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Clustering-Based Adaptive UX in E-Learning Systems: Aligning Microservices with the 4C Framework

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Abstract

This study introduces a clustering-driven adaptive User Experience (UX) architecture for e-learning systems, aligning machine learning segmentation with the 21st-century 4C educational framework (critical thinking, communication, collaboration, creativity). The objective is to dynamically personalize digital learning interactions through a microservices architecture responsive to users' UX profiles. A quantitative survey was conducted involving 50 active users of Shopee and Tokopedia, whose interaction feedback was mapped using the User Experience Questionnaire (UEQ). Three unsupervised clustering techniques—KMeans, Agglomerative, and DBSCAN—were compared. KMeans outperformed the others with a silhouette score of 0.157, compared to 0.146 for Agglomerative and −0.017 for DBSCAN, identifying three meaningful clusters representing high, medium, and low UX proficiency. A one-way ANOVA test confirmed statistically significant differences ($p < 0.01$) among the clusters in dimensions such as error clarity, support responsiveness, and user confidence. These UX profiles were then mapped to individualized microservices: Cluster 0 received autonomous content with minimal support, Cluster 1 was offered guided prompts, and Cluster 2 was provided with simplified interfaces and proactive assistance. Each cluster was aligned with specific 4C competencies to ensure pedagogical relevance. The proposed architecture, built with gRPC-based microservices, enabled asynchronous, low-latency personalization based on user cluster membership. The novelty of this research lies in its dual alignment—technological (microservices + machine learning) and educational (4C competency mapping)—to construct a scalable and responsive e-learning environment. The system design, although validated through simulation, demonstrates a practical foundation for future deployment in platforms like Moodle or OpenEdX. By linking behavioral UX clustering to pedagogical intervention strategies, this study offers a model for adaptive, data-informed instructional systems that are both scalable and learner-centered.

Keywords: User Experience (UX), Microservices Architecture, Clustering Algorithms, 4C Framework, KMeans, Adaptive UX, gRPC Communication, Personalization

1. Introduction

The fast development of digital learning environments has changed the scene of education and opened hitherto unheard-of chances for learner autonomy, scalability, and customization [1], [2], [3]. This development does, however, also provide difficult difficulties in providing a UX that is both pedagogically sensitive and technically effective [4], [5], [6], [7]. Particularly in terms of adaptively supporting users with different degrees of technology fluency and cognitive engagement, traditional monolithic systems sometimes find it difficult to satisfy the needs of many students [8], [9], [10]. Although microservices architecture—known for its modularity and autonomous service deployment—offers a strong basis for system scalability—it sometimes runs apart from educational ideas that direct successful learning design [11]. Concurrent with these developments in machine learning—especially unsupervised clustering techniques—new opportunities for pattern recognition in user behavior present themselves [12]. Although these techniques have shown great value in user segmentation based on interaction data, their inclusion into adaptive learning

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systems is still restricted [13], [14]. Particularly, there is a gulf between algorithmic user segmentation and the educational models supporting meaningful learning—like the 4C model: Critical Thinking, Communication, Collaboration, and Creativity—that define the 21st-century competences [15], [16], [17].

This work introduces a UX-driven microservice architecture driven by machine learning clustering, therefore uniting these points of view [18], [19]. This study mimics an intelligent learning environment whereby consumers are categorized into different cognitive experience clusters by evaluating real-world UX interaction data gathered from users of leading e-commerce platforms—Shopee and Tokopedia [20], [21], [22]. These clusters guide the dynamic arrangement of microservices that dynamically provide customized content, assistance matched to each user's needs and linked to the 4C framework. Recent studies comparing deep learning and traditional machine learning techniques such as neural networks and K-NN have demonstrated the potential of these models in classifying user sentiment and behavior, which is essential for informing adaptive system responses and personalization strategies [23].

This work's core contribution is in its dual alignment: it supports different learners through 4C-centric adaptation by bridging a technological architecture (microservices with gRPC communication) with an educational purpose. By means of this integration, the suggested system guarantees both technical performance and instructional relevance by enabling responsive, data-informed personalizing in real time. Section 2 sets the research in existing literature on UX, microservices, and clustering; Section 3 addresses the technique applied to gather and segment UX data. Section 4 offers the results and analysis together with their application in system design and the efficiency of clustering models. Section 5 addresses consequences for intelligent learning systems; Section 6 ends with prospective paths for scalable, learner-sensitive system development.

