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# Profiling student performance for multi-agent personalization in virtual reality

**Ghalia Mdaghri Alaoui, Ilhame Khabbachi, Abdelhamid Zouhair, El Mokhtar En-naimi**
DSAI2S Research Team, Computer Science and Smart Systems Laboratory, FST of Tangier, Abdelmalek Essaâdi University, Tetouan, Morocco

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**ABSTRACT**

This study uses the open university learning analytics dataset (OULAD) to cluster student performance data to improve personalized learning. Three main aspects are the focus of the analysis: instructional involvement, behavior, and demographics. To create significant, comprehensible student profiles, the clustering algorithms k-means, k-modes, and k-prototypes were used for each dimension independently. In order to forecast student categories from input features, supervised classification models, such as support vector machines (SVMs) and random forests, were trained using these profiles as targets. Accuracy, F1-score, and cross-validation were used to assess the categorization models' performance. The outcomes demonstrate how well unsupervised and supervised learning strategies may be combined for adaptive learning. These profiles serve as a foundation for the future design of a multi-agent virtual reality (VR)-learning environment. In this envisioned system, specialized agents would handle behavioral adaptation, demographic personalization, and pedagogical coordination, offering a personalized learning experience tailored to each learner's profile.



***Corresponding Author:***

Ghalia Mdaghri Alaoui
DSAI2S Research Team, Computer Science and Smart Systems Laboratory, FST of Tangier
Abdelmalek Essaâdi University
Tetouan, Morocco
Email: ghalia.mdaghrialaoui@etu.uae.ac.ma

## 1. INTRODUCTION

Technological developments in education have created new opportunities for individualized learning, tailoring experiences to the unique characteristics and requirements of each student. Personalization has become a key tool for advancing inclusiveness, engagement, and adaptable pedagogy in an increasingly digital educational environment. With its immersive and interactive surroundings that reinvent teaching possibilities, virtual reality (VR) is one of the most revolutionary breakthroughs [1], [2].

VR offers immersive surroundings that boost motivation and engagement, but the multi-agent system (MAS) depends on several cooperating agents to provide real-time individualized support. By classifying students according to their behavior or performance, clustering approaches enhance these technologies by exposing unique profiles that guide adaptive training. When combined, VR, MAS, and clustering provide a strong basis for dynamically customizing learning experiences in which agents direct and adapt to the changing needs of each learner [3], [4].

Clustering has proven effective in building learner profiles from engagement, achievement, and personal attributes [5], [6], offering valuable insights to support individualized instruction [7], [8]. Over the past decade, educational data mining (EDM) and learning analytics have grown to encompass a broad range of approaches, including academic analytics and data-driven education [7]. Large-scale datasets such as open university learning analytics dataset (OULAD) [9], covering more than 32,000 students, facilitate comprehensive analyses across behavioral, cognitive, and performance dimensions, ultimately enabling more adaptive and data-informed learning interventions [10], [11].

Prior research has highlighted the effectiveness of clustering and classification methods in identifying patterns linked to academic performance and dropout risk. Classification algorithms have been leveraged to detect at-risk students early, drawing on demographic, psychometric, and performance data to guide timely interventions [12], [13]. Alongside these, clustering approaches such as multi-view clustering have revealed hidden learner profiles and behavioral tendencies, informing the design of personalized educational strategies [14].

Immersive VR has shown significant benefits for motivation, sense of presence, and perceived learning outcomes, encompassing both cognitive and affective dimensions [15]. Meanwhile, artificial intelligence (AI)-driven personalization holds strong potential for fostering inclusivity and human–machine collaboration, though concerns such as algorithmic bias and data privacy remain critical challenges to address [16].

VR-based instruction greatly improves practical abilities, especially in medical education, according to a meta-analysis by Yang *et al.* [17]. The biggest improvements are seen when VR is paired with traditional practice. In his investigation of AI integration in higher education, Walter [18] focused on writing tools and adaptive features that enable individualized coaching for a variety of learners. A human-AI synergy model in hybrid learning environments was presented by Kong *et al.* [19], who discovered low-to-moderate synergy levels and gained knowledge for creating more successful human-AI educational frameworks.

Despite these advances, most existing works rely on simulated data and rarely embed empirically derived learner profiles within VR-based MAS, limiting personalization depth. To the best of our knowledge, this work is the first to integrate clustering-based learner profiling with MAS in a VR setting for adaptive, data-driven personalization. To validate this approach, we compare a baseline agent system (SMA1) providing uniform recommendations with an enhanced version (SMA2) that tailors content and support based on learner profiles, offering quantitative and qualitative evidence of the benefits of data-driven personalization in VR.

This study aims to: i) analyze the OULAD dataset across multiple dimensions, ii) identify meaningful learner profiles using advanced clustering, iii) develop a replicable methodology for clustering educational data in VR contexts, and iv) establish a data-driven foundation for a novel MAS architecture. Section 2 reviews related work on clustering, MAS, and VR learning; section 3 details the dataset and methodology; section 4 presents results and discussion; and section 5 concludes with future research directions.

