International Conference
New Perspectives in Science Education
15th Edition

Exploring the Impact of Learning Styles on Predictive Models of Learner Achievement

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19 - 20 March 2026

Abstract.

This study examines how **learners' behavioral traits relate to academic achievement using machine learning.**

Beyond **VARK learning styles**, it analyzes broader behaviors such as **LMS interaction**, **collaboration**, and **engagement patterns** on Moodle.

Using **decision tree and random forest models**, the study **evaluate**s the predictive power of **learning preferences and behavioral data**.

Results show that learning styles alone have limited impact, while **combined behavioral factors provide stronger predictions** of academic success.

These findings **support** data-driven strategies for **personalized learning** and **curriculum improvement**.

1 Introduction

Learning styles are important but represent only **one factor** influencing **academic success**.

Student behaviour—such as time spent on tasks, content choices, collaboration patterns, and LMS engagement—also strongly **affects outcomes**.

This study **enhances** traditional **self-report learning style** measures **by combining** them **with behavioural data** from online platforms.

Using **learning analytics and machine learning** (decision trees and random forests), the research **identifies** patterns linking **learning styles**, **behaviour**, and **performance**.

The **goal** is to develop a **dynamic, predictive framework** that supports personalised and evidence-based education.

2 Related Work

Students have different **learning preferences**, commonly described by models such as **VARK** (visual, auditory, reading/writing, kinesthetic).

However, research shows that learning styles alone do not reliably predict academic achievement.

Meta-analyses indicate that matching instruction to learning styles has little consistent impact on performance. **Stronger predictors** include **time management**, **engagement**, and **goal orientation**.

Due to limitations of self-report questionnaires, recent studies use **behavioral data** and **machine learning to identify learning patterns** more accurately.

Learning styles are **dynamic** and **context-dependent**; combining behavioral analytics with ML offers a more reliable approach to predicting and supporting student success.

3 Methodology

The study was carried out at **TTK University of Applied Sciences** (TTK UAS), **Estonia**, with a group of 15 students learning **2D design using AutoCAD**. The **intensive training** was arranged within the framework of the national contract for further training from the European Union's Cohesion and Internal Security Policy program "Development of adult education and provision of non-formal learning opportunities". The **European Social Fund and the Estonian state funded** the training for the students' participation.

3.1 Data collection: learning style and behavioral indicators

Data collection involved:

- Pre- and post-course learning style surveys conducted with an optimized VARK tool enhanced using machine learning techniques.
- Demographic information included age group, education level, and language proficiency.
- Behavioral data were extracted from Moodle activity logs, detailing time spent on materials, types of learning activities utilized, and whether activities were completed individually or in groups.
- Final assessment scores, which formed the basis for categorizing academic performance.

Participant	Time	You work best			Please indicate your preferences when using the educational material in order of importance (1 is low, 5 is high)																			
		in group	alone	so - so	I prefer pictures, charts, and diagrams when learning	I remember things better when I see them written down	I use mind maps or sketches to organize my thoughts	I understand instructions better with illustrations	I enjoy using colours and symbols to highlight important points	I learn best when I hear explanations	I enjoy discussions and verbal explanations	I remember things better when I read them aloud	I prefer audiobooks over reading	I like to repeat things verbally to reinforce learning	I take detailed notes to understand new topics	I prefer textbooks over lectures	I enjoy reading and summarizing information	Writing things down helps me remember them	I like making lists and structured notes	I learn best through hands-on experience	I prefer doing physical activities over listening or reading	I enjoy building or crafting things	I understand better when I can physically interact with materials	I enjoy role-playing or acting out concepts
P1	before		1		5	4	4	4	5	4	4	3	2	3	4	3	4	2	3	5	5	5	5	4
	after		1		5	4	4	4	5	4	5	3	2	2	4	2	4	4	4	5	5	5	5	4
P2	before	1			4	4	4	5	4	5	3	2	2	4	2	4	4	4	5	5	5	5	4	2
	after		1		3	3	2	2	4	4	3	3	2	2	3	3	4	4	5	5	4	4	3	3
P3	before		1		5	5	4	5	4	2	1	3	1	2	1	1	2	2	4	5	2	4	3	1
	after			1	5	5	3	5	5	3	2	3	1	4	1	1	3	2	3	5	4	4	2	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
P15	before			1	4	4	4	4	4	4	4	4	4	4	4	3	4	4	4	4	4	4	4	4
	after	1			4	3	4	3	4	4	4	3	4	3	4	2	3	4	4	4	4	4	4	4

A machine-learning-based optimisation approach to select the most informative questions from the existing VARK and Kolb questionnaires.

3.2 Machine Learning Models

Model Development
Implemented in Python (Google Colab) using Scikit-learn
Two classifiers applied:
Decision Tree and Random Forest

Dataset & Setup
18 Likert-scale behavioural features
Binary performance label (0 = low, 1 = high)
70/30 stratified train–test

Data Preprocessing
Cleaned questionnaire data (Excel)
Converted Likert responses (1–5) to numeric
Removed incomplete responses (<10 answers)
Final dataset: 18 features + 1 binary target

Evaluation
Models trained on 70%, tested on 30%
Compared with classification metrics
An assessment of the forecasting accuracy and generalizability

Metric	Model		Definition
	Decision Tree	Random Forest	
Accuracy	66.7%	77.8%	% of total predictions that were correct
Precision	80.0%	83.3%	% of predicted high performers that were high performers
Recall	66.7%	83.3%	% of actual high performers that were correctly identified
F1 Score	72.7%	83.3%	mean of precision and recall – balances both metrics

4 Results

Model Performance

Random Forest outperformed Decision Tree across all metrics:

- Reduces overfitting
- Combines multiple trees (less noise sensitivity)
- Handles small, correlated datasets effectively

Key Findings

- Study behavior alone predicted academic success (no grades needed).
- Active, hands-on engagement was a strong predictor of high performance.
- Static styles (visual/auditory) were less predictive than behavioral traits.

Important Predictors

- Time spent on interactive tasks
- Shift toward group work
- Change to active learning input
- Multilingual profile
- Video engagement

5 Discussion

- The study demonstrated that self-reported study behavior can be used to predict academic performance using machine learning.
- Active, experience-based behavior proved to be a stronger predictor than static learning style categories.
- The random forest algorithm demonstrated the best results (77.8% accuracy; 83.3% precision and recall).
- Practical, kinesthetic behaviors (such as learning by doing, creativity, and role-playing) were significantly associated with higher academic performance.
- Passive strategies (reading, note-taking) were less effective on their own, but more significant when combined with reflective practices.
- Experience-based characteristics proved to be the primary predictor.

Limitations

- Performance label was simulated (no final grades available).
- Small dataset from a single course.
- Only behavioral variables included (future work: cognitive, motivational, social factors).

6 Conclusion

- Self-reported study behaviors—especially active, kinesthetic strategies—can predict academic achievement.
- Machine learning enabled performance prediction without prior grades or test scores, highlighting the value of behavior-based analytics.

Main Findings

- Behavioral indicators provide meaningful predictive insight.
- Random Forest performed well even with limited data.
- Active strategies (doing, creating, constructing) were strongest predictors.
- Supports a shift from fixed "learning styles" to dynamic, behavior-based profiling.

Future Directions

- Validate with larger, diverse samples.
- Conduct longitudinal studies.Include cognitive and contextual variables.
- Develop adaptive systems using real-time behavioral data.

The study promotes evidence-based, adaptive, and learner-centered education aligned with real learning behaviors.