Behavioral Clustering for Adaptive Learning: A Data-Driven Alternative to Static Learning Style Models

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Manuscript received July 9, 2025; revised August 7, 2025; accepted August 29, 2025; published January 16, 2026

***Abstract*—The existing predetermined paradigms of learning styles, including the Felder-Silverman Learning Style Model (FSLSM), VARK, Kolb's experiential learning theory, and the Honey and Mumford model, have found significant application in personalized e-learning settings. However, these models typically rely on fixed, self-reported surveys that are not validated against actual learner behavior. This research addresses this shortcoming by conducting a behavioral analysis based on engagement data within a Learning Management System (LMS), incorporating elements such as content interaction, forum participation, and assessment performance. The K-Means++ clustering algorithm was employed to cluster learners and uncover latent behavioral profiles, which were then empirically compared with conventional models of learning styles to evaluate alignment. The FSLSM exhibited the strongest level of correlation with the behaviorally derived clusters (ARI = 0.87; NMI = 0.81), suggesting that it might encapsulate some persistent behavioral tendencies. But some key differences emerged in terms of time-on-task dynamics, student interaction behavior, and patterns of stress, none of which are wrapped within the FSLSM framework. This suggests that behavioral clustering describes actionable insights beyond profiles, which are static and self-reported, and allow for adaptive interventions responding to the real-time state of the learner.**

***Keywords*—learning styles, clustering, adaptive learning, student engagement, K-Means, academic performance**

I. INTRODUCTION

Learning style theories are not new in education research since they can determine the instructional strategy an instructor can use to accommodate individual students [1, 2]. The problem of personalization according to the learning styles is even more important in the field of digital learning environments, where the direct observation is hardly possible [3]. Behavioral data can provide useful insights into engagement and content interest. These insights enable more timely and focused instructional interventions [4, 5]. Regardless of their popularity, traditional learning style models, including the VARK model, Kolb Experiential Learning Theory, and the Felder-Silverman model, have landed under criticism of insufficient empiricism and over-dependence on subjective preferences of learners [6, 7].

Besides, several empirical studies have shown mixed results in terms of the efficiency of aligning of instructional strategies with prefixed styles of learning [8, 9], and therefore doubts exist about the usefulness of such models when using e-learning systems in modern, data-rich e-learning systems. Consequently, the learning styles are being more and more thought of not as an immutable feature, but rather as a behavior-related construct [10]. This paradigm transition highlights more observable signals, e.g. learner interactions, time-on-task, resource consumption, and reaction to instruction strategies compared to self-reports [11]. Rich behavioral data on a granular level has become available due to the popularization of digital learning environments, enabling teachers to use more adaptable and responsive pedagogical practices [12].

Machine learning further improves the analysis of patterns of engagement, and it is possible to cluster learners on the basis of similar behavioral patterns and performance indicators. This data dynamics-based segmentation can be used to inform the design of personalized learning interventions that are personalized in real-time based on learners' specific profiles [13]. Even though learning styles have been widely discussed on the theoretical level, very little has been done on the empirical level with regard to behavioral validation of the learning styles theory, especially using unsupervised learning methods.

In the majority of available studies, learner profiles are considered fixed, whereas the approach is very based on subjective surveys, which often do not correlate with real learner engagement. The current paper seeks to alleviate this shortage by undertaking K-Means clustering on behavioral data of a large and heterogeneous group of learners in hopes that segments will be empirically derived and compared to the conventional learning style models. The result of this effort is a new area of unsupervised clustering and adaptive learning design providing the evidence-based approach to behavior-informed personalization in automated e-learning systems [14, 15].

A. Theoretical Positioning

This study adopts a refinement approach rather than a wholesale rejection of traditional learning style models. While behavioral clustering offers a dynamic, data-driven alternative, we recognize that established models such as FSLSM retain explanatory value for certain learner traits. Our framework, therefore, integrates behavioral profiles with selected elements of LS theory to enhance interpretability and pedagogical relevance. This integration is empirical rather than conceptual: we use FSLSM and other models as reference points to evaluate alignment, but not as fixed determinants of learning paths. In doing so, we position behavioral clustering as an evolution of LS models—preserving their pedagogical strengths while overcoming their reliance on static, self-reported measures.

B. Research Questions

1) Do K-Means clustering with behavioral data display usable profiles of learners?
2) In what ways are clustered learner types congruent to traditional learning style theories?

3) What are the appropriate adaptive strategies implied by behavior-based clusters?

