PROFILING K-12 LEARNERS IN SMART E-LEARNING: A COMPARATIVE STUDY OF K-MEANS AND FUZZY C-MEANS USING THE TAM, TTF, AND SUS FRAMEWORKS

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Abstract

The rapid rise of smart technologies in education has reshaped STEM and coding learning,promoting adaptive and data-driven learning for diverse K-12 students. This study integrates the Technology Acceptance Model (TAM), Task Technology Fit (TTF), and System Usability Scale (SUS) to analyze students' perceptions of usability, motivation, satisfaction, and learning outcomes. Data were collected from 450 students across elementary, middle, and high school levels to explore variations in digital learning experiences. Clustering analysis using K-Means and Fuzzy C-Means was applied to identify learner profiles based on perception and interaction patterns. The results show that Fuzzy C-Means produced more interpretable and coherent clusters than K-Means, capturing smoother boundaries and overlapping learner characteristics. Three profiles emerged: Young Explorers, Motivated Builders, and Independent Coders, reflecting developmental transitions across educational levels. These findings highlight how clustering approaches can enhance understanding of learner diversity and inform adaptive design in e-learning. The study contributes to personalized learning analytics by linking behavioral perspectives with computational modeling, offering insights for developing inclusive and user-centered digital education systems.

Keywords: Educational data mining; Fuzzy C-Means; K-12 learners; K-Means; Smart e-learning

INTRODUCTION

The advancement of smart technologies has transformed digital learning, especially in science, technology, engineering, and mathematics (STEM). In these environments, user interface (UI) and user experience (UX) design are crucial for accessibility, engagement, and learning outcomes. Smart e-learning systems that adapt to learners' cognitive development and motivation are therefore essential for sustaining effective learning. Theoretical models such as the Technology Acceptance Model (TAM) (Davis, 1989), Task Technology Fit (TTF), and System Usability Scale (SUS) have been widely used to explain how learners interact with technology. These models emphasize perceived usefulness, usability, motivation, and satisfaction as key predictors of learning success (Šumak, Heričko, & Pušnik, 2011). However, most prior studies have examined higher education or adult learners, while research on child-centered digital learning remains limited (Chuenyindee et al., 2022; Mailizar et al., 2020; Salloum et al., 2019). Furthermore, earlier work relied mainly on confirmatory approaches such as Structural Equation Modeling (SEM) (Ngampornchai & Adams, 2016; Wang et al., 2023), with fewer studies adopting exploratory or data-driven methods for K-12 UX contexts.

In K-12 STEM and coding education, students exhibit diverse cognitive and motivational characteristics that evolve with age. Younger learners tend to respond to gamified and visual elements, while older students prefer autonomy and challenge-based learning. Understanding these variations is crucial for adaptive UI and UX design that supports engagement and achievement. Clustering methods have been increasingly adopted in educational research to model learner diversity and identify hidden behavioral patterns (Bouatrous et al., 2023; Jiang, 2024; Talavera-Mendoza et al., 2022; Belluano et al., 2025). However, prior studies have generally focused on specific applications without comparing the interpretability or precision of different clustering algorithms. This study addresses that gap by examining K-Means and Fuzzy C-Means to explore learner segmentation across K-12 levels. Most prior research employs a single clustering method without addressing how different algorithms may influence the interpretation of learner diversity. Even studies using multiple approaches, such as Belluano et al. (2025), have focused on application outcomes rather than methodological comparison. This highlights the need for a systematic evaluation of clustering techniques in educational UX research, particularly to better capture the complexity of K-12 learner behavior levels. To address this gap, the study integrates the Technology Acceptance Model (TAM), Task Technology Fit (TTF), and System Usability Scale (SUS) as the conceptual foundation following Chuenyindee et al. (2022). The framework includes five key constructs: usability, motivation, satisfaction, learning outcomes, and attitude, which collectively represent the cognitive and affective dimensions of learner experience. The analysis explores learner segmentation across K-12 levels using K-Means and Fuzzy C-Means clustering to reveal behavioral diversity and inform adaptive UX design. Therefore, this study aims to compare the effectiveness of K-Means and Fuzzy C-Means in identifying meaningful learner profiles across K-12 levels and to determine which approach provides better cluster validity and interpretability. The findings are expected to contribute to the development of adaptive, child-centered, and sustainable smart e-learning ecosystems that align with diverse learner perceptions and behaviors.

