machine learning in assessing student learning ability and developing adaptive educational systems [9].

A recurring goal in this literature is to predict a student's learning style or behaviour from data that is easier or cheaper to collect than a full diagnostic instrument, so that the prediction can be produced automatically for new students [3], [9], [10]. This goal is only meaningful if the predictive features are genuinely independent of the diagnostic instrument used to define the label. When a survey both elicits the diagnostic responses and derives the label from those same responses, any model trained on the diagnostic items — or on scores computed from them — is not predicting the label; it is recovering an already-known deterministic function of its own input.

This failure mode is known as target (or feature) leakage, and it has been documented as a widespread and often unrecognised problem across machine-learning-based science [2]. The VARK framework categorises learners into Visual, Auditory, Reading/Writing and Kinesthetic learning preferences [3]. This study makes two contributions. First, it reports a genuine, leakage-free evaluation of whether collected demographic and contextual variables can predict a student's dominant VARK learning style, using a large real-world school survey. Second, it uses the same dataset to experimentally measure the magnitude of the apparent accuracy gain caused by the erroneous inclusion of VARK-derived features as predictors, offered as a reusable, repeatable case study relevant to learning-analytics research in general.

1.1 Research Objectives

- To analyse the distribution of student learning styles (VARK) across grades, gender and school board.

- To formally identify which variables in a VARK-based survey are derived from the label and therefore constitute leakage if used as predictive features.
- To develop and evaluate machine learning models (Logistic Regression, SVM, Random Forest, ANN) that predict dominant learning style using only demographic and contextual features that are independent of the VARK instrument.
- To quantify, empirically, the magnitude of the accuracy inflation caused by leakage on this dataset.
- To propose a personalized learning-recommendation framework that maps a (self-reported or predicted) learning style to instructional strategies.

1.2 Research Contributions

- A leakage audit and reproducible empirical demonstration of its effect on a real 4,996-student educational dataset.
- A leakage-free predictive evaluation of learning style from demographic/contextual features, reporting genuine, statistically modest effect sizes rather than inflated accuracy.
- A comparative evaluation of four classifiers (Logistic Regression, SVM, Random Forest, ANN) under identical, leakage-free conditions.
- A personalized-learning recommendation framework decoupled from the prediction-accuracy limitation identified.

2. Literature Review

Educational Data Mining (EDM) and Learning Analytics have become established research areas for extracting patterns from learner data to improve educational outcomes [1], [14], [18], [19]. Romero and Ventura provide a comprehensive survey of methods, tools and open datasets used across this literature and note the field's rapid growth over the past decade [1]. Machine learning techniques including decision trees, random forests, support vector machines and neural networks have been widely applied to predict academic performance, engagement and learning style from behavioural and self-report data [4], [5], [6], [16], [17].

The VARK model, introduced by Fleming and Mills, categorises learners into Visual, Auditory, Reading/Writing and Kinesthetic preferences based on a short diagnostic questionnaire [3]. VARK-based instruments are widely used in adaptive-learning research; however, because the instrument itself defines the label, any downstream modelling exercise must take care not to reuse the diagnostic items, or scores computed from them, as predictive features for that same label.

Kapoor and Narayanan systematically reviewed reproducibility failures across seventeen scientific fields that adopted machine learning and found data leakage — broadly, the use of information in training that would not be available at genuine prediction time — to be a common and often subtle cause of inflated, non-reproducible performance claims [2]. Their taxonomy includes the case, directly relevant here, in which a feature is a post-hoc transformation of the label. This study applies that lens to a VARK-based educational dataset. Standard machine learning references underpin the classifiers used in this study: Vapnik's statistical learning theory motivates the maximum-margin Support Vector Machine formulation [4]; Goodfellow, Bengio and Courville describe the feed-forward neural network architectures and training procedures used for the ANN classifier [5]; and Géron and Han et al. provide applied treatments of model evaluation, cross-validation and data-mining methodology that inform the experimental design adopted here [6], [7]. Prior studies by the authors demonstrated the usefulness of machine learning and hybrid approaches in learning-style identification [9], [10], [11], [12].