## 2. LITERATURE REVIEW

### 2.1. Clustering techniques in educational data mining

Clustering has become a key technique in EDM, enabling the detection of meaningful patterns across student performance, engagement, and behavior. Early student modeling approaches, including overlay models, fuzzy logic, and Bayesian networks, offered foundational insights into knowledge mastery, yet often remained fragmented and failed to integrate cognitive, affective, and behavioral dimensions, restricting their use in adaptive systems [20]. More recently, clustering has been applied to online learning environments to generate actionable learner profiles. For instance, Šarić-Grgić *et al.* [21] used engagement-based clustering within AC-ware Tutor to identify learner groups benefiting from personalized guidance, though findings were limited by small sample sizes. Hooshyar *et al.* [22] proposed the PPP algorithm, achieving 96% prediction accuracy, though performance declined with increasing cluster numbers, raising scalability concerns. Navarro and Ger [23] found that k-means and PAM generally outperform other partitioning methods, while DIANA proves effective under specific conditions; however, relying solely on internal validation metrics without pedagogical interpretation limits practical applicability. Fuseini and Missah [24] confirmed clustering's dominance in higher education, noting its limited extension to primary and secondary levels, whereas Li *et al.* [25] applied ensemble clustering to detect mainstream and anomalous behaviors, though within a single institution. Valarmathy and Krishnaveni [26] offered largely descriptive overviews, while Križanić [27] enriched analysis by combining clustering with decision trees, yet without external validation. Vital *et al.* [28] looked at personal and societal factors that affect academic achievement, but their findings were quite context-specific. K-means, k-medoids, FCM, and EM were benchmarked by Govindasamy and Velmurugan [29] with mixed results and little pedagogical understanding. Although real-time deployment is limited by computational complexity, Prabha and Priyaa [30] identified difficult pupils using fuzzy k-medoids. Hafdi and Kafhali [31] explored predictive modeling on small datasets, leaving scalability unaddressed. While deep learning shows promise for dropout prediction in MOOCs [32], it lacks the interpretability of explicit learner clusters, reinforcing the value of clustering-based profiling. Although personalized feedback yields clear benefits, privacy concerns and context-specificity remain ongoing challenges [33]. Engagement, sociodemographic, and behavioral signals are widely used, yet motivational dimensions are often neglected, and single-course datasets limit generalizability [34], [35]. Without offering a technical or moral critique, Rabelo *et al.* [36] emphasized the strategic significance of EDM platforms. Despite these developments, a number of restrictions still exist. Post-hoc analysis, single-institution datasets, and small sample sizes limit practical use and generalizability. Scalability and real-time flexibility are rarely tested, and validation measures frequently have little educational value. These drawbacks show that clustering is still underutilized in large-scale, adaptive educational systems despite its effectiveness in identifying learner patterns. Our integration of clustering-based profiles into MAS in VR environments is motivated by this gap. We use empirical datasets like OULAD to reconcile algorithmic rigor with pedagogical relevance and provide individualized, actionable learning experiences.

### 2.2. Multi-agent systems in educational environments

MAS have gained traction in education for their ability to coordinate autonomous agents toward personalized learning. Outay *et al.* [37] proposed a recursive spiral model managed by a MAS to support competency building, validated through an augmented reality-based training app, though without exploiting clustering-based profiles, limiting adaptability to diverse learner behaviors. Melesko and Kurilovas [38] developed an intelligent MAS for engineering courses combining ontologies and Felder–Silverman learning styles, achieving pedagogical coherence but lacking responsiveness to real-time engagement changes. Fazazi *et al.* [39] advanced this by integrating a MAS with Q-learning to recommend personalized paths accounting for learning styles and disabilities, yet validation remained largely conceptual with limited empirical testing on large-scale data.

To improve personalization, further research has looked into integrating MAS with deep learning and recommender systems. Although reliance on predetermined style models limits flexibility to changing learner behaviors, Mohamedhena *et al.* [40] created a four-agent MAS employing CNN and MLP to recommend learning objects depending on knowledge levels and learning styles, effectively enhancing engagement. A modular MAS framework that integrates ontologies and multi-agent reinforcement learning for tailored support across virtual environments was developed by Hare and Tang [41]. However, the technique is still mostly theoretical and has not received enough empirical validation for large-scale or dynamic student populations.

### 2.3. Virtual reality in educational applications

VR applications in education have a lot of potential for developing immersive, customized learning experiences. Merchant *et al.* [42] carried out a meta-analysis that showed VR's efficacy in K–12 and higher education, emphasizing its ability to engage students and enhance knowledge retention. Nevertheless, they pointed out that there is variation in instructional designs and discovered that certain VR modalities, like virtual worlds or repeated assessments, can have variable or even detrimental effects on learning gains. VR can produce rich behavioral data, such as gaze patterns, interaction frequency, and physiological responses, which can be used to model individual learner behaviors, as demonstrated by Hamilton *et al.* [43]. However, the majority of the immersive VR studies they reviewed used brief interventions, concentrated on a narrow range of scientific topics, and frequently used subpar assessment techniques, which limited generalizability. Radianti *et al.* [2] emphasized the need for adaptive VR systems capable of processing complex multimodal data streams to provide responsive, individualized learning experiences; nevertheless, they found that many VR studies focus on usability rather than actual learning outcomes, rely on experimental or development settings instead of regular teaching, and rarely integrate learning theories into VR design. Collectively, these studies highlight a gap: most current VR learning platforms rely on preset adaptation rules or user input rather than empirically derived, data-driven learner profiles, which our work aims to address by integrating clustering-based analysis for real-time personalized interventions.

### 2.4. Research gaps and integration opportunities

Significant gaps persist across existing research. Most MAS remain theoretically grounded with little connection to empirically derived learner profiles, while clustering-based cohorts are rarely embedded into adaptive systems. Rich datasets such as OULAD remain largely underexploited for grounding intelligent educational systems. No existing approach has yet fully unified immersive VR, multi-agent coordination, and clustering-based profiling, a convergence that represents a compelling opportunity to advance toward truly intelligent and personalized learning environments.

## 3. METHOD

This section outlines the methodology used to develop a clustering-based student-profiling system for personalized VR learning environments. The process covers research design, data acquisition, clustering implementation, evaluation protocols, and system architecture development.