2. Literature Review

Reviewed here is current work relevant to the development of adaptive learning systems by means of modular system architecture, machine learning, and user experience analytics. The discussion begins with considering how UX shapes learner interaction with digital platforms and then shifts to user segmentation applied by clustering methods. It then considers how microservices might be applied in educational technology and finishes with the pedagogical repercussions of the 4C framework—Critical Thinking, Communication, Collaboration, and Creativity—as a platform for personalization. Combining these fields gives the evaluation a foundation for the recommended approach that fits technical adaptability with instructional relevance.

2.1. UX in Digital Learning Systems

Particularly in educational environments, UX determines significantly the success and interactivity of digital platforms [24], [25]. Good UX increases usability, satisfaction, and retention while bad UX adds to frustration, disengagement, and dropouts [26], [27]. UX has to support not only navigational convenience but also pedagogical goals in educational environments including motivation, cognitive support, and learner autonomy [28]. Studies on UX elements like clarity of interface, feedback responsiveness, and error handling have shown that learning success and platform trustworthiness are highly related with them. Despite their importance, many systems still rely on set, one-size-fits-all interfaces that cannot adapt to human variation.

2.2. Clustering in UX Personalization

The concept of clustering in unsupervised machine learning has proved very successful for user segmentation based on behavioral patterns. It helps systems group like users without prior labeling, hence it is suitable for exploratory contexts such as UX review [29], [30]. Digital channels have seen the application of clustering to identify user profiles, forecast attrition, and personalize content distribution. Algorithms include KMeans and Agglomerative Clustering are rather popular because to their interpretability and application to numerous data types [31], [32]. In e-learning, meantime, the use of clustering to dynamically guide system behavior—particularly in real-time UX adaptation remains rare.

2.3. Microservices Architecture in Education Technology

Microservices architecture separates challenging systems into independently deployable services spanning lightweight platforms like gRPC or REST [33]. Against monolithic systems, this approach increases scalability, maintainability, and robustness [34]. Microservices have let educational systems add modules of capability including analytics, content delivery, and authentication [19]. Recent studies on how microservices build intelligent tutoring systems and flexible learning environments have revealed how Still under development, though, its use in offering real-time UX adaptation depending on machine learning-driven segmentation presents an opportunity for additional creativity.

Furthermore, the proposed architecture in this study emphasizes scalability by leveraging stateless microservices, asynchronous communication via gRPC, and container-based deployment. While empirical benchmarking was not conducted in this phase, previous studies—such as those by Nguyen and bolanowsky [33] —have shown that similar architectures can sustain thousands of concurrent requests under managed orchestration environments like Kubernetes. This foundational structure enables future expansion to large-scale adaptive learning platforms with minimal redesign.

2.4. The 4C Framework and Adaptive Learning

Focusing four fundamental competencies—critical thinking, communication, teamwork, and creativity collectively known as the 4C framework the 21st-century educational approach focuses These competencies define digital fluency and lifetime of learning [35], [36]. Effective learning systems should assist the acquisition of these skills by means of their adaptation to the cognitive state and interaction behavior of the learner [37], [38], [39]. While several systems have featured adaptive content or recommendation algorithms, few have particularly matched their personalizing approaches with 4C-driven pedagogical goals [40]. Combining behavioral clustering with 4C-aligned help provides a feasible path for producing technically robust and educationally meaningful intelligent systems.

2.5. Research Gap

While past efforts have addressed UX assessment, clustering for customizing, and microservices architecture in isolation, there is obviously a need in aggregating these components into a unified system. Particularly understudied are the combinations of educational alignment with the 4C architecture, microservice orchestration, and UX-based user clustering. This work fills in that demand by proposing a scalable, real-time architecture using clustering techniques that fits user experience profiles and provides educational interventions via microservices in line with learning objectives of the twenty-first century.

