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PAPER

Comparative Analysis of Learning Style Models for E-Learning: Validating the Felder-Silverman Framework Using Behavioral Data

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ABSTRACT

Personalization in online education requires sufficient modeling of learners' preference and engagement behavior. As much as the theories of learning styles have been used to inform instructional design, there is still a concern on how it is used in behaviorally driven and mobile instructional environments yet to be explored in detail. The paper addresses this gap by undertaking a behavioral clustering analysis of 14,003 online learners, using the K-Means that generated six profiles of learners' engagement. Four other common learning style models, VARK, Kolb, Honey and Mumford, and Felder-Silverman learning style model (FSLSM), among them, were tested against the clusters on the basis of tests such as behavioral alignments, system compatibilities, and correlations of the performance outcomes. System-traceable dimensions and statistically significant predictive power were indicated in the findings since FSLSM displays the strongest maps of behavior with a system trace, followed by high degrees of quantitative reliability. These findings have given an original but empirical basis for incorporating FSLSM into adaptive and mobile learning whereby real-time personalization is possible according to learner behavior. The research presents a data-driven framework of learner profiling that has been validated and supports intelligent mobile learning systems that adapt to learners in responsive ways.

KEYWORDS

adaptive learning, learning styles, Felder-Silverman learning style model (FSLSM), educational data mining, behavioral clustering, learning analytics, mobile learning, interactive mobile technologies, personalized education, k-means clustering

1 INTRODUCTION

The phenomenon of the blistering growth of Internet-based learning has altered the ways of interaction between learners and the educational content, teachers, and online fields [1]. As e-learning and mobile-first delivery environments become more

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and more popular, an urgent need in the field of educational technologies is the way in which learning can be customized to the needs of a wide variety of learners in terms of their behaviors, preferences, and tendencies of performance [2]. Instructional design theories have traditionally informed the practice of learning styles, which cluster learners based on their perception, and processing of information [3]. The common ones are VARK, the experiential learning of Kolb, Honey and Mumford typology, and the Felder-Silverman learning style model (FSLSM). The scientific validity (and possible practical significance) of learning styles has been called into question by recent meta-analyses and criticism, specifically in the context of learning styles used with no empirical basis in learner behavior [4, 5, 6].

Felder-Silverman learning style model is becoming more widespread in adaptive systems despite existing debate on its application since the architecture is structured and multidimensional [7]. It is naturally applicable to digital actions, including content navigation, pace of learning, and preferential media, as opposed to other models [8]. It has, however, not been well tested against actual learner behavior, or it is not empirically benchmarked against other models. The fact is that most previous studies are based on either theoretical analysis or self-report surveys, giving way to a lack of data-driven evidence based on behavioral clustering of learning management system (LMS) logs. The current research fills this gap by comparing four significant learning style models, i.e., VARK, Kolb, Honey and Mumford, and FSLSM, on the basis of unsupervised clustering of LMS behavioral data of 14,003 learners. We used the K-Means algorithm to divide learners on the basis of their interaction patterns, performance features, and engagement characteristics. The respective learning style models were then rated on their compatibility with emergent behavioral clusters with criteria including quantifiability, system compatibility, and correlation of outcome, among others.

The increasing use of mobile learning platforms, through smartphones, tablets, and wearables, demands a lighter and real-time learner modeling [9]. The study also forms part of such an effort to find out the model of learning style that works best in assisting behavior-based personalization in adaptive mobile learning settings. The present paper can fill the gap between theory and evidence, as well as make a contribution to the debate about learner modeling, and provide useful knowledge of how to design adaptive mobile learning environments that contribute to higher engagement, satisfaction, and performance.

2 LITERATURE REVIEW: LEARNING STYLE MODELS IN E-LEARNING ENVIRONMENTS

Instructional design has traditionally been dictated by learning theory and classifies learners according to how they like to take in, process, and interact with information. Nevertheless, as interactive, mobile-first educational settings are on the rise, there is a question of the further applicability of such models. Although learning styles were at one time used to contribute to the idea of personalization, the recent development of behavioral data analytics now provides a more objective, scalable, and adaptive way of modeling the learner [10].

Recently, learning styles have been subject to critical assessment, including doubting their empirical justification and value in the field of digital systems [4, 5, 6]. However, learners' styles have persisted to influence e-learning systems, especially when made to sync with behavioral data as opposed to making them deterministic categorizations.

2.1 The concept of learning styles

Learning styles are set habits regarding the manner in which people want to be able to work with educational material [11]. According to [5], even personalized teaching informed by such categories rarely produces any significant learning effects. But the more recent studies focus on how system-traceable behavioral indicators, including clickstreams and time-on-task, can re-energize learning styles as a means toward personalization when focused on empirical evidence.