II. State of Art

As the world converts to long-distance learning, it is e-learning that stands out as the medium of education in institutions [16]. This is easily accessible, expandable, and flexible, and is an acceptable alternative to classroom-based lessons [17]. Nevertheless, with the current fast development of technology, several e-learning systems fail to support all the differing needs of the learners. The students often incorrectly termed as slow learners, that is, those students who need more time, feedback modulated to their needs, and scaffolded learning, are inadequately served in the traditional online platforming [18]. Such learners are not inept; they enjoy the learning tempo and style, and that is served through self-paced feedback-rich learning environment [19].

Such systems of individual learning paths are often not supported by the traditional e-learning systems, and thus the individuals have less engagement and performance in academic disciplines [20]. As an answer, there has been the utilization of Learning Style (LS) models in educational research over time to deal more comprehensively with learner heterogeneity. Examples of such frameworks include the Experiential Learning Theory of Kolb, the VARK model (Visual, Auditory, Reading/Writing, Kinesthetic), and the Felder-Silverman Learning Style Model (FSLSM), each of which gives a more structured explanation of how people prefer to receive and process information [1, 21, 22]. Kolb laid his stress on the experiential learning processes, whereas VARK typifies examples with respect to preferred sense, and FSLSM makes use of aspects of Koncept Active-reflective and Visual-verbal [23]. These theories have, over the years, greatly impacted the design of instructions, delivery of the content, and evaluation in face-to-face and online classes [7].

The coupling of clustering methods-mostly K-Means, in behavioral profiling of educational systems is starting to bear fruit largely due to preceding studies such as Tin Tin [24], and Calderon-Valenzuela [25]. These papers validate the applicability of a data-driven segmentation of the learner as a basis for adaptive and personalized e-learning environments.

Several empirical studies demonstrate the practical value of behavioral analytics for adaptive learning. For example, Uzir *et al.* [26] showed that time-on-task and navigation sequences in LMS logs could predict course completion with over 80% accuracy. [27] successfully used clickstream data to model self-regulated learning phases, enabling personalized prompts that improved retention. Similarly, [28] integrated forum participation metrics into adaptive recommendation systems, resulting in measurable gains in learner engagement. These studies validate the feasibility and effectiveness of behavior-driven personalization strategies in real-world educational settings.

However, in the modern context of the educational literature, the LS-based interventions have been increasingly questioned in spite of their popularity. There have been several systematic reviews and well-controlled studies that have described very little empirical evidence regarding the potential of LS-aligned instruction to enhance academic outcomes [8, 9, 29]. Also, in the traditional face-to-face classrooms, the educators could change the teaching strategy instantly following the visual and verbal signals of the students. But this degree of dynamism in responsiveness is commonly wanting in online learning conditions, in which an instructor proactively communicates with extensive cohorts distantly [30]. Consequently, teachers are usually bound to specific existing instructional strategies and lose the flexibility they could use to personalize learning as initially conceived of by LS frameworks [3]. This disjuncture brings to bear a central problem in the translation of theoretical models of learning style to practice into actionable models of education in the digital environment.

Online communication also contributes to the disadvantages of Learning Style (LS) models because digital media are reverse and are inclined towards uniformity and a lack of immediate interpersonal communication [31]. As an example, kinesthetic learners might not have a large physical interaction in the virtual space, and learners with low reading skills would have difficulties in reading-based courses. As a result, e-learning environments, which use fixed LS design models, do not take into consideration the flexibility of the engagement modes of learners as well as cognitive needs [12].

Recent studies also tend to advocate the idea that learning preferences are not inherent characteristics but change over time and according to the context [7]. The way individuals process information is affected by factors like the type of task to be undertaken, the learning setting, and the topic being learnt. Unlike basing on single self-reported LS inventories, scholars recommend behavior-based modeling, which examines the interactions and engagement pattern of learners and evaluates their performance parameters to determine their learning preference [4, 5]. This world view is important especially to slow learners whose intellectual improvement can vary dynamically as the mode and the field of study create relevance [18].

To this extent, there is a move to applying the measurable and real-time behavioral measurement to promote adaptiveness in online teaching. Machine learning and educational data mining have advanced to the point where it is now possible to extract patterns of behavior within massively large datasets, and base instruction techniques around them based on data [32]. One benefit of this kind of systems is that, it is able to group learners dynamically in accordance with the immediate social interactions and outputs and can hence aid in the development of constructive, extensible and situation computing learning ecologies [5, 33].