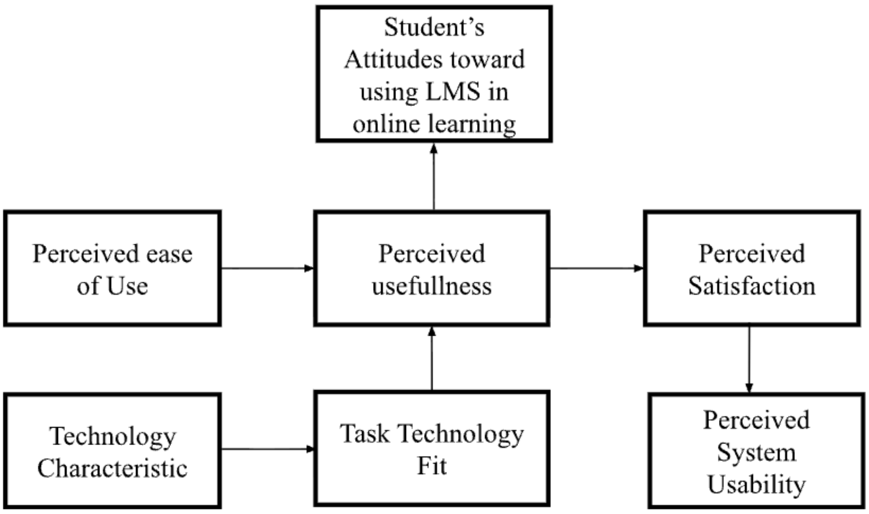

Figure 1. Conceptual framework for clustering variables (adapted from Chuenyindee et al., 2022)

METHOD

Research Design

This study employed a quantitative exploratory design to compare the clustering performance of two unsupervised learning algorithms, K-Means and Fuzzy C-Means (FCM). The research utilized variables derived from the Technology Acceptance Model (TAM), Task Technology Fit (TTF), and System Usability Scale (SUS), covering usability, motivation, satisfaction, learning outcomes, and attitude. The overall procedure involved instrument validation, data collection, preprocessing, and clustering analysis. This design enabled the identification of learner segments based on user perception and experience across K-12 education levels.

Participants and Data Collection

A total of 450 K-12 students participated in the study, representing elementary, middle, and high school levels. Stratified sampling ensured proportional representation across educational stages. Data were obtained through an online questionnaire distributed via school learning platforms under teacher supervision, with parental consent secured. The survey consisted of five-point Likert-scale items adapted from validated instruments reflecting the conceptual framework. The questionnaire was pretested with a smaller group of students to confirm clarity and reliability, yielding satisfactory internal consistency across all constructs.

Data Preprocessing

Data were screened to ensure completeness and accuracy. Incomplete or inconsistent responses were removed during initial cleaning. Minor missing values were imputed using the mean substitution method. All variables were examined for distribution and multicollinearity to confirm data quality. Finally, the dataset was standardized through z-score normalization to allow comparability across variables before clustering analysis.

Clustering Procedures

The Clustering analysis was performed using Python with the scikit-learn and scikit-fuzzy libraries. The standardized dataset, containing usability, motivation, satisfaction, and learning outcome variables, was analyzed using K-Means and Fuzzy C-Means algorithms. The optimal cluster number was identified through the elbow method and Silhouette Coefficient, followed by evaluation of cluster validity and interpretability. As shown in Figure 2, the data-to-design pipeline delineates the sequential transformation of TAM–TTF–SUS variables into analytical outputs and design insights. This pipeline clarifies how standardized learner-perception data were processed through clustering algorithms and subsequently translated into UI/UX implications, ensuring methodological coherence between the analytical procedures and the resulting prototype development.