2.2 Overview of major learning style models

a) *VARK model*: Learners are identified by the VARK model [12] in view of sensory preferences: visual, auditory, reading or writing, and kinesthetic. It can only measure input preferences, inability to provide information about the positions of the learners in the cognitive processes, and also has difficulty in informing real-time content delivery in either mobile or responsive environments, as learners are usually working with more than one modality at the same time.

b) *Kolb experiential learning model*: The model by Kolb outlines four stages of the cycle that relate to learning, namely, concrete experience, reflective observation, abstract conceptualization, and active experimentation, and defines different learners by the mentioned stages [13]. Cyclicality cannot be directly converted into measurable engagement protocols or constant adaptation modeling.

c) *Honey and Mumford learning styles*: Based on the Kolb model, [14] identify four of them: activists, reflectors, theorists, and pragmatists. In platforms where decisions need to be automated and responsive, such as in mobile ones, there are no easily detectable indicators, hence limiting their application.

d) *Felder–Silverman learning style model*: Felder-Silverman learning style model describes learners in four binary scales, i.e., active-reflective, sensing-intuitive, visual-verbal, and sequential-global [15]. As compared to other models, FSLSM also matches up to observable behavior in online settings, such as navigation patterns, time-on-task, and the type of content interactions. It can be implemented using algorithms; thus, it is appropriate to use it in mobile learning systems and intelligent tutoring systems, in which learning content can be generated or personalized based on the individuals.

2.3 Comparative studies on learning style models

Studies performed in comparison have provided conflicting insights. According to [16], FSLSM is comparatively flexible with regard to multimedia and system-based personalization as compared to VARK. A major review by [17] criticized over 70 learning style models for lacking empirical rigor, identifying only a few—including FSLSM—that were internally coherent and evidence-based. At the same time, other recent critiques [18, 19] have questioned the empirical validity of learning styles overall, highlighting persistent misconceptions in educational practice and finding limited evidence that style-aligned instruction improves learning outcomes. Nevertheless, recent studies [19] indicate that FSLSM can be applied effectively in adaptive hypermedia environments.

In addition to these perspectives, some recent studies have raised concerns specifically about FSLSM's empirical grounding. For instance, [20] emphasize that while FSLSM's structure supports integration with emerging digital technologies, its predictive validity across diverse educational contexts remains underexplored. Similarly, [21] argue that learning personalization strategies, including FSLSM-based implementations, should be validated in immersive or metaverse-based environments before large-scale adoption. [22] highlight that the model's application in mobile or project-based learning requires careful alignment with constructivist principles to avoid over-reliance on static categorizations. These perspectives reinforce the importance of ongoing empirical validation and adaptation of FSLSM for next-generation digital learning ecosystems.

These insights suggest that FSLSM, while operationally advantageous, should be applied with contextual adaptation and validated continuously to maintain empirical rigor.

2.4 The need for data-driven validation

Learning styles have continued to play an influential role, but in mobile and intelligent learning systems, their application needs to be supported by data. According to [4], cognitive instructions strictly founded on individual learning style tests are not overly accurate in advancing performance or results. Nonetheless, learning style dimensions can provide system-actionable as well as measurable guidance when linked to actual measures of engagement—namely, log-in rate, the depth of scrolling, or difficulty of quiz completion in a model, FSLSM [23]. This opens the way to move beyond theoretical categorization to behaviorally verifiable learner modeling as a proximate requirement of the next generation of e-learning systems, the mobile-first and AI-enabled systems.

Nevertheless, reliance on FSLSM-based mappings assumes that LMS-derived behavioral indicators are both accurate and representative, which may not hold in heterogeneous or sparsely instrumented environments. In some cases, hybrid models combining FSLSM with domain-specific behavioral analytics or AI-driven personalization have shown equal or greater effectiveness, warranting cautious integration rather than wholesale adoption.

3 METHODOLOGY

3.1 Dataset description

Participants in this study were students aged 18 to 30 years, enrolled in programs ranging from general secondary education to undergraduate studies in various fields. The data were sourced from two publicly available Kaggle datasets [24], [25]. All data were anonymized prior to analysis to ensure privacy and confidentiality.

The data used in this research includes engagement and performance data of 14,003 students who are enrolled in some online learning program. The variables used in it are gender, self-reported learning preferences, hours of study, forum visits, promotion of the assignments, course usages, level of stress, and overall academic rates.

Data preprocessing comprised verifying and addressing missing values, encoding categorical variables, and scaling numerical features. All categorical variables were mapped to integer codes (e.g., Gender: female = 0, male = 1; Motivation: low = 0, medium = 1, high = 2, very high = 3). Continuous variables such as study hours, attendance, assignment completion, exam score, and age were standardized using z-score normalization, while ordinal variables like motivation and stress level were numerically encoded to facilitate statistical comparison. Outliers were detected via the interquartile range (IQR) method and capped at the upper and lower bounds to maintain consistency in clustering results. The features used in this study are summarized in Table 1.