Although there are a variety of traditional LS models used as frameworks on which digital pedagogy has been shaped such as the VARK, Kolb and FSLSM, moment-to-moment variation tends to be ignored when it comes to its application. In addition, most of these models are confirmed with self-report measures but not center on behavioral ones. Remarkably, no comparative research exists on theoretically based profiles of learners against behaviorally based ones is available. Such a disparity indicates that data-driven solutions are needed to determine the match between the relationship between LS models and real engagement patterns-especially in large-scale e-learning ecosystems.

III. Methodology

In this research, the K-Means clustering algorithm is used to perform the analysis of the behavioral engagement and academic performance data of the students to come up with different learning profiles [9]. The first one is to formulate a dynamic framework that can support individual and dynamic needs of learners, especially in an online learning context [5]. Five key steps include the methodological pipeline of data collection, data preprocessing, feature selection, clustering via K-Means++, and cluster validation based on the known evaluation criteria [30, 32]. The general workflow is shown in Fig. 1.

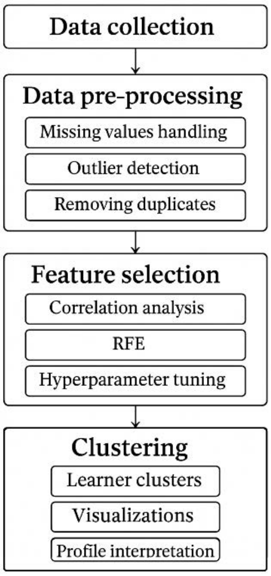

Fig. 1. Clustering pipeline and modeling framework.

Fig. 1 explains the procedure used to conduct the study. Initial data collection is performed, then comes the stage of pre-processing missing values, looking at outliers, and normalizing the data. Before performing the K-Means clustering, correlation analysis, RFE, and hyperparameter tuning are used for choosing the relevant features. Adaptive learning is recommended, and the technology gives students creative profiles and custom learning insights

A. Data Collection and Description

The information employed was based on two publicly available educational datasets sourced from Kaggle, both focusing on learning styles and digital engagement indicators [34, 35]. These datasets include variables such as student age, gender, academic level, study period, class attendance, resource usage, learning style preferences, and academic performance. Following preprocessing and integration, a consolidated dataset comprising 14,003 student records and 16 key behavioral features relevant to online learning was created [32, 33]. While detailed contextual metadata about the dataset's institutional origin or geographic background is not explicitly documented, the combined data offers a comprehensive view of learner behavior in digital education environments, providing a solid foundation for behavior-based personalized learning system development. However, the limited information on the cultural and institutional contexts of these datasets may restrict the generalizability of the findings, underscoring the need for future research involving more diverse and well-documented datasets to validate and extend these results (Table 1).

Table 1. Overview of student-related variables used for analysis

Variable	Type	Description
Age	Numeric	Student's age in years
Gender	Categorical	Gender (encoded as 1 = Male, 0 = Female)
Learning Style	Categorical	Self-reported learning style (VARK/FSLSM)
Motivation	Categorical	Motivation level (Low to Very High)
Internet	Binary	Access to internet (1 = Yes, 0 = No)
Resources	Binary	Access to learning resources
Edu-Tech	Binary	Use of educational technology
Extracurricular	Binary	Participation in extracurricular activities
Online Courses	Numeric	Number of online courses completed
Discussions	Binary	Participation in classroom discussions
Study Hours	Numeric	Average weekly study hours
Attendance	Numeric (%)	Percentage of classes attended
Assignment Completion	Numeric (%)	Percentage of assignments completed
Exam Score	Numeric	Final exam score
Stress Level	Categorical	Self-reported stress level (Low to Very High)
Final Grade	Categorical	Final academic grade (A, B, C, D)

Table 2. Encoding of categorical variables for analysis

Variable	Original Values	Encoded Values
Gender	Male / Female	1=Male, 0=Female
Learning Style	Visual, Auditory, Kinesthetic, Reading	1=Visual, 2=Auditory, etc.
Motivation	Low, Medium, High, Very High	0=Low→3=Very High
Internet, Resources, Edu-Tech, Extracurricular, Discussions	Yes / No	1=Yes, 0=No
Stress Level	Low, Medium, High, Very High	0=Low→3=Very High
Final Grade	A, B, C, D	0=A→3=D

Categorical values were encoded numerically during preprocessing. Details provided in Table 2.

B. Data Pre-Processing

Data preparation was done to ascertain the strength and efficiency of the clustering process. The missing data was imputed in terms of mean imputation in the case of numerical attributes and mode imputation in the case of categorical features, thus maintaining the completeness of the dataset but not at the risk of statistical bias [33]. The Interquartile Range (IQR) method was applied to find outliers, and thus remove them effectively, so that the clusters were more separated, and then the corresponding outcomes of segmentation were reliable [32]. Also, 32 identical records were discovered and removed to ensure the integrity of the data and avoid the biased clustering tendency.