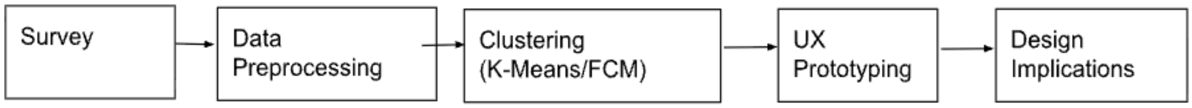

Figure 2. Data-to-Design pipeline illustrating the transformation from K-12 learners' survey data to clustering analysis and prototype UI/UX development.

The optimal number of clusters was set to three (K = 3) based on the elbow method , which identifies the inflection point where additional clusters provide minimal improvement in within-cluster variance. As shown in Figure 3, the elbow point appears at K = 3, where the reduction in SSE begins to plateau. This indicates that three clusters provide an optimal balance between model simplicity and within-cluster cohesion, and therefore were adopted for both the K-Means and Fuzzy C-Means analyses.This criterion, widely used for efficient data partitioning (Syakur et al., 2020; Kodinariya & Makwana, 2013), indicated that three clusters sufficiently represented learner diversity. Similar configurations were also reported in prior studies using K-Means and Fuzzy C-Means (Auliya et al., 2024).

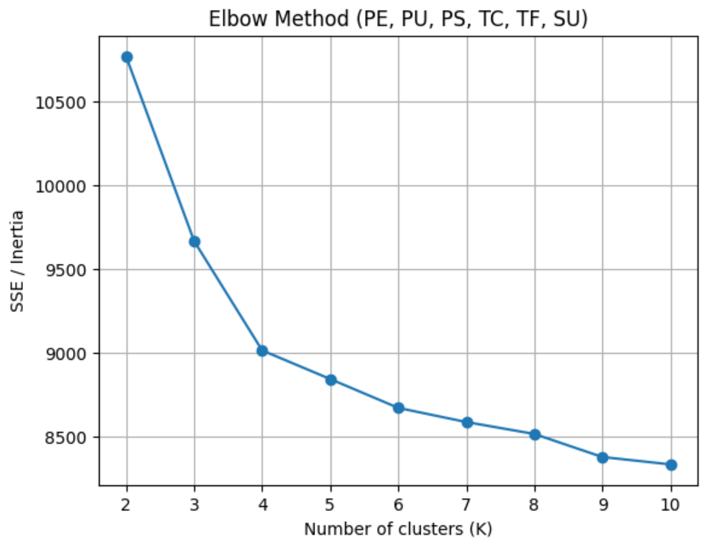

Figure 3. Elbow plot demonstrating that K = 3 provides the most stable balance between within-cluster variance and model parsimony.

Model Evaluation

Cluster performance was assessed using the Silhouette Coefficient and Davies Bouldin Index to evaluate compactness and separation.These two indices are well-established validity measures widely applied in clustering research. The Silhouette Coefficient was introduced by Rousseeuw (1987), while the Davies Bouldin Index was proposed by Davies and Bouldin (1979). Higher Silhouette values and lower Davies Bouldin scores indicate stronger cluster structure. Higher Silhouette and lower Davies Bouldin values indicated better cluster validity. Interpretability was examined through centroid comparison and participant distribution across education levels. Visual analyses, including scatterplots and membership heatmaps, were used to illustrate variable relationships and cluster patterns.

RESULTS AND DISCUSSION

Clustering Performance and Model Comparison

All 450 valid responses were included in the clustering analysis. K-Means and Fuzzy C-Means (FCM) were applied to standardized scores of usability, motivation, satisfaction, and learning outcomes derived from the TAM, TTF, and SUS frameworks. The elbow method and Silhouette Coefficient identified a three-cluster solution as optimal for both models. As shown in Table 1, Fuzzy C-Means produced stronger internal validity than K-Means, indicated by a higher Silhouette Coefficient (0.64) and a lower Davies Bouldin Index (0.40). These results suggest that the Fuzzy C-Means model formed clusters with clearer structure and smoother boundaries, capturing overlapping learner behaviors more effectively. This pattern reflects the complex nature of user interaction and perception in e-learning environments, where cognitive and motivational traits often intersect.