3. Methodology

The methodological framework followed to create and assess the suggested UX-driven microservice architecture is described in this part. The research used survey data in a quantitative manner to identify user experience trends from digital marketplaces. Data collecting and preprocessing; application of machine learning clustering techniques; interpretation and labeling of clusters; construction of a responsive microservices system; Every user group found by clustering was also mapped to focused interventions fit with the 4C educational paradigm. Each phase in great depth is covered in the following subsections, therefore creating a repeatable road from raw data to adaptive system deployment.

3.1. Ethical Consideration

This study complied with institutional ethical standards for user experience research involving human subjects. All participants were informed about the objectives of the study and voluntarily provided their informed consent before completing the UX questionnaire. No Personally Identifiable Information (PII) was collected at any point in the research process. All responses were anonymized and processed in aggregate form using normalized Likert-scale data.

The study was conducted within an academic environment, specifically under the Informatics Engineering study program. The research protocol was reviewed internally by the Ethics Committee of the Department of Electrical Engineering and Informatics, which concluded that no formal IRB approval was necessary due to the anonymous and non-interventional nature of the data collected.

3.2. Data Collection and Instrumentation

This study gathered UX data from consumers of digital markets—more especially, those using Shopee and Tokopedia platforms—by a quantitative survey method. Adapted to assess user interactions with system faults, feedback, and support systems, the survey was grounded on the UEQ framework. Respondents shared their experiences across 15 UX-related products covering frequency of problems, clarity of error messages, simplicity of problem solving, and satisfaction with help responsiveness. Purposive sample from undergraduate students actively using these platforms for at least six months yielded 50 replies overall.

Although data were collected from Shopee and Tokopedia users, the UX dimensions measured—clarity, feedback, responsiveness, and navigation—mirror those found in most e-learning platforms. The rationale for this approach lies in the shared interaction models between commerce and education platforms, particularly in app-based environments where user autonomy, feedback, and interface responsiveness are critical for both task completion and learning outcomes.

While the data were collected from users of e-commerce platforms (Shopee and Tokopedia), the selected UX dimensions—such as clarity of feedback, responsiveness to errors, and navigation—are also critical in e-learning environments. Prior studies have shown that digital behavior patterns in transactional apps often mirror those in learning platforms, particularly in self-service, feedback-driven contexts. Hence, although contextual differences exist, the cognitive and interactional UX constructs remain transferable for exploratory analysis in adaptive e-learning system design. This study was conducted in an academic environment with voluntary and anonymous participation. No personally identifiable information was collected, and all responses were treated confidentially. As a result, the research did not require formal institutional ethics approval according to internal departmental guidelines.

3.3. Data Preprocessing

Every survey answer was first cleaned to guarantee numerical homogeneity. Fields non-numeric like open-text IDs were not included. The remaining UX item values were Likert scale numerical form (1–5). Median substitution substituted missing values to maintain data distribution. Using z-score normalization, standardization was used to remove scale bias and guarantee equitable treatment of all features by clustering systems. Clustering was fed the ready data matrix, which included 15 UX elements across 50 users. While the number of users (n=50) may appear limited, it aligns with standard practices in exploratory UX clustering studies. The goal at this stage is not generalization but pattern recognition to inform the architecture prototype. Future studies with larger datasets are planned for validation in real e-learning environments.

Although Likert-scale data are technically ordinal, they are commonly treated as interval-level measurements in machine learning contexts to enable distance-based analysis. This practice may introduce minor distortions when applying algorithms such as KMeans. To mitigate this, z-score normalization was applied to standardize all features, ensuring uniform scale sensitivity and preserving the comparative structure of the dataset. Future extensions may explore ordinal-specific methods or non-metric clustering techniques for robustness.

3.4. Clustering Techniques

The standardized dataset was clustered using three unsupervised machine learning techniques to explore patterns in user understanding. KMeans Clustering was first employed to categorize users into clusters representing high, medium, and low levels of understanding, with the optimal number of clusters—typically k=3—determined through silhouette analysis and the elbow method. In addition to this, Agglomerative Hierarchical Clustering provided a complementary perspective by applying a bottom-up merging strategy based on average linkage, allowing for the observation of hierarchical relationships among users. To detect noise and handle complex, non-spherical cluster shapes, the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm was utilized, where the parameters eps and min_samples were empirically tuned to suit the dataset characteristics. The quality of each clustering outcome was then quantitatively evaluated using the Silhouette Score, a metric that reflects both the compactness within clusters and the degree of separation between them.