Dichotomy data were encoded as may be needed to be processed by the K-Means algorithm. Categories (e.g., for motivation and stress levels) were mapped to integer codes, and so were aspects with a binary value (e.g., having access to the internet). Gender was coded as 1 in case of male and 0 in case of female, so that categorical variables can be used in the machine learning algorithm. Notably, all the values were encoded on a binary basis rather than ordinal, such as 1 and 2, to discourage the artificial ranking or bias of the unsupervised learning process [36].

All the numerical variables were put through Min-Max normalization, where all features became [0, 1]. It was important since K-Means uses Euclidean distance, which is easily affected by the scale of the data. Consequently, work done on homework, the number of classes, and the hours spent studying became as similar as possible, facilitating clustering.

C. Feature Selection

We improved how well the clusters were grouped by using several feature selection methods [33]. Initially, Pearson's correlation was applied to assess linear relationships among numerical variables, while Chi-square tests were used to evaluate associations between categorical features [27]. Features that exhibited high multicollinearity or contributed minimally to the clustering process were removed to reduce redundancy and noise in the data [34, 35].

To further enhance the relevance of the feature set, Recursive Feature Elimination (RFE) was employed to iteratively rank and retain the most discriminative attributes for distinguishing student clusters [36]. This was followed by a domain-specific validation phase, where the coauthors—two senior educational technologists—reviewed the remaining variables. Their selection was guided by pedagogical relevance, alignment with adaptive learning frameworks, and prior empirical associations between learning styles, stress levels, engagement indicators, and academic performance [37].

D. Clustering Algorithm

K-Means clustering algorithm was chosen to perform this experiment, taking into consideration its efficiency, scalability, and success in a range of previously reported data mining tasks in the field of education, where it is used to segment learners based on their behavioral patterns [32, 33]. Its mechanism makes use of the centroid and as a result it is highly interpretable and is imperative in developing relevant, contextual learner profiles in line with the behavior patterns and their conceived learning styles. K-Means scales to normalized and fairly high-dimensional data, and hence a good fit to the data that is going to be used in this study. However, compared to them, other algorithms like DBSCAN are sensitive to different densities, and they also face problems of global structures in clustering, and hierarchical clustering produces non-stable and non-scalable solutions when used on large datasets, as this type of clustering is computationally complex.

To increase the performance of the clustering, the K-Means++ initialization method was used, which helped to make the choice of initial centroids that was optimal as well as well distributed to increase both speed and accuracy of convergence and clustering [38].

Earlier studies published have proved that the K-Means clustering algorithm can be applied to the Learning Management System (LMS) context and thus the relevance in the current study [39]. The algorithm would recalculate cluster centroids with iterations until it has converged either by stabilizing the centroids or by reaching the maximum iterations. To find the best number of clusters, we used the Elbow Method which detects the position where extra clusters after a certain number of them would result in reduced intra-cluster variance [40]. The Silhouette coefficient was computed further to corroborate the goodness of the clustering pattern. This measure quantifies the degree of correspondence between each data point with its assigned cluster, as contrasted with adjacent, clusters and provides an idea of cluster cohesion and segregation [41]. The above validation methods were used before the downstream analysis was employed to ascertain that the generated clusters were not only meaningful but also statistically sound.

E. Technical Implementation

Python was used to run the computational process, including data manipulation, numerical analysis, clustering, and model validation, using well-established libraries such as Pandas, NumPy, and Scikit-learn [42–44]. Principal Component Analysis (PCA) was employed to reduce the feature space dimensionality and enhance the interpretability of the resulting clusters. PCA is a commonly used technique in educational data mining that enables dimensionality reduction while preserving the most significant variance in the dataset [44]. In this study, the first two principal components retained approximately 72% of the total variance, allowing a meaningful visual representation of the clustering output without major information loss. This step also improved clustering efficiency by reducing computational complexity. To determine the optimal number of clusters, the Elbow Method was applied by plotting the within-cluster sum of squares (WCSS) against different values of K. The inflection point observed at K=6 indicated the most appropriate trade-off between model complexity and performance. This selection was further supported by internal validation metrics.

IV. Results

Findings by Cluster and Analysis. This section presents the results obtained from applying the K-Means clustering algorithm to the normalized and preprocessed dataset, comprising behavioral engagement records from 14,003 students. The analysis identified six distinct learner clusters, each representing a unique behavioral engagement profile.