Table 1. Comparison of clustering validity indices for K-Means and Fuzzy C-Means

Algorithm	Silhouette Coefficient	Davies–Bouldin Index	Interpretation
K-Means	0.56	0.52	Distinct clusters but with rigid boundaries
Fuzzy C-Means	**0.64**	**0.40**	Better separation and smoother membership transitions

Figure 4 compares the visual structure of clusters produced by the two algorithms. Panel (a) shows that K-Means forms sharply separated groups, indicating fixed membership for each learner. Panel (b) displays the Fuzzy C-Means output, where the softer boundaries reflect gradual shifts in learner characteristics. This visualization helps illustrate how FCM captures transitional and overlapping learner profiles that commonly occur across K-12 developmental stages.

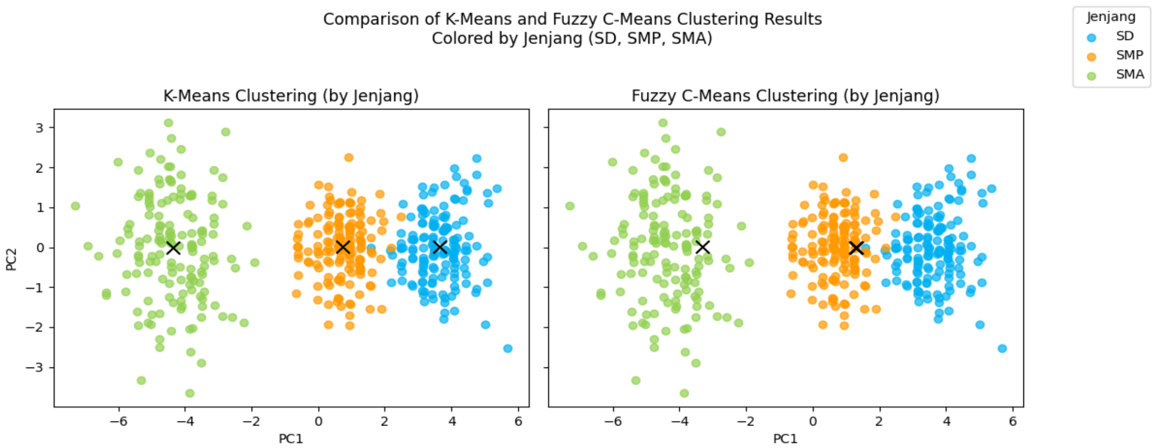

Figure 4. Visualization of learner clustering using (a) K-Means and (b) Fuzzy C-Means algorithms

Cluster Interpretation and Learner Profiles

Both algorithms consistently revealed three learner clusters aligned with educational levels. However, the Fuzzy C-Means model provided a richer interpretation due to its ability to represent overlapping learner traits.

Table 2. Cluster characteristics and implications for adaptive UI/UX design

Cluster	Level	Key Traits	UI/UX Implications
Cluster 1 – Young Explorers	Elementary	High usability, strong response to gamification, lower satisfaction and outcomes	Emphasize intuitive layout, bright visual cues, and game-based interaction to sustain attention
Cluster 2 – Motivated Builders	Middle School	Balanced motivation and satisfaction, positive task-technology alignment	Include challenge-based activities, peer collaboration, and progress feedback
Cluster 3 – Independent Coders	High School	High learning outcomes, strong autonomy, low gamification preference	Provide advanced content depth, autonomy-supportive dashboards, and analytics feedback

The FCM's smoother cluster boundaries further revealed transitional learners between elementary and middle levels, emphasizing the need for adaptable UI/UX designs that accommodate mixed motivational states. These findings align with motivational and engagement theories, where younger students depend on extrinsic cues while older students develop intrinsic motivation and self-regulation. Overall, the results confirm that adaptive e-learning interfaces should flexibly support learners' evolving autonomy, satisfaction, and engagement across educational stages.