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Every group's mean UX score helped to interpret and label the KMeans produced clusters. High UX Proficiency was Cluster 0 (highest mean score); Medium UX Proficiency was Cluster 1; Low UX Proficiency was Cluster 2. The behavioral patterns and common traits of every group—including error management capacity, contentment levels, and support-seeking behavior—were investigated by means of a descriptive statistical analysis.

3.5. Microservices Architecture Design

The clustering results served as the foundation for designing an adaptable microservices architecture tailored to user experience profiles. At its core, the architecture featured a Clustering Engine Service responsible for hosting and regularly updating the machine learning clustering model. A dedicated user profiling service managed and stored user metadata, including assigned cluster labels, ensuring each user's interaction context was preserved. To monitor user behavior and system interaction, the UX Monitoring Service tracked feedback, interaction logs, and the frequency of errors encountered. Building on this data, the Adaptation Service dynamically adjusted interface components and support mechanisms based on the user's cluster classification, enabling a more personalized experience. Complementing this, the Content and Support Services delivered educational resources and assistance aligned with varying levels of user proficiency.

Finally, a Feedback Service played a critical role in sustaining system relevance by periodically retraining models using continuous user feedback, allowing the system to evolve in tandem with user needs. Low-latency and high-throughput interactions were guaranteed by the use of gRPC-mediated service-to-service communication. The overall architecture of the adaptive clustering system is visualized in figure 1.

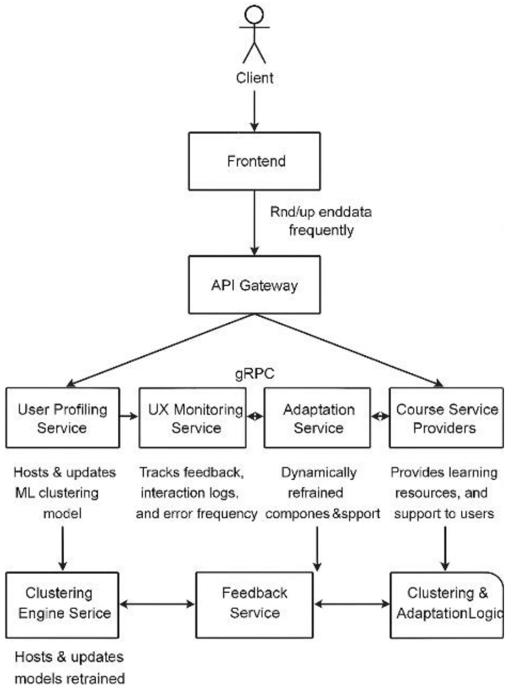

Figure 1. Adaptive Microservices Architecture for UX Clustering

Figure 1 illustrates the microservices-based architecture used to support real-time UX adaptation. Each service—profiling, clustering engine, UX monitoring, adaptation layer, content access, and feedback—operates independently, communicating via gRPC. The architecture enables dynamic interface changes and content recommendations based on cluster membership. The architecture proposed in this study is currently implemented at a conceptual and simulation level, serving as a design prototype to validate clustering-driven adaptation strategies. Although it has not yet been deployed in a full production-grade LMS, the modular design using containerized microservices and gRPC communication allows for straightforward integration in platforms such as Moodle or OpenEdX in future development phases. To support scalability, each microservice was containerized to enable independent deployment, fault isolation, and load balancing. While formal benchmarking was not conducted, the modularity and use of gRPC allow for horizontal scaling with minimal overhead, aligning with standard practices in distributed architectures.

3.6. Mapping to the 4C Framework

To support individualized interventions, each user cluster's behavioral profile was aligned with one or more of the 21st-century learning skills known as the 4Cs—Critical Thinking, Communication, Cooperation, and Creativity. Users in the high-proficiency cluster were associated with Critical Thinking and were provided with self-directed challenge modules to stimulate independent problem-solving. Those in the medium-proficiency group were linked to Communication and received structured cues along with system-generated feedback to guide their interactions more effectively. Both high- and medium-level users were also encouraged to engage in Cooperation through the activation of peer support systems, fostering collaborative learning. Meanwhile, users identified as low-proficient were prompted to explore solutions through interactive and multimodal assistance tools, helping them build confidence and gradually enhance their skills through guided support.