To ensure the robustness and interpretability of the clustering solution, several internal validation measures were employed, including inertia (within-cluster sum of squares), the Silhouette Coefficient, and the Davies-Bouldin Index (DBI) [45, 46]. Inertia was used to assess the compactness of each cluster, reflecting the tightness of data points within the same group.

The Silhouette Coefficient provided a quantitative measure of both cluster cohesion and separation, with values closer to 1.0 indicating well-defined, non-overlapping clusters. The maximum silhouette score of 0.62 was observed at K=6, suggesting a strong internal structure and clear separation between behavioral profiles. Fig. 2 illustrates the variation in silhouette scores for different values of K (ranging from 2 to

10), with a clear peak at K=6, supporting the selection of this configuration as the most stable and interpretable.

The Davies-Bouldin Index (DBI) also supported this conclusion, reaching a minimum value of 0.47 at K=6, which indicates minimal intra-cluster variance and high inter-cluster separation. This combination of a high silhouette score and a low DBI at K=6 demonstrates that the identified clusters are both internally cohesive and externally well-separated, providing a strong empirical foundation for subsequent analysis.

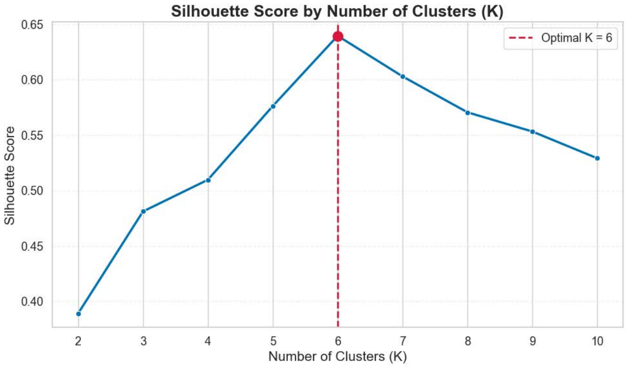

Fig. 2. Silhouette analysis for optimal cluster selection.

Silhouette coefficient as a function of the number of clusters (K) for K-Means clustering. The maximum silhouette score (0.62) at K=6 (dashed line) demonstrates strong intra-cluster cohesion and inter-cluster separation, supporting the selection of six distinct learner profiles for further analysis (see Fig. 2).

The silhouette analysis provides strong internal validation for the six-cluster solution. The clear maximum in the silhouette score, alongside supporting metrics such as the Davies-Bouldin Index, reinforces the stability and distinctiveness of the identified learner groups. These findings provide a solid empirical basis for subsequent profiling and analysis of each cluster.

A trend analysis of the silhouette score across K values (2 to 10) consistently indicated that K = 6 yields the most stable and interpretable structure. Accordingly, further analyses and interpretations in this study are based on the six-cluster solution.

A. Tools Used for Clustering Evaluation

Inertia also refers to the Within-Cluster Sum of Squares. For each data point, the Inertia Eq. (1) measures the distance from that point to its assigned cluster centroid. As compute a smaller value, the data is more tightly grouped. It can be determined by a formula as follows:

$$inertia = \sum_{i=1}^{k} \sum_{x_j \in C_i} \left\| x_j - \mu_i \right\|^2 \tag{1}$$

where:

x_j is a data point in cluster c_i

μ_i is the centroid of cluster c_i

k is the number of clusters

B. Silhouette Coefficient

The Silhouette Coefficient measures how well a data point fits within its cluster compared to other clusters. It is defined in Eq. (2) as:

$$S(i) = \frac{b(i) - a(i)}{\max\left(a(i), b(i)\right)} \tag{2}$$

where:

$a(i)$: average distance between i and all other points in the same cluster

$b(i)$: lowest average distance of i to all points in any other cluster

Values close to 1 suggest well-clustered points, while values near 0 indicate overlapping clusters.

C. Cluster Profiles

Each cluster distinctly represents a homogeneous group of students sharing closely aligned behavioral and academic characteristics, allowing targeted and highly effective pedagogical interventions.