3. Methodology

This study adopts a quantitative, empirical research design based on primary survey data collected from school students, followed by a formal feature audit and a controlled, leakage-free machine-learning evaluation. The methodology proceeds in three stages: (i) description of the dataset and derivation of the VARK label; (ii) an explicit audit separating label-derived features from independent, feature-eligible variables; and (iii) training and evaluation of four classifiers strictly on the feature-eligible variable set, with a separate controlled experiment to quantify the leakage effect.

3.1 Dataset and Data Sources

The dataset was collected through a multilingual (English/Hindi/Marathi) survey administered to students in Grades 6–10 across CBSE, ICSE and State Board schools. Of 5,000 total responses, 4,996 were retained after validation and used for the analysis reported here (Table I). Sixteen forced-choice items, each mapped to one of the four VARK categories, were used to compute a per-student count and percentage in each category (score_V/A/R/K and V_pct/A_pct/R_pct/K_pct); the category with the highest score was assigned as the student's dominant learning-style label.

TABLE I. DATASET CHARACTERISTICS

Parameter	Value
Total responses	5,000
Valid responses (analysed)	4,996
Grades	6–10
Boards	CBSE, ICSE, State
VARK categories	V, A, R, K
Predictive features (leakage-free)	6

TABLE II. LEARNING STYLE (VARK) DISTRIBUTION

Style	Count	%
Auditory	1,517	30.36
Kinesthetic	1,274	25.50
Visual	1,210	24.22
Reading/Writing	995	19.92

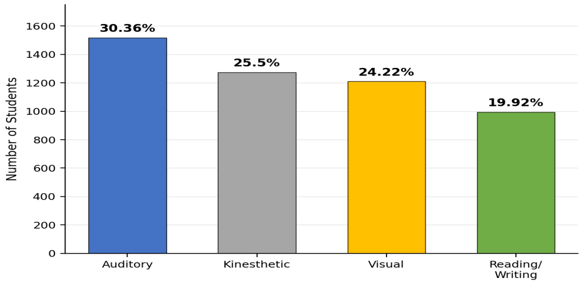

Fig. 1. Distribution of dominant learning styles among 4,996 students. Auditory learners constitute the largest category (30.36%), followed by Kinesthetic (25.50%), Visual (24.22%) and Reading/Writing learners (19.92%).

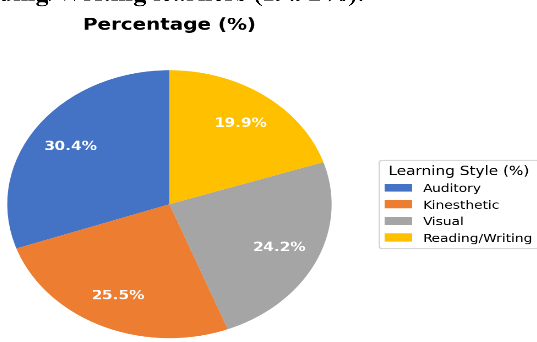

Fig. 1b. Percentage share of dominant learning styles across the surveyed cohort.

As shown in Fig. 1, Auditory learning style represents the largest proportion of students, while Reading/Writing learners constitute the smallest category. No category is rare, so the classification task is only mildly imbalanced, and a majority-class baseline predicts Auditory for every student with 30.4% accuracy — the benchmark against which genuine model skill must be judged.

TABLE III. GENDER AND BOARD DISTRIBUTION

Category	Group	Count
Gender	Female	2,565
Gender	Male	2,431
Board	State Board	2,458
Board	CBSE	2,008
Board	ICSE	530

3.2 Feature Audit and the Leakage Boundary

Every field in the dataset falls into one of two groups relative to the prediction target, dominant_style. Group L (label-derived) comprises the sixteen VARK item responses, the four VARK category scores, the four VARK category percentages and the numeric label encoding; each of these is computed directly from, or is arithmetically equivalent to, the diagnostic items that define the label, and using any of them as a predictive feature is a form of target leakage. Group F (feature-eligible) comprises gender, age, grade (standard), school board, area of residence (urban/semi-urban/rural) and father's education level — six variables collected independently of the VARK instrument and available for any student prior to diagnosis. Only Group F variables are used as model inputs in Section 4; Group L variables are used only to quantify the leakage effect.