This mapping guarantees that system interventions were pedagogically in line with contemporary educational objectives, thereby providing not only technological adaptation but also cognitive support. For instance, the "Communication" competency for Cluster 1 users was operationalized via integrated chatbot microservices that provide step-by-step system guidance and instant feedback. Meanwhile, "Collaboration" in Cluster 0 was activated by enabling peer-assisted discussion services where advanced users could contribute solutions to community problems. The Creativity aspect in Cluster 2 was facilitated through the deployment of gamified learning paths and drag-and-drop content editors, allowing users with low UX proficiency to express their understanding through interactive interfaces.

4. Results and Discussion

Among the three clustering methods tested, KMeans produced the best segmentation of UX profiles, with a silhouette score of 0.157. Although the separation was modest, the algorithm provided distinct clusters that reflected user comprehension levels—high, medium, and low. The elbow method and silhouette analysis both supported the selection of k = 3. These clusters served as the foundation for downstream service personalization in the adaptive microservices architecture. Its ability to generate clearly defined segments makes it critical for tasks such as content delivery strategies and real-time UX interface adaptation in microservices-based environments.

Closely followed with a somewhat lower silhouette score of 0.146 was Agglomerative Hierarchical Clustering. Although this method also showed promise in identifying natural categories inside the data, its dependence on average linkage and bottom-up merging makes it somewhat less effective in distinguishing several UX segments. Still, if interpretability and dendrogram analysis take front stage, its close proximity to KMeans's performance points to hierarchical approaches remaining reasonable alternatives.

DBSCAN performed the worst overall at -0.017. This result suggests that many of the data points were interpreted as noise or did not meet the density threshold for forming a cluster. The poor performance can be attributed to DBSCAN’s sensitivity to the eps and min_samples parameters, which are difficult to tune optimally in datasets with overlapping or uniform density distributions like those in this study. To evaluate DBSCAN’s parameter sensitivity, several combinations of eps (ranging from 0.3 to 0.8) and min_samples (from 3 to 7) were tested. Across all configurations, the silhouette scores remained low (ranging from −0.021 to 0.045), indicating persistent difficulty in identifying well-separated clusters. These results reinforce the notion that the dataset’s uniform density and low variance in user behavior make it ill-suited for density-based clustering techniques such as DBSCAN.

Using PCA-reduced feature space for KMeans, Agglomerative Clustering, and DBSCAN, figure 2, figure 3, figure 4 show the 2D clustering results for each method respectively. Each figure offers a visual perspective on how the 50 UX profiles were grouped based on varying degrees of comprehension: high, medium, and low. Table 1 summarizes the key characteristics and comparative metrics of each clustering approach.

Figure 2 illustrates that KMeans divides the data into three somewhat small and reasonably separate clusters. The internal cohesiveness inside every cluster point to consistency in user behavior; the choice limits are are obvious. This approach assumes spherical cluster structures, which fit the normalized UEQ data rather well, so KMeans is useful for grouping with similar UX competency. The implementation followed the standard KMeans procedure of iterative centroid initialization, assignment, and update until convergence. For a detailed representation of the algorithm's logic, the full pseudocode is provided in Appendix A.