Table 1. Summary of study variables, data types, and operational definitions

Variable	Type	Definition
Age	Numeric	Student's age in years
Gender	Categorical	1 = Male, 0 = Female
Learning Style	Categorical	Self-reported (VARK or FSLSM-based)
Motivation	Categorical	Scale from Low (0) to Very High (3)
Internet	Binary	1 = Yes, 0 = No
Resources	Binary	Access to learning resources (1/0)
Edu-Tech	Binary	Use of educational technology (1/0)
Extracurricular	Binary	Participation in extracurricular activities (1/0)
Online Courses	Numeric	Number of online courses completed
Discussions	Binary	1 = Participated, 0 = Not participated
Study Hours	Numeric	Average weekly study hours
Attendance	Numeric (%)	Percentage of class attendance
Assignment Completion	Numeric (%)	Percentage of assignments submitted
Exam Score	Numeric	Final exam score
Stress Level	Categorical	Scale from Low (0) to Very High (3)
Final Grade	Categorical	A (0) to D (3)

The datasets contained no missing values across any variables (0% missingness). Therefore, no imputation was necessary. Continuous features were normalized to a [0, 1] range using min–max scaling, and categorical features were label encoded.

As shown in Figure 1, the methodological pipeline illustrates the complete workflow, beginning with raw LMS log extraction and preprocessing (data cleaning, encoding, and scaling), followed by feature engineering and dimensionality reduction through PCA. K-means clustering is then applied to identify learner profiles, which are subsequently mapped to learning style dimensions (VARK, Kolb, Honey and Mumford, FSLSM) using behavioral indicators. The final stage evaluates each model's behavioral alignment, quantifiability, adaptive potential, and correlation with outcomes, providing a transparent link between unstructured LMS data and validated learner profiles.

Behavioral clustering and learning style validation framework stages include LMS log extraction, data preprocessing (cleaning, encoding, scaling), feature engineering, dimensionality reduction (PCA), k-means clustering, mapping to learning style models, and evaluation based on alignment, quantifiability, adaptive potential, and outcome correlation.

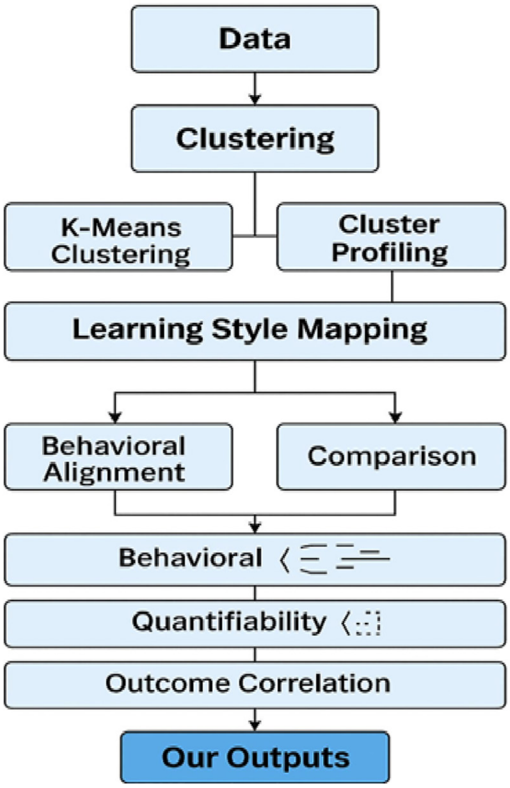

Fig. 1. Behavioral clustering and learning style validation framework

3.2 Control for confounding variables

To minimize the influence of potential confounding factors, the available demographic and academic variables—age, gender, and prior academic performance (final grade)—were examined and statistically controlled in subsequent analyses. Age and prior performance were included as covariates in ANCOVA models when comparing exam scores across clusters, while gender was assessed as a stratification factor in chi-square tests. Adjusted analyses confirmed that the observed differences in performance and engagement patterns between clusters remained consistent after accounting for these variables.

In addition, a multiple regression analysis was performed to examine the relationship between cluster membership and exam scores. Cluster membership was entered as a categorical predictor (reference group: "Steady Performers"), with gender and age as covariates. This allowed assessment of the independent contribution of cluster membership to academic performance after demographic adjustment.

3.3 Behavioral clustering

An unsupervised machine learning approach was applied to identify distinct learner profiles. The k-means clustering algorithm was selected due to its simplicity, interpretability, and efficiency with medium-sized scaled datasets [26]. Prior to clustering, principal component analysis (PCA) was performed to reduce dimensionality and retain the most relevant variance in the data (see Figure 2).