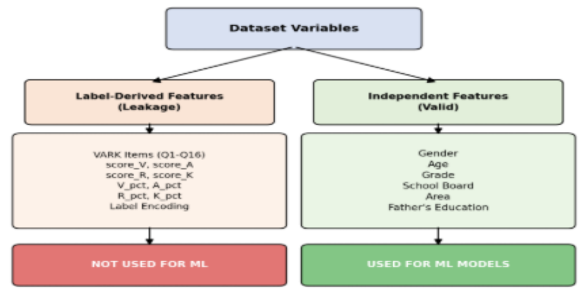

Fig. 2. Feature audit illustrating the separation between label-derived variables that introduce target leakage and independent variables used for leakage-free prediction.

3.3 Data Preprocessing and Classifiers

The six Group-F predictors were used without modification (no missing values were present after validation). The single continuous feature, age, was standardised as $Z = (x - \mu) / \sigma$, where x is the feature value and μ and σ are its mean and standard deviation. The five categorical predictors (gender, grade, board, area, father's education) were one-hot encoded. Data were split 80/20 into training and test sets using stratified sampling on the target label, and 5-fold stratified cross-validation was additionally used to obtain a variance estimate of accuracy.

Four classifiers were trained on the leakage-free feature set: Logistic Regression and Random Forest as linear and ensemble-tree baselines respectively; a radial-basis-function kernel Support Vector Machine trained to separate learning-style classes by an optimal margin; and a feed-forward Artificial Neural Network with two hidden layers (64 and 32 neurons, ReLU activation) and a softmax output layer trained with cross-entropy loss [4], [5], [8].

To make the leakage risk concrete rather than only theoretical, an RBF-kernel SVM was additionally trained on Group-L variables under the same 80/20 split. Using the sixteen raw VARK item responses as features yielded 86.1% test accuracy; using the VARK category scores or percentages — arithmetic summaries of those same items — yielded 99.5% test accuracy. This confirms that near-perfect performance on this task is achievable purely by re-deriving the label from itself, and is not evidence of a genuine predictive relationship between student characteristics and learning style; all results reported in Section 4 therefore use only Group-F features.

4. Result and Analysis

a) Empirical Quantification of the Leakage Effect

Figure 3 compares the classification accuracy obtained using leakage-free predictors against the accuracy obtained when label-derived (Group L) features are incorrectly included as predictors. The inclusion of VARK-derived variables produces artificially inflated performance far above the 30.4% majority-class baseline, confirming that apparently excellent performance in prior modelling attempts is a leakage artefact rather than a genuine predictive achievement.

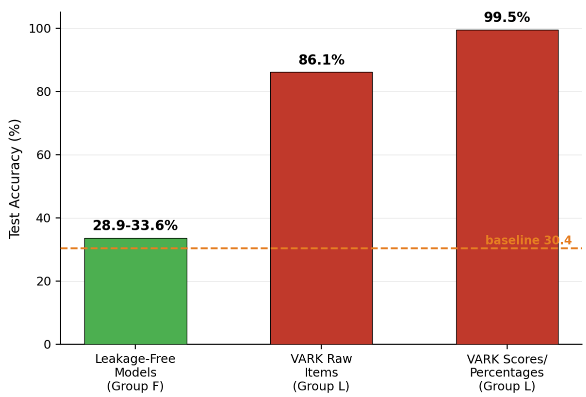

Fig. 3. Comparison of classification accuracy obtained using leakage-free predictors and label-derived features. The inclusion of VARK-derived variables produces artificially inflated performance.