### 3.1. Research design and chronological approach

The research adopts a four-phase sequential methodology conducted over approximately ten weeks. The OULAD dataset was chosen, acquired, and preprocessed during Phase 1 (weeks 1-3). Three clustering algorithms (k-means, k-modes, and k-prototypes) that were customized for various student data types were implemented and tested during Phase 2 (weeks 4–6). Phase 3 (weeks 7–10) involved cluster interpretability tests and comparative analyses utilizing internal validation measures. Phase 4, currently in progress, aims to conceptualize a multi-agent VR learning architecture based on the insights derived from the clustering outcomes. This chronological design ensures that each stage is methodically validated before advancing to the next, in line with established practices in EDM research.

### 3.2. Data acquisition and preprocessing procedures

There were 32,593 records in the OULAD dataset [44] at first. To maintain demographic and performance distributions, a stratified sample of 3,000 students was selected after cleaning and normalization. This sample was divided into 2,000 for clustering and 1,000 for external validation. To guarantee data integrity, preprocessing techniques included Z-score normalization, one-hot encoding, median/mode imputation, and outlier identification [45]. The variables, their computation, and agent mappings are summarized in Table 1, where student profiles are based on clustering results rather than pre-established categories.

Table 1. Student variables, computation, agent mapping, and profiles for simulation

| Dimension | Variables used | Computation/representation | Agent mapping | Simulation/synthetic profiles |
|---|---|---|---|---|
| Demographic | Gender, age band, highest education level | Categorical encoding, grouped into categories (young/adult, basic/higher education) | Demographic agent | Profiles defined according to clustering results |
| Behavioral | Total clicks, number of previous attempts, engagement patterns | Normalization (z-score), discretization into low/medium/high engagement | Learner agent | Profiles defined according to clustering results |
| Performance | Average score, assessment type, activity type, weight, module length | Average score normalized; assessment/activity grouped as formative vs. summative; weight scaled 0–1; presentation length categorized | Pedagogical agent | Profiles defined according to clustering results |

### 3.3. Selected clustering algorithms

#### 3.3.1. K-means

K-means is a widely used clustering algorithm that iteratively assigns data points to the nearest centroid and updates cluster centers until convergence. The number of clusters k is set in advance, and initial centroids are randomly selected. While computationally efficient, k-means is sensitive to outliers, which can distort centroid positions and affect clustering quality [46].

#### 3.3.2. K-modes

K-modes extends k-means to handle categorical data by replacing centroids with modes and Euclidean distance with a simple matching dissimilarity measure. Each data point is assigned to the closest mode, which is updated by selecting the most frequent category value within each cluster, enabling effective clustering of purely categorical attributes [47].

#### 3.3.3. K-prototypes

K-prototypes combines k-means and k-modes to handle mixed datasets containing both numerical and categorical features. It applies a hybrid cost function using Euclidean distance for numerical attributes and a matching dissimilarity measure for categorical ones, balanced by a weighting parameter $\gamma$. This makes it well-suited for the heterogeneous data commonly found in real-world educational contexts [48]. The three algorithms are selected to match different data types present in this study, as summarized in Table 2.

Table 2. Comparison of k-means, k-modes, and k-prototypes clustering algorithms

| Criterion | K-means | K-modes | K-prototypes |
|---|---|---|---|
| Data type | Numerical only | Categorical only | Mixed |
| Similarity measure | Euclidean distance | Hamming dissimilarity | Euclidean+hamming |
| Cluster center | Centroid (mean) | Mode (most frequent) | Combination of centroids and modes |
| Use in this study | Student behavioral data | Demographic data | Performance and engagement data |

### 3.4. Testing and validation procedures

Clustering quality was assessed through both internal and external validation on 2,000 training and 1,000 testing students. Internal validation used three metrics: the silhouette score measuring intra-cluster cohesion [-1 to +1], inertia reflecting cluster compactness, and the Calinski-Harabasz Index evaluating between- and within-cluster variance [49]-[51]. Metrics were computed for k=2–7, with cluster stability assessed through assignment consistency and centroid robustness. External validation trained supervised classifiers (random forest, support vector machine (SVM)) on cluster labels and tested them on the holdout set, with high predictive performance confirming cluster robustness and suitability for guiding personalized interventions within the MAS-based VR system.

### 3.5. System architecture development

Figure 1 illustrates the system workflow from data processing to VR integration across four interconnected layers. The clustering layer processes 3,000 OULAD students using k-means for behavioral profiling, k-modes for demographic segmentation, and k-prototypes for mixed-type patterns, achieving 99–100% classification accuracy on the test set. The MAS layer comprises three specialized agents — learner, demographic, and pedagogical — collaborating to generate personalized learning strategies through rule-based interventions derived from cluster labels, currently simulated within the java agent development framework (JADE). The VR integration layer represents a planned future phase, designed to translate agent decisions into immersive adaptive environments. The modular architecture ensures scalability and supports continuous improvement through feedback mechanisms.

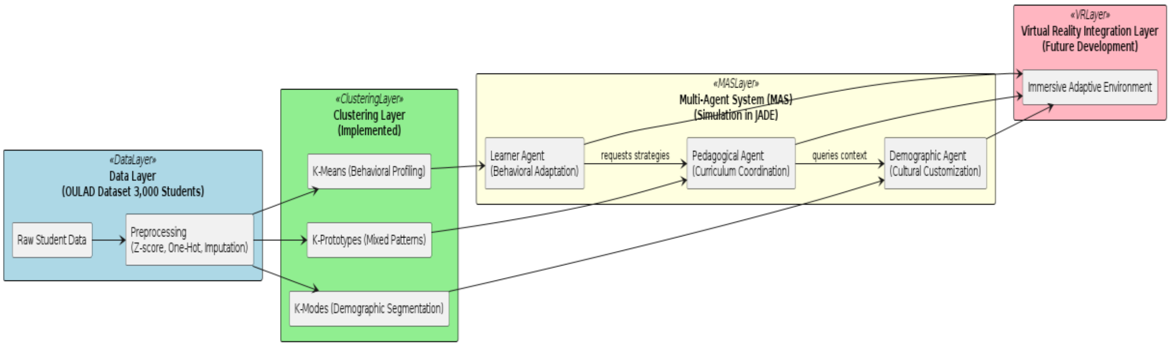



Figure 1. Architecture of the proposed adaptive learning system

Table 3 provides an illustrative example mapping of student profiles to the corresponding MAS agents and the pedagogical adaptations they would receive. This conceptual mapping demonstrates how the system is designed to respond to distinct learner characteristics, before the practical implementation and empirical evaluation.