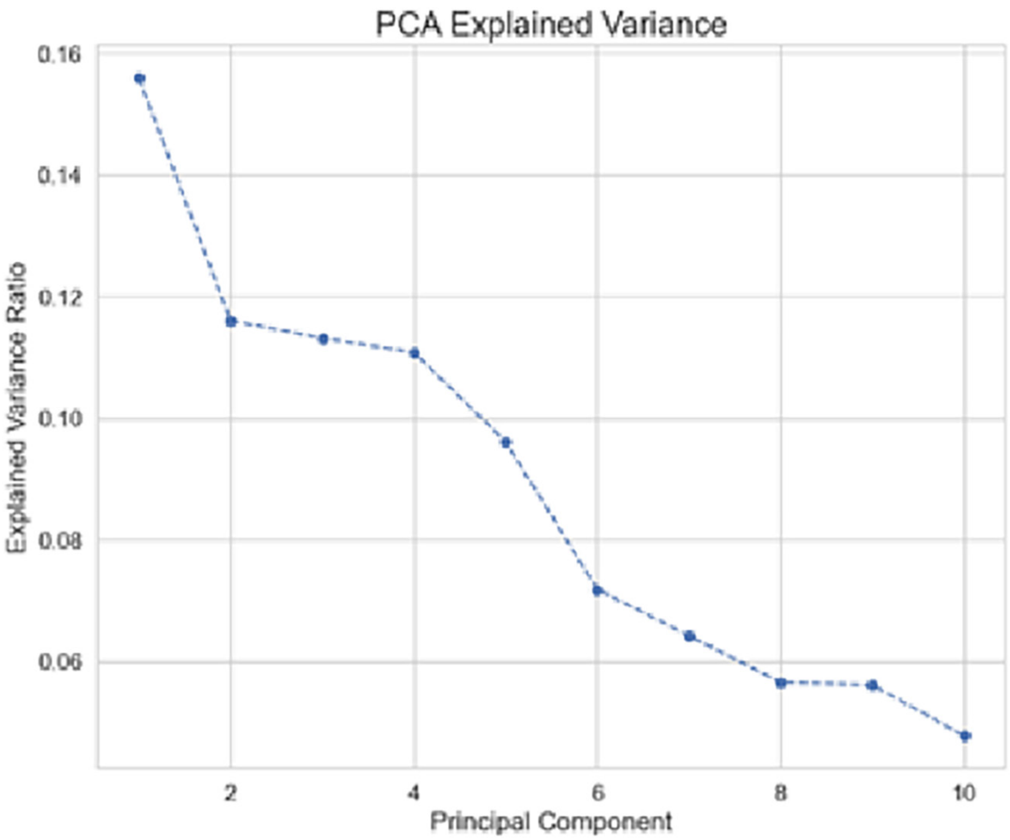

Fig. 2. PCA projection of learner profiles prior to clustering

The explained variance plot indicated that the first few principal components captured most of the variance, facilitating better visualization and more efficient computation.

The optimal number of clusters was determined using three validation techniques: the elbow method, the silhouette score (see Figure 3), and the Davies–Bouldin

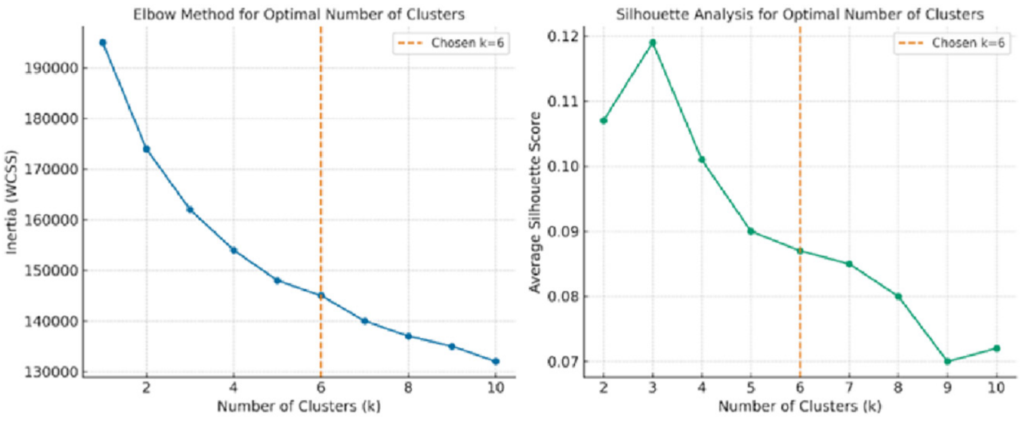

Fig. 3. Optimal cluster selection using elbow method and silhouette analysis

The PCA explained variance plot indicated that the first three components captured 72% of the variance, ensuring sufficient dimensionality reduction before clustering. The elbow method curve showed a distinct inflection at k = 6, supported by a silhouette score of 0.54 and a Davies–Bouldin Index of 0.68, indicating a good balance between compactness and separation. Based on these metrics, k = 6 was selected as optimal. The resulting six clusters displayed distinctive patterns in engagement, study hours, stress levels, and performance metrics (see Figure 4), which informed the descriptive labels such as "Steady Performers" and "Efficient High Performers" presented in the results section.