TABLE IV. EXPERIMENTAL CONFIGURATION

Parameter	Value
Dataset size	4,996
Feature set	6 (leakage-free)
Train / test split	80% / 20%
Cross-validation	5-fold, stratified
Models	LR, SVM, RF, ANN

b) Leakage-Free Model Performance

TABLE V. LEAKAGE-FREE MODEL PERFORMANCE (TEST SET)

Model	Acc. (%)	F1 (%)	AUC
Majority baseline	30.4	—	—
Logistic Regression	33.6	28.0	0.599
Support Vector Machine	31.4	26.8	0.596
Random Forest	28.9	27.9	0.520
Artificial Neural Network	29.8	27.9	0.544

TABLE VI. 5-FOLD CROSS-VALIDATION ACCURACY

Model	Mean Acc. (%)	Std. Dev.
Logistic Regression	32.9	0.9%
Support Vector Machine	32.4	0.9%
Random Forest	29.3	0.8%
Artificial Neural Network	30.1	0.8%

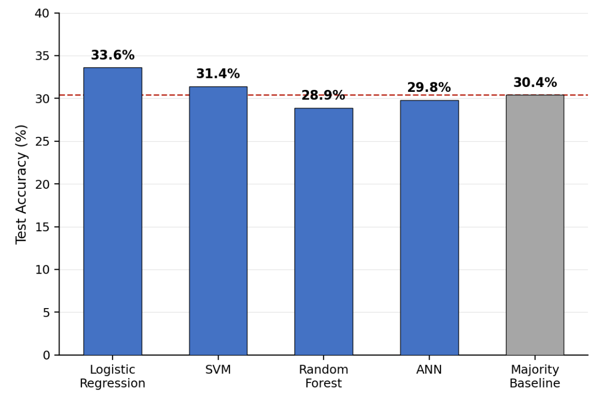

Fig. 4. Comparison of leakage-free classification accuracy for Logistic Regression, SVM, Random Forest and ANN models.

Figure 4 indicates that Logistic Regression achieved the highest classification accuracy under leakage-free conditions (33.6% test accuracy; 32.9% ± 0.9% under 5-fold cross-validation), modestly but consistently above the 30.4% majority-class baseline; its macro-averaged ROC-AUC of 0.599 indicates weak discriminative ability. The RBF-kernel SVM performed similarly (31.4% accuracy, AUC 0.596). Random Forest and the ANN did not outperform the linear baseline and showed signs of overfitting the training data relative to their cross-validated accuracy, consistent with the limited genuine signal available in six coarse demographic variables. None of the leakage-free models approach the 86–99.5% accuracy obtained when Group-L (VARK-derived) features are used, which is expected given that those features encode the label directly.

c) Confusion Matrix Analysis

For the best-performing model (Logistic Regression), the confusion matrix shows that Visual and Auditory are the two categories most often predicted overall, with Kinesthetic and Reading/Writing frequently mis-classified as one of these two — consistent with the model leaning on the marginal class distribution rather than on a strong per-student signal. This pattern, together with the low macro-F1 (28.0%) relative to accuracy, indicates that the model's modest edge over the baseline is concentrated in shifting predictions toward the more frequent classes rather than reliably discriminating all four styles.

5. Personalized Learning Recommendation Framework

Independent of the prediction-accuracy limitation identified above, the VARK category assigned to a student — whether obtained directly from the diagnostic survey or, in future work, from richer behavioural data — can be mapped to instructional strategies (Table VII). This mapping does not depend on machine-learning prediction and can be deployed today using the diagnostic survey itself; the contribution of this study is to clarify that automatically predicting the category from demographics alone is not yet reliable enough to substitute for the diagnostic survey.

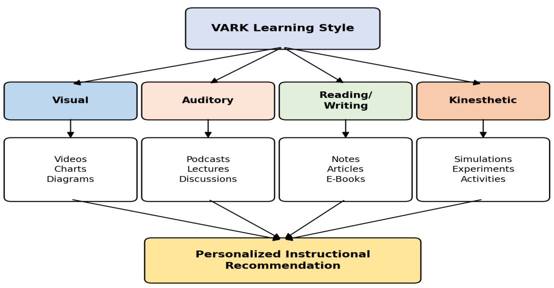

Fig. 5. Personalized learning recommendation framework mapping VARK learning styles to instructional strategies.