1) Cluster 0: Strategic Self-Directed Achievers: These learners demonstrate consistently high study hours, robust class attendance, and moderate stress levels, reflecting strong self-regulation and intrinsic motivation. They embody mastery-oriented strategies and stand to benefit significantly from self-paced, enriched learning modules and access to advanced digital resources that foster deep learning.
   - Average study hours: 20.08
   - Class attendance: 80.40%
   - Resource utilization: 1.10
   - Participation in extracurriculars: 0.58
   - Participation in discussions: 0.57
   - Stress level: 1.28
   - Educational technology use: 0.73
2) Cluster 1: High-Stress Underperformers: Despite comparable study hours and attendance to top performers, this group exhibits elevated stress coupled with suboptimal academic outcomes, indicating possible cognitive overload and ineffective coping mechanisms. Tailored scaffolding, emotional support resources, and adaptive pacing are critical to mitigate stress and unlock their learning potential.
   - Average study hours: 19.74
   - Class attendance: 79.68%
   - Resource utilization: 1.10
   - Extracurriculars: 0.58
   - Discussions: 0.60
   - Stress level: 1.32
3) Cluster 2: Consistent but Plateaued Learners: Maintaining high engagement and attendance, these students experience a performance plateau, highlighting the need for interventions that develop metacognitive skills and introduce varied instructional approaches. Such strategies will be essential to stimulate continuous academic growth.
   - Study hours: 20.07
   - Highest class attendance: 80.85%
   - Resource usage: 1.10
   - Discussions: 0.62
   - Stress level: 1.34
   - Tech use: 0.69
4) Cluster 3: Intensively Engaged Achievers: Characterized by the highest study hours and moderate stress, this resilient group thrives on challenging, problem-based learning experiences and benefits greatly from peer mentoring opportunities that deepen

understanding and sustain motivation.

- Study hours: 20.43 (highest among all clusters)
- Attendance: 79.82%
- Resources: 1.08
- Discussions: 0.62
- Stress level: 1.27

5) Cluster 4: Overextended Multitaskers: These learners juggle numerous extracurricular and online commitments, resulting in the highest stress levels and the lowest study hours. Effective support through time management training, workload balancing, and flexible deadlines is vital to maintain sustainable engagement and prevent burnout.

- Study hours: 19.49 (lowest)
- Attendance: 79.99%
- Extracurriculars: 0.60
- Online course participation: 10.28
- Stress level: 1.35 (highest)

6) Cluster 5: Flexible but Inconsistent Performers: Displaying adaptable learning behaviors paired with low stress, this group's inconsistent academic performance suggests a need for adaptive learning systems offering diversified content delivery and goal-setting tools, which can help stabilize and enhance outcomes.

- Study hours: 19.89
- Attendance: 79.44%
- Resource use: 1.11 (highest)
- Stress level: 1.21 (lowest)

To enhance interpretability and practical application, each cluster label is rigorously grounded in quantitative behavioral metrics—such as study hours, attendance, and stress—and directly linked to actionable pedagogical strategies. Complementary visualizations, including heatmaps with z-scored feature means, distinctly characterize each cluster, ensuring that the categorization is both data-driven and deeply educationally meaningful.

D. Cluster–Learning Style Alignment Analysis

To quantify the correspondence between the behaviorally derived clusters and self-reported FSLSM types, we computed the Adjusted Rand Index (ARI) and Normalized Mutual Information (NMI) between the two label sets. Results showed a strong alignment (ARI = 0.87; NMI = 0.81), indicating that FSLSM categories capture many aspects of learner behavior, yet some variance remains unique to behavioral clustering. This supports the argument that behavioral clustering provides complementary insights beyond those offered by static LS models.

E. Cluster Distribution

Measurement Results in Fig. 3 clearly show that clusters are clearly divided according to the studied variables. It is possible to see in Fig. 4 that clusters have populations of different sizes and possess unique characteristics.

Here, the six student groups identified by behavior and performance are shown on a chart made from the two leading principal components. Every cluster is clearly associated with a certain color, proving that learners with similar behaviors are grouped.

Fig. 4 demonstrates how the students are spread across the six clusters and what percentage each group represents. The largest group, Cluster 5, points to a big percentage of students who have changed engagement habits and many different outcomes. The next clusters are 2 (Consistent but Plateaued Learners) and 4 (Overextended Multitaskers), where learners take part actively, but Overextended Multitaskers seem to feel more stressed and are involved in more activities outside school. There are similar numbers of students in groups 0 (Strategic Self-Directed Achievers) and 3 (Intensively Engaged Achievers), which suggests a fair share of devoted learners. Even though Cluster 1 holds the least number of students, it needs the most specific teaching strategies. Since students are divided into many different clusters, effective learning programs should be designed for each type of student, as one profile doesn't dominate.