Table 3. Use-case scenarios: student profiles and agent adaptations

| Student profile type | MAS agent responsible | Adaptation/intervention example |
|---|---|---|
| High achievers | Learner agent | Advanced content, challenge projects and accelerated pacing |
| At-risk learner | Learner agent | Personalized tutoring, re-engagement reminders, and scaffolded exercises |
| Consistent performer | Pedagogical agent | Standard curriculum reinforcement and occasional enrichment tasks |
| Disengaged students | Demographic agent | Contextual examples, motivational prompts, pacing adjustments, adaptive |
| Struggling with repeats | Learner+pedagogical agents | difficulty, frequent feedback, and structured practice sessions |
| Student profile type | MAS agent responsible | Adaptation/intervention example |

### 3.6. Formal unified modeling language modeling and agent communication

To ensure formal specification and reproducibility of the proposed MAS, a unified modeling language (UML) representation is provided. While Figure 1 illustrates the workflow, Figure 2 formalizes the internal MAS structure and interaction mechanisms. Specifically, Figure 2(a) presents the structural view through a class diagram that defines agent roles, inheritance relationships, and system dependencies, whereas Figure 2(b) depicts the interaction view that models the communication protocol triggered by cluster assignment using FIPA-ACL performatives within the JADE framework.

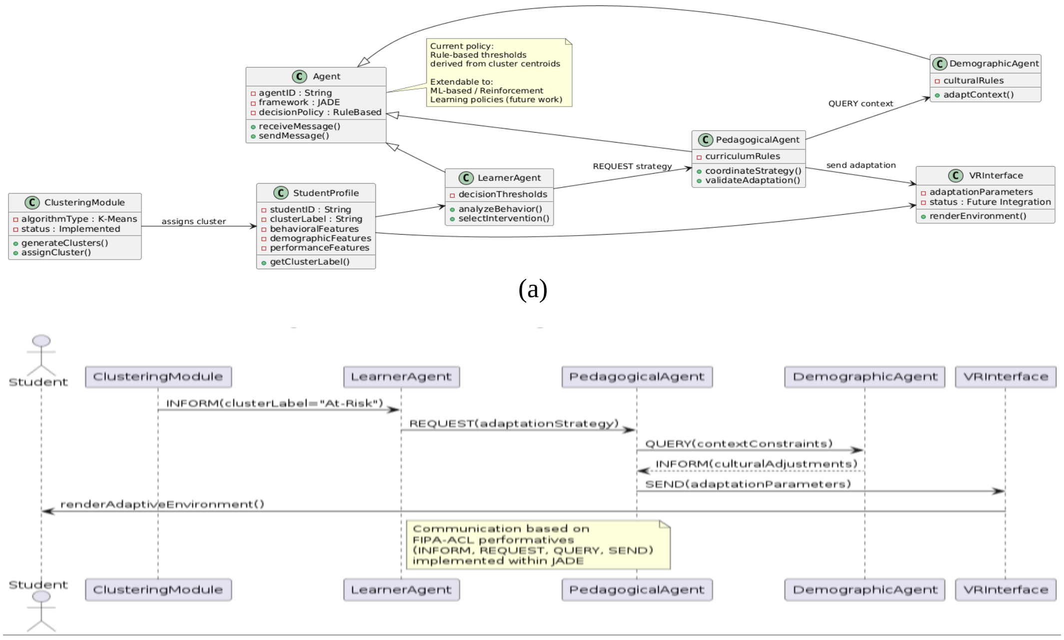



Figure 2. UML-based formal representation of the proposed MAS; (a) structural view: class diagram of the MAS and (b) interaction view: agent communication scenario

### 3.7. Current implementation, future integration, and limitations

At this stage, the system has been partially implemented. The k-means clustering process has been integrated into the JADE-based MAS, enabling personalized recommendations based on cluster assignments. A baseline MAS without clustering was also designed for comparison, simulating a uniform recommendation strategy. All experiments were conducted using the OULAD dataset in a controlled and reproducible setting. Full VR integration and comprehensive empirical validation remain part of future work.

## 4. RESULTS AND DISCUSSION

### 4.1. Dataset overview

Three complementary clustering algorithms were applied to 2,000 training students using distinct variable sets. K-modes segmented students by demographic attributes (age, gender, and education level), k-means captured behavioral patterns (academic performance, VLE engagement, and prior attempts), and k-prototypes handled mixed variables (assessment type, activity type, weight, and module length) to derive academic and engagement profiles. The remaining 1,000 students were reserved for external validation via supervised classification.

### 4.2. K-modes clustering

#### 4.2.1. Optimizing the number of clusters

As illustrated in Figure 3, the optimal number of clusters was determined by evaluating three metrics for k=2 to 7. The silhouette score improved steadily from 0.320 at k=2 to 0.665 at k=7, while inertia declined consistently from 1,806 to 513. The Calinski-Harabasz Index reached 18,903.9 at k=7, supporting the selection of k=7 as optimal based on the best balance between clustering quality and interpretability.

#### 4.2.2. Validation by supervised classification

External validation confirmed the robustness of k-modes clusters, with both random forest and SVM classifiers achieving near-perfect performance on the test set. Random forest attained flawless scores across all metrics, while SVM reached 99.9% accuracy, collectively demonstrating strong cluster separability and consistency. Detailed metrics are presented in Figure 4.