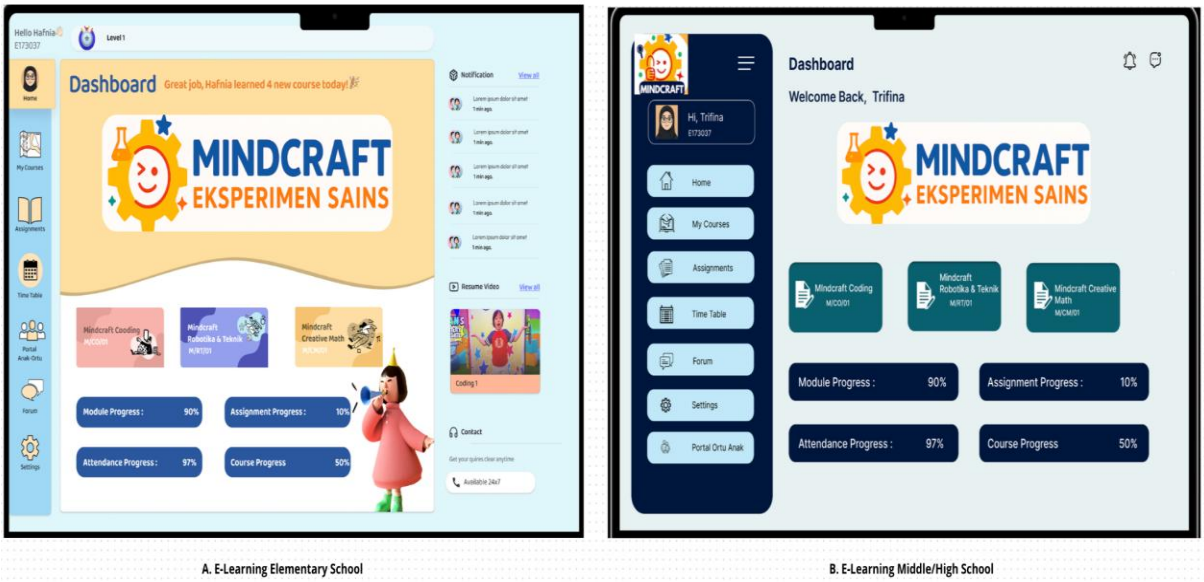

Figure 5. Adaptive UI/UX prototypes for K-12 learners: (a) Elementary version emphasizing gamified visuals and simplified navigation; (b) Middle–high school version focusing on progress analytics and task organization aligned with cluster-based learner profiles.

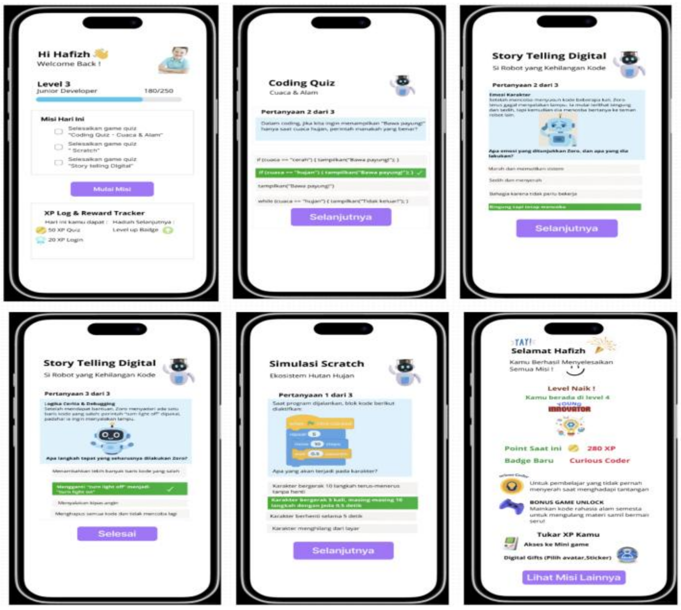

Figure 6. Gamified learning modules designed for elementary learners: Coding Quiz on Weather and Nature introducing mission-based coding practice,Digital Storytelling module fostering problem-solving and emotional engagement through narrative-driven learning, and Scratch Simulation demonstrating task–technology fit between visual programming and environmental concepts