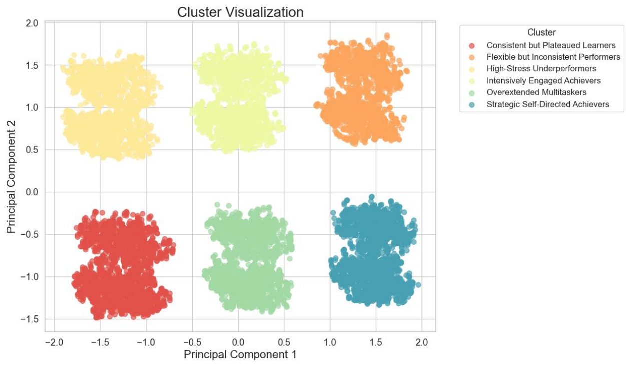

Fig. 3. Clustering results of students' behavior.

Fig. 4. Distribution of student clusters.

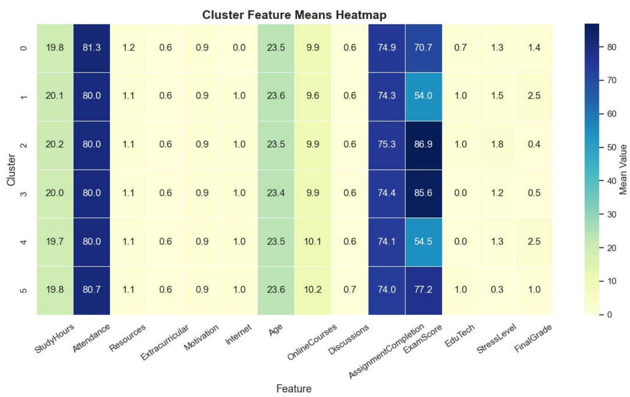

Fig. 5. Heatmap of mean feature values across learner clusters.

The heatmap in Fig. 5 provides a compact visual comparison of feature means across all clusters. Consistent high attendance rates are evident across clusters, with subtle variations in study hours and assignment completion. Clusters 2 and 3 stand out with the highest exam scores (86.9

and 85.6, respectively), aligning with their strong assignment completion rates. In contrast, Cluster 1 and Cluster 4 show comparatively lower exam scores (54.0 and 54.5) despite moderate study hours, suggesting that factors beyond time investment—such as study strategy or resource use—may influence performance. Stress levels remain generally low across clusters, although Clusters 2 and 3 report slightly higher levels, possibly reflecting greater academic effort. These patterns highlight the multidimensional nature of engagement and performance differences among learner groups.

V. Discussion

A. Cluster Learner-Profiles and Implications

The K-Means clustering was used to identify learner profiles in subgroups in terms of behavior engagement and academic performance, which is why diversified pedagogical approaches should be used.

Cluster 0 was a high-achieving and low stress group of learners showing a high preference towards structured and self-directors learning environment. These students were extremely independent and in line in their performance, thus making them to be appropriate when offered advanced self-paced learning modules and enriched digital materials. Their description coincides with previous studies of personalized learning scenery that is focused on independent learners [47].

Cluster 1, in its turn, represented learners with regular attendance and efforts, and low academic performance but high-level stress. It is possible that such a group needs a two-pronged strategy, including a better instructional design and emotional and mental health management. Both their cognitive and well-being levels may improve through formative feedback loops, stress-counseled pacing, and scaffolded learning tasks [48].

Clusters 2 and 3 revealed students with high attendance and extended study time, yet only moderate academic success. These learners showed signs of motivation, but inefficiencies in learning strategies and stress management were evident. Implication and Discussion

Individual measures on metacognitive skills development and time management assistance could be especially useful to Cluster 4, the Overextended Multitaskers, who also registered the highest level of stress. Such learners are also prone to having a cognitive overload caused by multitasking demands in scholarly and extra-scholarly spheres. In order to help address their requirements, flexible content delivery mechanisms and stress-sensitive pacing strategies that are designed to improve academic resilience should be included in adaptive learning systems [49, 50].

Cluster five, or Flexible but Inconsistent Performers, as they can be called, showed a reduced level of stress and flexible attitude but had irregular academic performances. Their dynamics of interaction imply that they prefer new experiences and content in various forms. The group is more likely to respond to adaptive platforms that automatically change the mode of delivery according to behavioral inputs and can work in line with their diverse preferences [51].

These behavioral findings also stress the necessity to base personalized learning system information on empirical data of engagement or rather than on static theories of Learning Style (LS). Several clusters identified similar needs of longer duration of tasks, decreased cognitive load, and non-standardized pace, frequent aspects of traditional LS modelling. This illustrates the possibility of behavioral clustering that can be used in informing the feedback loops and adaptivity in real-time in intelligent tutoring systems [37, 52]. Behavioral segmentation, unlike self-reported surveys, can be freely personalized in real time according to the context and is not subject to bias and outdated assumptions.