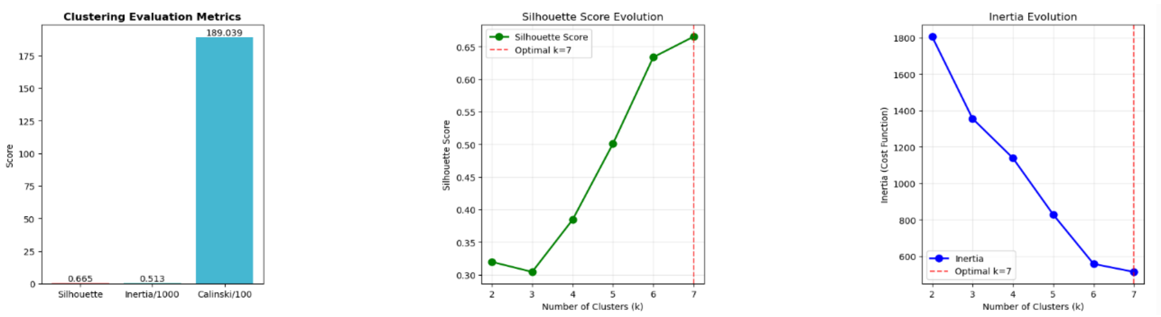



Figure 3. K-modes clustering performance analysis: evaluation metrics and optimal cluster selection

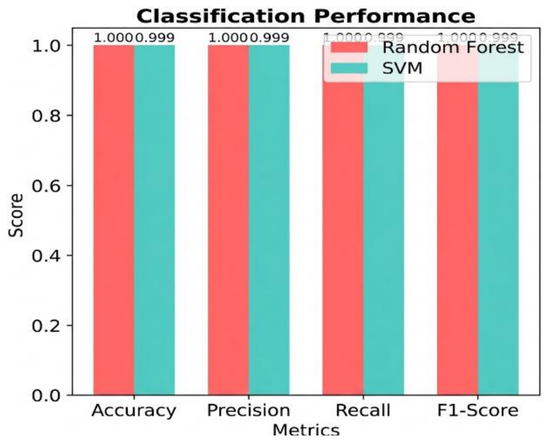



Figure 4. Classification performance comparison: random forest vs. SVM on k-modes clustered data

**4.2.3. Labeling and interpretation of clusters**

Table 4 summarizes the 7 clusters identified through k-modes clustering based on gender, age band, and highest education level, each accompanied by a descriptive label to support interpretation within the learner profiling framework.

Table 4. K-modes clustering results: student profile segmentation and cluster characteristics

| Cluster ID | Proposed label | Justification |
|---|---|---|
| Cluster 0 | Mature educated women | 100% female, 100% aged 35–55, 42% with A-level qualifications |
| Cluster 1 | Young inexperienced men | 100% male, 79% aged 0–35, 78% with education below A-level |
| Cluster 2 | Young women in transition | 100% female, 100% aged 0–35, 95% with education below A-level |
| Cluster 3 | Experienced professional men | 100% male, 99% aged 35–55, 53% with A-level qualifications |
| Cluster 4 | Ambitious young men | 100% male, 100% aged 0–35, 100% with A-level qualifications |
| Cluster 5 | Educated young women | 100% female, 100% aged 0–35, 100% with A-level qualifications |
| Cluster 6 | Elite academic women | 100% female, 98% aged 0–35, 100% with higher education qualifications |

**4.3. K-means clustering**

**4.3.1. Optimizing the number of clusters**

The optimal cluster number was determined by comparing three metrics across k=2 to 7. The silhouette score peaked at k=5 (0.581) before declining, inertia decreased consistently from 4,071 to 957.7, and the Calinski-Harabasz Index reached its maximum at k=5 (1,621.4). Balancing clustering quality and behavioral interpretability, k=5 was selected as optimal, as illustrated in Figure 5.

**4.3.2. Validation by supervised classification**

External validation confirmed the robustness of k-means clusters, with random forest achieving near-perfect performance across all metrics (99.9% accuracy, precision, recall, and F1-score), and SVM closely following at 99.1%. Both results demonstrate strong cluster separability and validity for predictive modeling, as detailed in Figure 6.

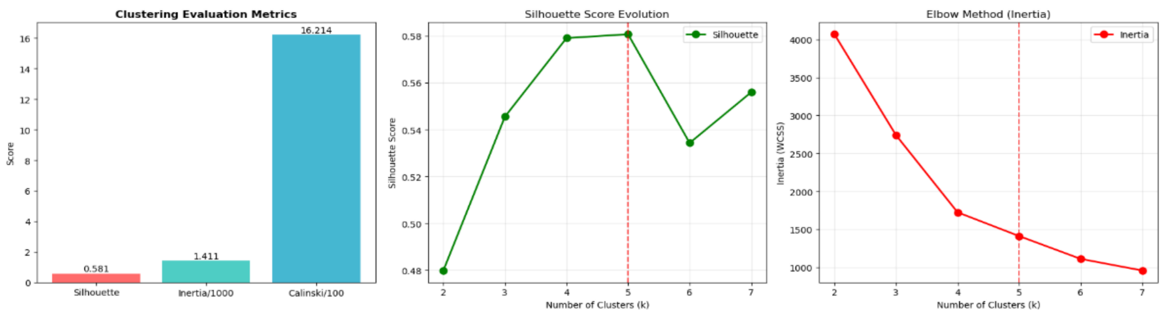



Figure 5. K-means clustering performance analysis: evaluation metrics and optimal cluster selection

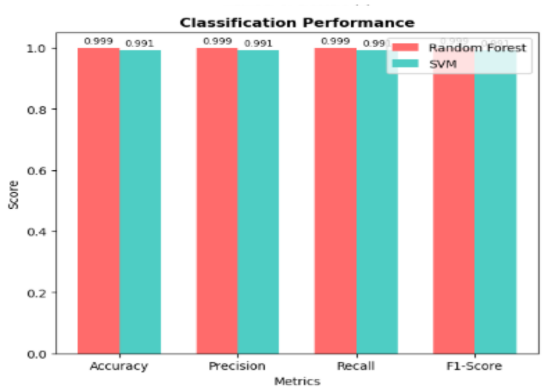



Figure 6. Classification performance comparison: random forest vs. SVM on k-means clustered data

#### 4.3.3. Labeling and interpretation of clusters

The five behavioral clusters reveal distinct learning patterns characterized by average score, platform engagement, and prior attempts. Table 5 summarizes each cluster, providing descriptive labels and key characteristics to inform personalized pedagogical strategies.