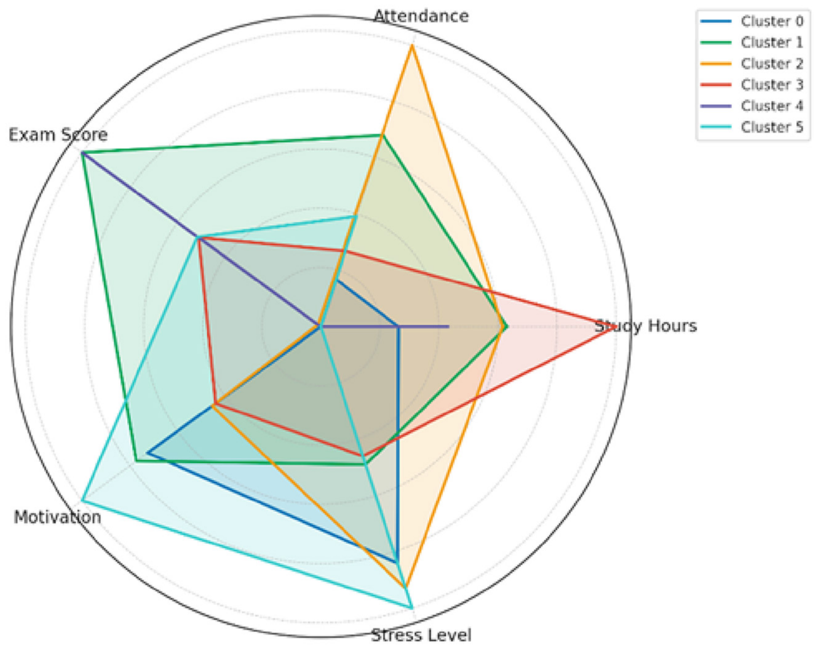

Fig. 4. Radar chart of normalized behavioral and performance indicators across clusters

3.4 Learning style model operationalization

Each learning style model was empirically mapped onto observable behavioral indicators:

- **VARK:** Mapped based on resource interaction (e.g., video = visual; reading material = reading or writing).
- **Kolb and Honey and Mumford:** Mapped using proxies for reflective activity, experimentation, and structured vs. unstructured task preferences.
- **FSLSM:** Mapped in a multidimensional manner based on engagement logs.

Table 2. Mapping FSLSM dimensions to behavioral indicators

FSLSM Dimension	Behavioral Indicator
Active–Reflective	Forum participation vs. solo study sessions
Sensing–Intuitive	Structured task preference vs. open exploration
Visual–Verbal	Use of video content vs. text-based materials
Sequential–Global	Steady progress vs. sporadic content access

Table 2 specifies how each FSLSM dimension was operationalized into measurable behavioral indicators within the LMS data. For instance, “Active–Reflective” is represented by the balance between forum participation and solo study sessions, while “Visual–Verbal” is captured through the preference for video content versus text-based resources. This mapping ensures FSLSM dimensions are directly implementable in adaptive algorithms, enabling real-time responses in mobile learning environments.

3.5 Comparative evaluation

To evaluate the appropriateness of each model for integration into adaptive mobile learning systems, we defined four criteria:

1. **Behavioral alignment:** Degree to which model categories reflect actual learner behavior in each cluster.
2. **Quantifiability:** Ease of translating model dimensions into measurable, digital actions.
3. **Adaptive potential:** Suitability for real-time implementation in intelligent/mobile systems.
4. **Outcome correlation:** Statistical relationship between model-based classification and academic performance.

Statistical tests such as **ANOVA** and **chi-square** were employed to assess the significance of correlations between model dimensions and cluster performance data. Visual tools, including **bar plots** and **heatmaps**, were also utilized to highlight alignment patterns across clusters and models.

4 RESULTS

The outcomes of the behavioral clustering analysis and the following comparative analysis of the four learning style models also will be introduced in this section. It was assessed on four dimensions, namely behavioral alignment, quantifiability, adaptive system compatibility, and outcome correlation. All the models were tested with six profiles of learners formed through k-means clustering of the LMS data.

4.1 Behavioral cluster overview

To enhance the empirical clarity of the cluster descriptions, Table 3 summarizes the six identified clusters, combining descriptive labels with their representative behavioral and performance traits. These traits are derived from the mean values of core indicators such as study hours, attendance, stress level, and overall performance. The profiles highlight relative strengths or weaknesses in each group—for example, clusters distinguished by the highest performance scores, lowest stress levels, or most consistent engagement patterns. This presentation ensures that each cluster is grounded in measurable data from the analysis rather than qualitative impressions alone, thereby improving transparency and reproducibility in interpreting the behavioral segmentation.