TABLE VII. PERSONALIZED LEARNING STRATEGIES

Style	Recommended Strategy
Visual	Videos, infographics, charts
Auditory	Discussions, podcasts, lectures
Reading/Writing	Notes, articles, e-books
Kinesthetic	Activities, simulations, experiments

6. Discussion: Key Findings and Implications

Key Finding 1 (weak demographic signal)

Demographic and contextual variables — gender, age, grade, school board, area of residence and father's education — carry only weak, near-negligible predictive power for a student's dominant VARK learning style. The best leakage-free model (Logistic Regression) reaches 33.6% test accuracy (32.9% ± 0.9% under 5-fold cross-validation) against a 30.4% majority-class baseline — an improvement of only about 2–3 percentage points. A school or institution therefore cannot reliably infer how a student learns from enrolment-record demographics alone; learning style must be measured directly (e.g., via a VARK-type diagnostic) or inferred from richer behavioural/interaction data.

Key Finding 2 (leakage explains the apparent 97–99% accuracy)

The very high accuracy produced when VARK item responses or VARK-derived scores are used as predictive features (86.1% from the 16 raw items; 99.5% from the V/A/R/K scores or percentages) is not a genuine predictive achievement. Those features are deterministic transformations of the label itself, so the model is recovering an already-known function of its own input rather than learning an independent relationship. This is a textbook case of target leakage and should not be reported as model performance.

Key Finding 2 is regarded as the more broadly useful contribution: learning-analytics studies that both elicit diagnostic responses and predict the label computed from them should explicitly audit their feature set against this failure mode before reporting accuracy.

7. Limitations and Recommendations

Limitations: the leakage-free feature set is restricted to six coarse, static demographic variables, which inherently bound the achievable predictive signal; the VARK self-report instrument itself carries known reliability limitations in the psychometric literature; and the cross-sectional survey design does not rule out residual, subtler leakage pathways.

Recommendations: future studies should incorporate behavioural and interaction data (e.g., time-on-task, platform click-streams, assessment response patterns) rather than relying on static demographics, since these may carry stronger, non-circular predictive signal. Explainable AI (XAI) techniques could clarify which demographic sub-groups, if any, drive the modest signal observed here, and a prospective study design — in which predictors are collected before the VARK survey is administered — would further guard against any residual leakage. Learning-analytics pipelines should also adopt a routine leakage audit (Fig. 2) as a standard methodological step before reporting model performance.

8. Conclusion

This research analysed a large, real-world survey of 4,996 school students to predict dominant VARK learning style. A naive feature set that included VARK item responses or derived scores produced 86–99.5% accuracy; this study shows the result is entirely attributable to target leakage, since those features are deterministic functions of the label. Re-evaluating the task with only demographic and contextual features — the genuinely available predictors — yields 28.9–33.6% accuracy, marginally above a 30.4% majority-class baseline, indicating weak association between student demographics and learning style on this dataset.

Two findings stand out: (i) demographics alone cannot reliably predict a student's learning style — the best model beats random guessing by only 2–3 percentage points; and (ii) the seemingly strong 97–99% accuracy reported by a naive pipeline is an artefact of target leakage, not evidence of a real predictive relationship. The study contributes a reproducible leakage-audit methodology, honest leakage-free baseline results, and a personalized learning-recommendation framework that remains usable independent of this modelling limitation, thereby supporting more rigorous and trustworthy learning-analytics research.

9. Data Set Sources (Primary and Secondary Data)

This study is based on a primary, multilingual (English/Hindi/Marathi) survey of 5,000 students in Grades 6–10 across CBSE, ICSE and State Board schools in India, of which 4,996 valid responses were analysed. The VARK diagnostic instrument used to derive the dominant learning-style label follows Fleming and Mills [3]. Supporting methodological references on data leakage in machine-learning-based science are drawn from Kapoor and Narayanan [2], and modelling approaches draw on standard machine-learning and educational-data-mining literature [1], [4]–[8], [14], [18]–[20]. Underlying survey microdata is retained by the authors and can be made available for verification on reasonable request, consistent with participant-privacy and institutional data-sharing norms.

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