Table 5. K-means clustering results: student profile segmentation and cluster characteristics

| Cluster ID | Proposed label | Justification |
|---|---|---|
| Cluster 0 | Consistent performing students | High average score (73.1), moderate platform activity, no resits |
| Cluster 1 | Disengaged or at-risk students | Very low score (2.8), extremely low interaction, no attempts to retake |
| Cluster 2 | Returning or repeating students | Decent performance (70.7), 100% have previous attempts |
| Cluster 3 | Highly engaged high achievers | Excellent performance (82.4), very high platform activity, no retakes |
| Cluster 4 | Struggling students with repeated attempts | Moderate-to-low score (56.1), high variance, multiple resits (2.33) |

### 4.4. K-prototypes clustering

#### 4.4.1. Optimizing the number of clusters

Figure 7 summarizes the k-prototypes clustering evaluation using three metrics: inertia (Elbow method), silhouette score, and Calinski-Harabasz Index. The results consistently indicate that k=2 provides the most optimal solution, with the highest silhouette score (~0.41), a sharp inertia drop, and a strong Calinski-Harabasz value (~4,200), offering the best trade-off between cluster cohesion and separation.

#### 4.4.2. Validation by supervised classification

External validation of k-prototypes clusters yielded outstanding results, with random forest, SVM, and logistic regression all achieving perfect scores (100%) across accuracy, precision, recall, and F1-score on the test set. These results confirm the strong separability and consistency of the generated student profiles, as detailed in Figure 8.

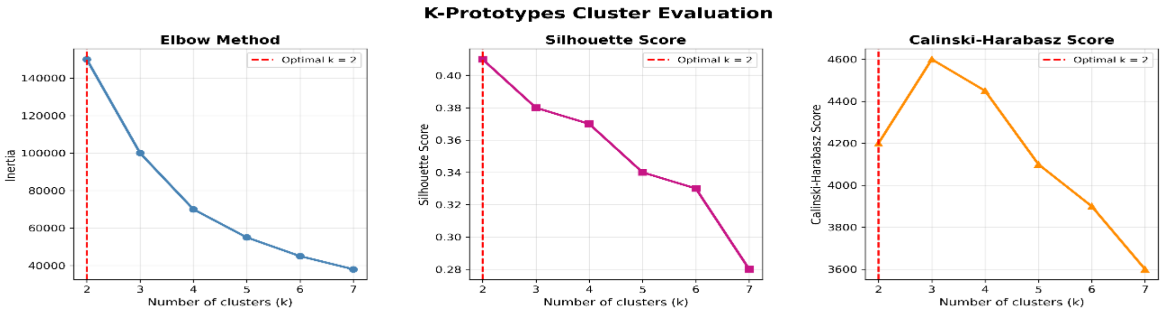



Figure 7. K-prototypes clustering performance analysis: evaluation metrics and optimal cluster selection

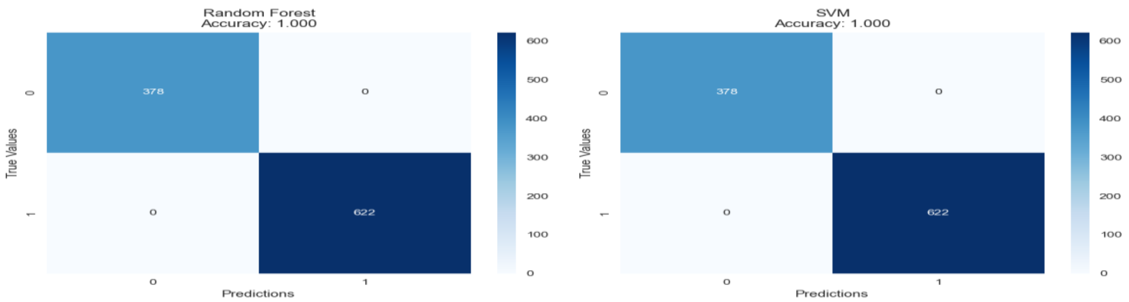



Figure 8. Classification performance comparison: random forest vs. SVM on k-prototypes clustered data

### 4.4.3. Labeling and interpretation of clusters

Table 6 presents a summary of the 2 clusters identified through mixed-type clustering, based on assessment type, activity type, weight, and module presentation length. Each cluster is given a descriptive label and justification to facilitate interpretation in the context of educational profiling.