While the high ARI/NMI scores might suggest strong equivalence between FSLSM and behavioral clustering, this interpretation is misleading. The overlap largely reflects stable cognitive-orientation traits (e.g., preference for visual vs. verbal information), but our behavioral model incorporates temporal, contextual, and affective indicators that FSLSM omits. This allows for real-time adaptation when learner behavior deviates from their nominal style — a flexibility critical for modern LMS-based environments.

B. Practical Implementation Framework

In an operational adaptive learning system, behavioral clustering can be implemented through real-time learner dashboards updated on a weekly basis. Intervention triggers may include: (1) deviation from typical cluster behavioral patterns by more than one standard deviation, (2) sustained high stress levels for two consecutive weeks, and (3) declining assessment performance despite high engagement. Instructors can receive automated recommendations—such as assigning targeted practice modules, initiating one-on-one check-ins, or adjusting pacing parameters—based on the learner's current cluster assignment. This cycle of continuous monitoring, clustering, and intervention ensures that personalization remains responsive to evolving learner needs.

C. Ethical and Practical Considerations

Segmenting students by behavioral profiles carries potential risks related to profiling bias, misclassification, and reduced learner agency. Instructors and system designers must ensure data privacy, implement fairness checks in clustering algorithms, and maintain human oversight in adaptive interventions. Policies should be in place to allow learners to contest or adapt their assigned profiles. Furthermore, the use of unsupervised clustering for pedagogical decision-making must remain transparent and accountable. Learners' profiles should not rigidly determine learning paths, and systems must remain adaptable to evolving learner behaviors and preferences.

D. Restrictions and Future Work

Despite the encouraging results, this study presents notable limitations. The use of open-source datasets may constrain the generalizability of findings, as they lack cultural and institutional diversity. Additionally, certain key features—such as motivation and stress—were self-reported, introducing potential response biases. While internal validation metrics (inertia, Silhouette Coefficient, DBI) support the structural robustness of the clustering, they do not directly assess pedagogical impact. Future research should incorporate diverse, real-world datasets and pursue external validation using concrete learning outcomes. Moreover, considering the dynamic nature of learner behavior, subsequent adaptive models should be capable of evolving over time while ensuring fairness, transparency, and ethical integrity in personalized interventions.

VI. Conclusion

This study employed unsupervised clustering of behavioral data to generate adaptive learner profiles within online educational environments. By applying the K-Means clustering algorithm to a large dataset of student interactions, six distinct learner types were identified—including Strategic Self-Directed Achievers, Overextended Multitaskers, and Struggling Learners. These profiles revealed nuanced insights into how students engage with digital platforms and highlighted the varying forms of support they require. Traditional learning style models, though historically influential, are increasingly critiqued for relying on self-reported preferences that lack stability and context-awareness. In contrast, the behavioral approach adopted in this study captures real-time engagement and facilitates dynamic personalization, making it especially effective for underserved populations such as cognitively overloaded or slower-paced learners.

K-Means clustering, when applied to educational data mining, offers substantial promise for the development of Intelligent Tutoring Systems (ITS) and adaptive learning environments. The study underlines that effective results depend on meticulous data preprocessing, careful feature engineering, and hyperparameter optimization, which collectively ensure that clustering outcomes are both interpretable and actionable. The implications for educational institutions and system designers are profound: interventions can be crafted to align with the needs of each learner profile. For instance, wellness-oriented modules may benefit high-stress students, while learners with high activity but inconsistent focus may thrive under scaffolded content with clearly defined progression paths.

Furthermore, the potential for real-time personalization is underscored through the idea of dynamically updated learner dashboards—tools that can adapt learner profiles as new behavioral data becomes available. Future research may enrich these models by incorporating psychological constructs such as grit, resilience, and self-regulation, and by examining how learner profiles evolve longitudinally. Comparing cluster assignments across diverse educational contexts could also reveal systemic factors that influence learner behavior and outcomes.

Overall, this study contributes significantly to the field of learning analytics by demonstrating that unsupervised machine learning can uncover latent learner typologies. These findings not only strengthen theoretical frameworks in online learning but also provide a practical foundation for scalable, personalized educational technologies. As the demand for inclusive and flexible digital education continues to grow, behavioral clustering offers a path forward for achieving equity and effectiveness in adaptive learning systems.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

The first author collected the data and conducted the study; the second author developed the methodology and assisted with the analysis; the third author reviewed the manuscript and interpreted the results; all authors approved the final version.

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