Integration with the TAM–TTF–SUS Framework

The clustering patterns reinforce the conceptual logic of the integrated TAM–TTF–SUS framework, where usability and task–technology fit act as key enablers that drive satisfaction and learning outcomes. The FCM visualization illustrates how these constructs interact dynamically across learner groups rather than linearly. Students with moderate usability but strong motivation may still report high satisfaction if task alignment is clear, while users with high usability but low intrinsic motivation tend to cluster with less-engaged groups. These variations highlight the motivational role that complements usability and system fit in shaping learning experiences (Chuenyindee et al., 2022; Venkatesh & Davis, 2000). These findings align with broader e-learning research showing that satisfaction depends on both system quality and perceived alignment between tasks and technological features (DeLone & McLean, 2003; Al-Fraihat et al., 2020). Within this framework, usability bridges usefulness and engagement, while satisfaction mediates the link between motivation and outcomes. Collectively, these results confirm that the integrated TAM–TTF–SUS model, when combined with clustering analysis, offers a practical multidimensional approach to understanding and differentiating learner behavior in adaptive K-12 e-learning systems.

Discussion of Findings

The comparative results indicate that Fuzzy C-Means provides a more comprehensive representation of learner diversity than K-Means by accommodating overlapping motivational and usability traits, particularly among transitional learners in middle school This finding strengthens the argument that user experience in education is continuous rather than discrete, aligning with spectrum-based UX theories emphasizing fluid learner engagement. These findings directly address the research gap identified in the introduction, where prior studies on e-learning acceptance predominantly employed confirmatory approaches such as SEM and rarely examined child-centered contexts (Ngampornchai & Adams, 2016; Chuenyindee et al., 2022; Wang et al., 2023). Unlike previous work that used single clustering techniques without evaluating their methodological implications (e.g., Bouatrous et al., 2023; Belluano et al., 2025), this study provides a comparative assessment of K-Means and Fuzzy C-Means and demonstrates that FCM more effectively captures transitional and overlapping learner characteristics. This comparative perspective offers methodological novelty by showing that learner experiences in K-12 UX are better represented as continuous rather than discrete categories, an aspect that earlier research has not explored. Beyond algorithmic differences, the findings contribute theoretically by demonstrating how usability, motivation, satisfaction, and task alignment interact dynamically within the TAM–TTF–SUS framework. The integration of unsupervised clustering with behavioral constructs extends the traditional use of these models beyond confirmatory analysis, offering an alternative approach for exploring latent learner typologies. This methodological innovation bridges psychological theory and machine learning, reinforcing the potential of clustering as a tool for educational data mining. Practically, the three cluster patterns inform adaptive interface design strategies that evolve with learners' cognitive maturity and motivational orientation from gamified engagement to autonomy-supportive environments. Future research can refine this approach by incorporating longitudinal tracking or cross-platform learning data to evaluate changes in learner profiles over time. Such extensions would enhance the predictive power of clustering-based UX analytics and further strengthen its role in building inclusive, personalized e-learning ecosystems.

CONCLUSION

This study compared K-Means and Fuzzy C-Means clustering in modeling learner profiles derived from the integrated TAM, TTF, and SUS frameworks among 450 of K 12 students. Both algorithms revealed three learner types: Young Explorers, Motivated Builders, and Independent Coders, representing differences in usability, motivation, satisfaction, and learning outcomes across educational levels. Fuzzy C-Means achieved higher validity and interpretability, as its membership structure captured smoother transitions and overlapping learner traits, providing a more accurate reflection of behavioral diversity in e-learning contexts. The findings demonstrate that clustering based analytics can strengthen adaptive UX design by linking learner segmentation with interface personalization. Theoretically, this research extends the application of TAM, TTF, and SUS into unsupervised learning, illustrating how data driven models can reveal hidden psychological and behavioral patterns. Practically, the identified clusters offer guidance for designing adaptive and user centered digital learning ecosystems that evolve with learners' cognitive and motivational development. Future research may explore cross context or longitudinal analyses to validate these patterns and expand the scalability of clustering driven educational analytics.

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