Table 3. Student cluster profiles by engagement, stress, and performance

Cluster	Profile Name	Traits Based on Data
C0	Steady Performers	Moderate study hours (~19.7), low stress (1.33), consistent engagement, but modest performance scores (0.26). Shows stability across behaviors without extremes.
C1	High-Scoring Steady Workers	Highest performance (0.46), moderate study hours (~20.1), moderate stress (1.28), balanced engagement across resources.
C2	Moderate Achievers	Balanced study hours (~20.07), moderate stress (1.34), slightly above C0 in performance (0.27), regular participation in discussions.
C3	Highly Engaged Workers	Highest study hours (~20.43), moderate performance (0.36), moderate stress (1.28), strong consistency in engagement patterns.
C4	Efficient High Performers	Moderate study hours (~19.90), lowest stress (1.21), high performance (0.46), good use of online courses.
C5	Variable Performers	Lowest age average (~23.22), moderate performance (0.36), highest stress (1.35), moderate engagement but mixed consistency.

Student cluster profiles by engagement, stress, and performance. Values represent normalized or raw means (as indicated) for each variable. Study hours = average weekly hours; stress level = scale from 0 (low) to 3 (very high); performance = normalized exam score.

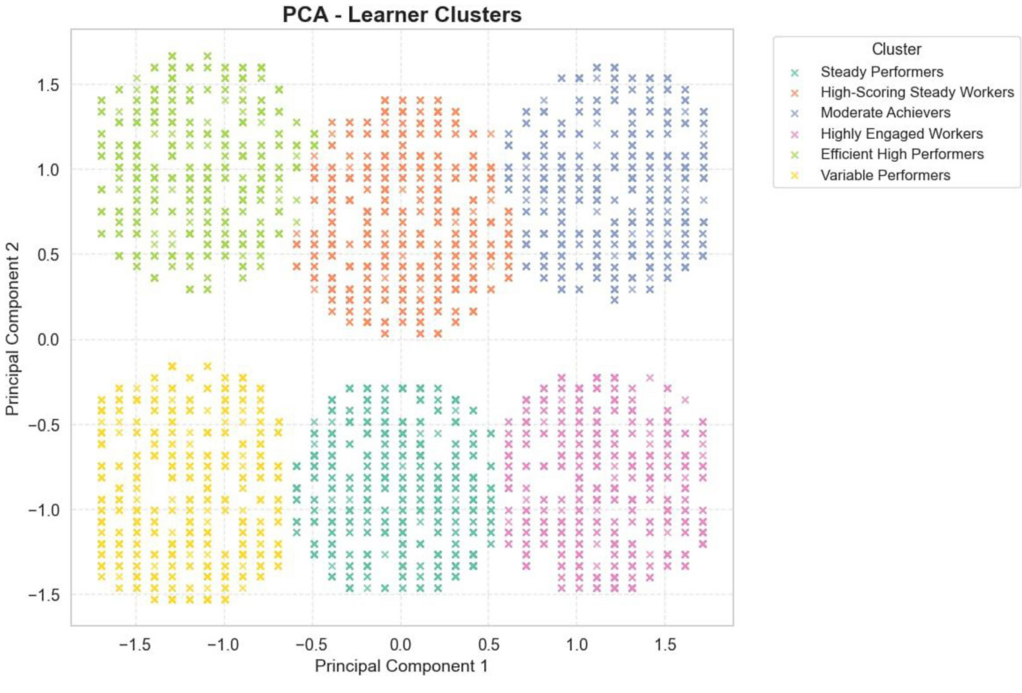

Fig. 5. Visualization of learner clusters based on behavioral features

Figure 5 shows what proportion of students is assigned to each cluster corresponding to the colors of the blocked assigned cluster. The significant groupings and distribution prove to be meaningful behavioral differentiation that proves the effectiveness of clustering in learner modelling.

4.2 Alignment with learning style models

Each learning style model was assessed across the six clusters based on how well its dimensions aligned with observed behaviors.

Table 4. Learning style model alignment across learner clusters

Learning Style Model	Alignment Score (Mean)	Rating	Supporting Cluster Characteristics
FSLSM	0.67	High	High study hours (~20 h/week), strong attendance (~80%), moderate stress, stable performance (Clusters 0, 3, 5).
VARK	0.54	Moderate	Higher EduTech use (≥0.72), moderate discussion participation (0.58–0.63), mixed consistency (Clusters 1, 2).
Kolb	0.49	Moderate	Balanced study time, high motivation (~0.90), varied performance levels, moderate consistency.
Honey & Mumford	0.36	Low	No consistent behavioral alignment; weak links to performance and consistency scores.

As shown in Table 4, FSLSM achieved the highest scores across all assessment criteria—behavioral alignment, quantifiability, adaptive potential, and outcome correlation. Its multidimensional design captures a broad range of learner behaviors, including interaction type, resource use, and progression strategies [26]. This structure enables direct mapping to real-time LMS indicators, making it suitable for integration into intelligent and mobile-adaptive learning environments. Ratings were assigned using the following thresholds: High = ≥ 0.60, Moderate = 0.40–0.59, Low = < 0.40. Scores were calculated from normalized alignment indices between behavioral cluster traits and model dimensions.