Table 6. K-prototype clustering results: student profile segmentation and cluster characteristics

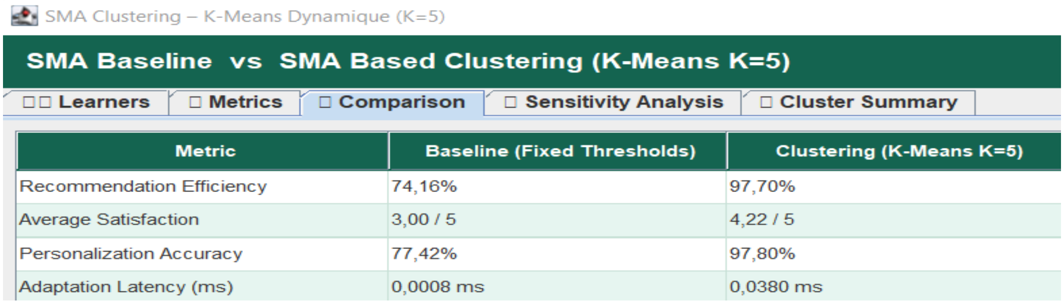
| Cluster ID | Proposed label | Justification |
|---|---|---|
| Cluster 0 | Interactive assessment students | 100% CMA assessment type, 100% forumng activity type, lower average weight (11.52), shorter module length (239.78 days) |
| Cluster 1 | Traditional assessment of students | 100% TMA assessment type, 100% oucontent activity type, higher average weight (14.19), longer module length (266.02 days) |

## 4.5. Comparative simulation: clustering-based vs generic approach

To evaluate the two proposed MAS, a controlled simulation was conducted using 1,000 learner profiles derived from the OULAD dataset, characterized by three behavioral variables: average assessment score, total platform interactions, and number of prior attempts. The SMA Baseline, relying on fixed score thresholds, achieved a recommendation efficiency of 74.16%, a personalization accuracy of 77.42%, and an estimated satisfaction of 3.00/5, reflecting the inherent limitations of a one-size-fits-all strategy. In contrast, the SMA clustering-based system, driven by k-means dynamic grouping (K=5), reached 97.70% recommendation efficiency, 97.80% personalization accuracy, and a satisfaction score of 4.22/5, demonstrating the clear benefit of adaptive, profile-driven recommendations. The only metric favoring the baseline was adaptation latency (0.0008ms vs. 0.038ms), an expected trade-off given the computational overhead of the clustering algorithm. As illustrated in Figure 9, these results confirm that the integration of k-means clustering into a multi-agent architecture significantly enhances the quality and relevance of pedagogical interventions, while the latency cost remains negligible in practice.

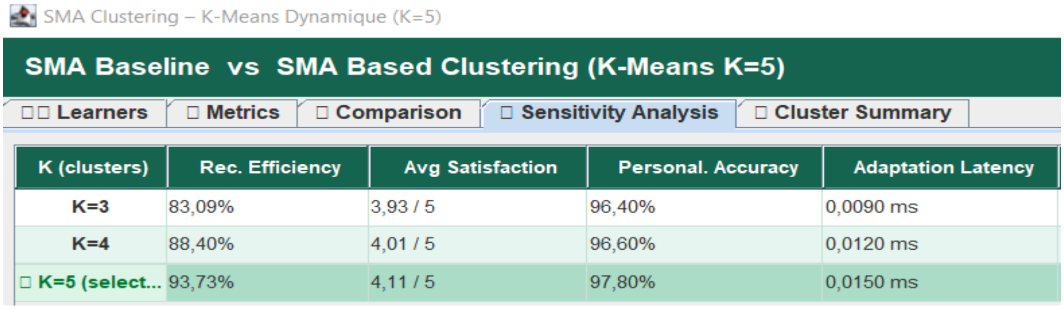
## 4.6. Sensitivity analysis

A sensitivity analysis was conducted to assess how varying cluster granularity affects recommendation quality in the clustering-based SMA. Three configurations (K=3, K=4, and K=5) were tested on 1,000 simulated learner profiles with all other parameters held constant. As shown in Figure 10, performance improved consistently with increasing K, reaching recommendation efficiency of 93.73%, personalization accuracy of 97.80%, and average satisfaction of 4.11/5 at K=5. While higher K values introduce a marginal latency increase (from 0.009 ms to 0.015 ms), this overhead remains negligible at the system's operating scale. These results confirm K=5 as the most effective configuration, achieving the best balance between recommendation precision and computational cost.




| Metric | Baseline (Fixed Thresholds) | Clustering (K-Means K=5) |
|---|---|---|
| Recommendation Efficiency | 74,16% | 97,70% |
| Average Satisfaction | 3,00 / 5 | 4,22 / 5 |
| Personalization Accuracy | 77,42% | 97,80% |
| Adaptation Latency (ms) | 0,0008 ms | 0,0380 ms |

Figure 9. Performance comparison: SMA baseline vs. SMA clustering-based system (K=5)




| K (clusters) | Rec. Efficiency | Avg Satisfaction | Personal. Accuracy | Adaptation Latency |
|---|---|---|---|---|
| K=3 | 83,09% | 3,93 / 5 | 96,40% | 0,0090 ms |
| K=4 | 88,40% | 4,01 / 5 | 96,60% | 0,0120 ms |
| K=5 (select... | 93,73% | 4,11 / 5 | 97,80% | 0,0150 ms |

Figure 10. Sensitivity analysis: impact of K on clustering performance (K=3, K=4, and K=5)

### 4.7. Pilot study design for future validation

To move from simulation toward real-world evidence, a pilot study involving 60 to 120 undergraduate students in an online or blended learning course is proposed. Participants would be randomly assigned to either the clustering-based adaptive system or a conventional recommendation interface over six weeks. Key measures would include learning gains assessed through pre- and post-tests, time-on-task derived from interaction logs, engagement indicators, and learner satisfaction measured through Likert-scale questionnaires. Statistical comparisons between groups would evaluate whether the improvements observed in simulation translate into measurable learning outcomes, providing a feasible pathway from computational validation to practical educational deployment.

### 4.8. Comparative analysis and discussion

Recent research has explored clustering techniques to profile students and support adaptive learning. Yet, most existing approaches suffer from methodological constraints such as reliance on a single clustering algorithm, lack of multi-source data, or limited validation frameworks. Our study addresses these gaps by applying three complementary algorithms—k-means, k-modes, and k-prototypes—to the OULAD dataset and validating them using a MAS. Table 7 summarizes the key performance metrics across algorithms.