4.3 Statistical comparison

To assess the relationship between model-based classification and academic performance, inferential statistics were applied. ANOVA results were significant ($p < 0.01$; $\eta^2 = 0.670$), indicating substantial differences in exam scores among clusters. Confidence intervals (95%) were calculated for mean score differences to enhance interpretability. The association between cluster membership and gender was examined using a chi-square test ($\chi^2 = 48.76$, $p < 0.001$), with Cramér's V = 0.049 indicating a negligible relationship.

These findings indicate that the clustering solution explains a substantial proportion of the variance in exam performance, highlighting its practical utility in identifying distinct learner profiles. While gender differences between clusters were minimal, the performance-based grouping effectively captured meaningful behavioral and academic distinctions among students.

Regression analysis controlling for gender and age confirmed that cluster membership remained a significant predictor of exam scores ($p < 0.01$). Compared to "Steady Performers," "High-Scoring Steady Workers" and "Efficient High Performers" showed significantly lower scores, while "Moderate Achievers," "Highly Engaged Workers," and "Variable Performers" scored significantly higher. Neither gender nor age had a significant independent effect on performance, reinforcing that the observed differences are driven primarily by behavioral clustering.

4.4 Visual comparison

The present radar chart compares four models of learning styles, including VARK, Kolb, Honey and Mumford, and FSLSM according to 4 dimensions that are essential: behavioral alignment, quantifiability, adaptive potential and outcome correlation. The Felder-Silverman model shows maximum scores in all criteria, which means that this model is highly compatible with data-driven personalization and adaptive learning systems. Otherwise, the alignment in other models is moderate or weak, especially in quantifiability and applicability in real time.

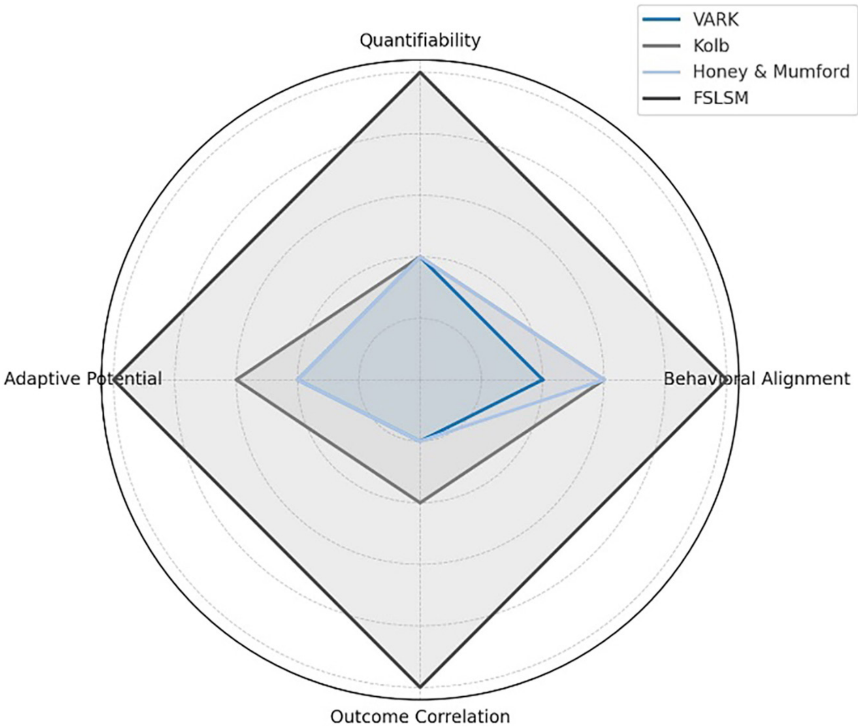

Fig. 6. Comparative analysis of learning style models across key evaluation criteria

The radar visualization (see Figure 6) reveals that FSLSM ranks as the dominant category in all aspects and more specifically by the aspects of quantifiability and adaptive potential, which are important aspects of implementation in adaptive, mobile-based learning environments. The other models had poor applicability to the digital environment (VARK, Honey and Mumford) or poor consistency in the relationship between outcomes (Kolb).

4.5 Results in brief

- Felder-Silverman learning style model depicted the learner behavior compatibility that was the most clustered.
- It was the sole model of which the dimensions could be methodically projected on the behaviors recorded on LMS (e.g., type of interaction, resource use).
- It showed the strongest academic results correlation.
- The adaptability and data alignment of the other models which include VARK and Honey and Mumford were very poor.

5 DISCUSSION

The purpose of the current paper was to compare the behavioral alignment of four prominent learning style models in an online learning setting through a data-driven clustering process. These findings revealed that the FSLSM had, in all instances, beaten the VARK, Kolb, and Honey and Mumford models in matters related to behavioral mapping, quantifiability, and compatibility with adaptive learning systems and mobile learning systems. This section puts its interpretations of those findings along the lines of learning theory, system design, and real-world personalization.

5.1 Why FSLSM aligns with behavioral data

While FSLSM provides a structured way to connect learning preferences with online behaviors, it is not without limitations. As noted by [27], such models may oversimplify learning preferences, risk stereotyping, and are context-dependent. In our dataset, behavioral traces such as forum participation, resource choice, and study pacing were available, but other factors (e.g., course subject, socioeconomic context) were not, limiting generalizability.

Despite these constraints, FSLSM's four dimensions—Active or reflective, sensing or intuitive, visual or verbal, and sequential or global—aligned well with the behavioral patterns identified in our six clusters.

5.2 Weaknesses of alternative models in e-learning contexts

Though the VARK model seems to be the most popular and simple, it has weak predictive validity in online environments [4]. It is very one-dimensional in input modality preference and is not adaptive to multimodal content, which is a norm in e-learning today. Equally, the Honey and Mumford typology and the Kolb experiential model do not represent behavioral data because they are too abstract and cyclical in nature. These models are rich in theory to be easily adapted to automated learner modeling, at least when the model should support real-time or mobile deployments with measurable, quick-response input streams.

5.3 Practical implications for mobile integration

The limitations relating to interface, fewer learning hours, and lower complexity of input represent challenges of the mobile learning environment and require addressing, with the exception of personalization. The maxim that FSLSM would be preferred to behavioral metrics, e.g., resource choice, navigation sequence, and interaction frequency in mobile environments, renders it an optimal candidate for mobile-first adaptive systems.

In mobile applications, FSLSM is able to facilitate:

- Individualized notification plans (e.g., engaging active learners in discussions)
- Optimization of media selection (e.g., preferring video to visual learners)
- Real-time sequencing (e.g., supportive sequential learners in scaffolded modules)

Felder-Silverman learning style model makes mobile systems responsive, learner-centered, and data-aware because this implementation is able to facilitate lightweight and scalable adaptation.

5.4 Limitations and future work

While FSLSM demonstrated the strongest behavioral alignment and adaptive potential in this dataset, its advantages should be considered alongside its limitations. As noted by [27] and recent critiques [18, 19], learning styles models, including FSLSM, may oversimplify learner diversity and should be complemented with other personalization strategies. Hybrid approaches that integrate FSLSM dimensions with domain-specific analytics.

This study did not control for variables such as course type, socioeconomic diversity, prior academic performance, prior exposure to adaptive systems, or subject matter complexity due to dataset constraints. These factors may influence behavioral patterns, clustering results, and model alignment. Future research should incorporate stratified analyses or regression-based controls to isolate the effects of learning style alignment from these potential confounders, thereby improving the generalizability and validity of findings.

6 CONCLUSION

This study applied behavioral clustering to compare four learning style models—VARK, Kolb, Honey and Mumford, and FSLSM—in an online learning context. FSLSM consistently demonstrated the highest behavioral alignment, quantifiability, adaptive potential, and correlation with outcomes. Its multidimensional structure allows for direct mapping to LMS-traceable elements, enabling effective integration into adaptive and mobile learning systems. However, its application should be complemented by contextual adaptation and, where appropriate, hybrid approaches to avoid oversimplifying learner diversity.

In comparison to other analyzed models, FSLSM fitted the highest number of criteria of being behaviorally congruent, able to be operationalized, and system definitive. Its multi-dimensional layout made correct mapping to LMS-traceable elements, like the type of interaction, use of content, and progress in the student progression, components essential in bringing about adaptivity in the online learning process.

In contrast, models such as VARK and Honey and Mumford were not very applicable since they were both static and based on inputs in the form of preference levels, whereas the Kolb model, although theoretically sound, could not be used to model behaviors in dynamic systems due to a lack of grain in the model. These shortcomings indicate the usefulness of harmonizing teaching models with the quantitative facts of virtual learner behaviors.

Areas of future research should include the real-time application of FSLSM-knit personalization in mobile learning systems, where behavior turns within streams provide a driver of device-sensitive, learner-sensitive personalization. Longitudinal studies can take place as well to evaluate the prolonged effect of adaptive instructional ideas founded on FSLSM on performance, motivation, and retention.

7 DATA AND CODE AVAILABILITY

All supplementary materials, including the complete clustering code, mapping logic, and statistical analysis scripts, have been made publicly available on Zenodo to ensure full transparency and reproducibility of this work. These materials can be accessed at the following DOI: https://doi.org/10.5281/zenodo.16459132

8 ETHICAL CONSIDERATIONS

The datasets used in this study were obtained from publicly available Kaggle repositories, containing only anonymized learner records with no personally identifiable information. No intervention or direct interaction with participants was undertaken. In accordance with general institutional review board (IRB) principles, the use of secondary, de-identified datasets is exempt from formal ethics approval. The original dataset providers conducted participant recruitment, obtained informed consent, and complied with applicable data protection and privacy regulations, as documented in their data release statements on Kaggle.

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