Table 7. Summary of key performance metrics across clustering algorithms

| Algorithm | Optimal clusters | Silhouette score | RF accuracy (%) | SVM accuracy (%) | Innovation |
|---|---|---|---|---|---|
| K-modes | 7 | 0.665 | 100 | 99.9 | Sociodemographic profiles |
| K-means | 5 | 0.581 | 99.9 | 99.1 | Behavioral profiles |
| K-prototypes | 2 | 0.41 | 100 | 100 | Mixed evaluation profiles |

The supervised validation yields exceptional classification accuracy across all three algorithms (99.1–100%), despite moderate silhouette scores (0.41–0.665), confirming that the generated profiles remain highly predictive and pedagogically relevant. As demonstrated in the preceding MAS evaluation, the clustering-based system consistently outperforms the fixed-threshold baseline across all key metrics, further validating the practical effectiveness of the proposed approach.

Compared to existing work, our approach offers notable advances. Prior studies either lacked practical validation [52], relied on single models with limited cross-validation [53], highlighted the challenges of applying k-means to mixed data types [54], or depended on large datasets for cluster optimization [55]. Our framework addresses these constraints through algorithm selection tailored to data type, multi-model classification validation, and MAS-based experimental evaluation, establishing a more comprehensive methodological foundation.

Several limitations warrant consideration. The MAS remains simplified, and satisfaction metrics were estimated rather than empirically collected, constraining external validity. Reliance on a single-institution dataset further limits generalizability, and variable selection omits motivational and cognitive dimensions that are particularly relevant in immersive VR contexts. Practical challenges such as VR fatigue and unequal access to immersive hardware may also hinder real-world deployment. From an ethical perspective, the use of learning data raises concerns related to data privacy and responsible data management, while clustering-based personalization may introduce risks of algorithmic bias. Ensuring transparency and explain ability in agent decision-making therefore remains essential to maintain trust in adaptive educational systems.

## 5. CONCLUSION

Personalizing adaptive learning systems requires moving beyond uniform instructional strategies toward approaches that account for the diversity of learner behaviors and backgrounds. This work introduced a complementary clustering methodology — combining k-modes, k-means, and k-prototypes — to construct multidimensional learner profiles from the OULAD dataset, whose practical value was examined through a dedicated MAS experiment. Across all evaluated dimensions, profile-driven recommendations proved substantially more effective than rule-based alternatives, yielding a methodology that is both replicable and transferable to immersive pedagogical settings. Beyond the empirical outcomes, the main contribution resides in coupling heterogeneous clustering strategies with agent-based validation as a unified evaluation pipeline, equipping educational designers with concrete instruments for proactive learner support. Subsequent investigations should explore deployment in authentic learning environments, broader learner modeling incorporating affective and self-regulatory dimensions, and the ethical and technical challenges inherent to large-scale VR-based personalization.

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## AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ghalia Mdaghri Alaoui | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Ilhame Khabbachi | | | ✓ | ✓ | ✓ | | | | | ✓ | | | | |
| Abdelhamid Zouhair | | | | ✓ | | ✓ | | | | ✓ | | ✓ | ✓ | |
| El Mokhtar EN-Naimi | | | | | | ✓ | | | | ✓ | | | | |

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## DATA AVAILABILITY

The data that support the findings of this study are openly available on Kaggle at: https://www.kaggle.com/datasets/anlgrbz/student-demographics-online-education-dataoulad.reference: Student Demographics and Online Education Dataset (OULAD) [44].

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**BIOGRAPHIES OF AUTHORS**


**Ghalia Mdaghri Alaoui** is a dedicated Ph.D. student passionate about the intersection of educational data mining, machine learning, and personalized learning in virtual reality. Her research focuses on clustering and classification techniques to analyze student performance, to create adaptive learning paths. She is particularly interested in leveraging AI-driven insights to enhance personalized education. Her work also explores the application of virtual reality to optimize learning experiences. She can be contacted at email: ghalia.mdaghrialaoui@etu.uae.ac.ma.

**Ilhame Khabbachi** is a dedicated Ph.D. student passionate about the intersection of deep learning, facial emotion recognition, and online education security. Her research focuses on developing a cheating detection system for online exams using real-time facial emotion recognition powered by deep learning. She aims to enhance the integrity of e-learning assessments by leveraging AI-driven techniques to detect suspicious behaviors. Her work contributes to the advancement of secure and reliable online examination systems. She can be contacted at email: ilhame.khabbachi@etu.uae.ac.ma.

**Abdelhamid Zouhair** is a Professor at the University of Abdelmalek Essaâdi, Faculty of Sciences and Techniques of Tangier, Department of Computer Sciences since March 2020, and a Professor at the National School of Applied Sciences of AL Hoceïma, between May 2016 and March 2020. He obtained his Ph.D. in Computer Sciences from the University of Le Havre (France) and the University of Abdelmalek Essaâdi, Faculty of Sciences and Technology of Tangier (Morocco) in 2014. He obtained his HDR in 2020 and is the Director of several Doctoral theses in Computer Sciences. He is an author/co-author of several articles, published in International Journals in Computer Sciences. He can be contacted at email: a.zouhair@uae.ac.ma.

**El Mokhtar En-Naimi** is a Full Professor at Abdelmalek Essaâdi University, Faculty of Sciences and Technologies of Tangier, where he has been teaching since 1999. He headed the Computer Science Department (2016–2020), coordinated the Computer Engineering Bachelor's Program (2012–2016), and currently leads the DSAI2S research team. A founding member of two research laboratories (LIST and C3S), he has also been an expert evaluator for ANEAQ since 2016. His research covers multi-agent systems, artificial intelligence, machine learning, deep learning, e-learning, big data, and smart systems. He has supervised multiple Ph.D. theses, organized international conferences, and since 2009 has been an associate member of the Institute of Complex Systems in Normandy, University of Le Havre. He can be contacted at email: en-naimi@uae.ac.ma.