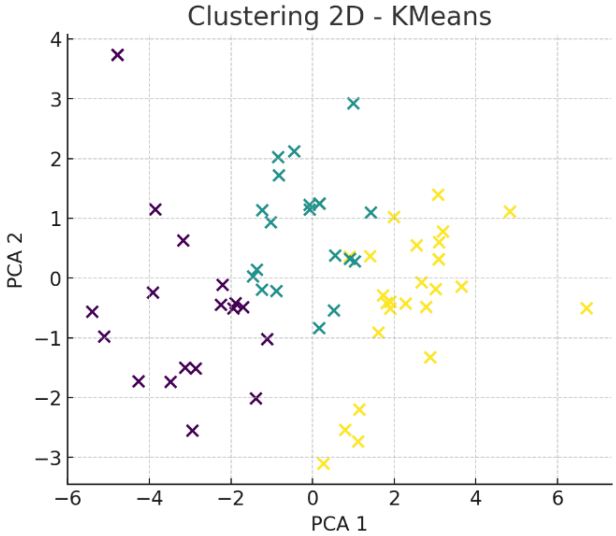

Figure 2. Clustering 2D K-Means

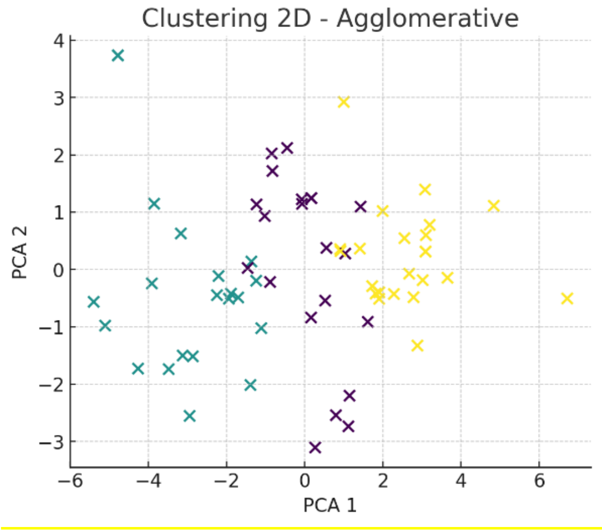

Figure 3. Clustering 2D Agglomerative

Though with somewhat more overlap and less difference between groups, figure 3, which shows Agglomerative Clustering, similarly generates three clusters. Although in this case it fared somewhat lower in terms of silhouette score, this approach is sensitive to linking criteria and may represent more complicated data distributions. Though lacking the robustness and separability shown in KMeans, the hierarchical method did offer reasonable interpretability.

Agglomerative Clustering in this study followed the standard bottom-up procedure, where each data point initially forms its own cluster and merges are performed iteratively based on average linkage. A detailed pseudocode of this process is presented in Appendix A. Figure 4 presents DBSCAN output in 2D space. The clustering structure is weak with many points marked as noise (-1), reflecting the method's sensitivity to density thresholds.

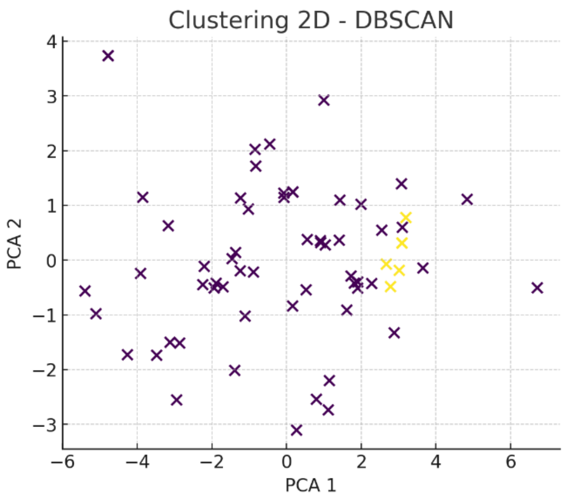

Figure 4. Clustering 2D Dbscan

Prior to this validation, a comparative analysis of clustering methods (summarized in table 1) supported the selection of KMeans as the most suitable algorithm for UX segmentation due to its higher silhouette score and clearer cluster separation. To validate whether the identified clusters differ significantly in their UX characteristics, a one-way ANOVA test was conducted across the three clusters formed by KMeans. Results showed statistically significant differences ($p < 0.01$) for multiple UX dimensions, including error clarity, support responsiveness, and user confidence.

These findings confirm that the segmentation produced not only structurally distinct clusters but also meaningful behavioral differentiation, supporting their relevance for targeted adaptation strategies. The detailed algorithmic steps used for implementing each clustering method—KMeans, Agglomerative, and DBSCAN—are provided in Appendix A. in their UX characteristics, a one-way ANOVA test was conducted across the three clusters formed by KMeans. Results showed statistically significant differences ($p < 0.01$) for multiple UX dimensions, including error clarity, support responsiveness, and user confidence. These findings confirm that the segmentation produced not only structurally distinct clusters but also meaningful behavioral differentiation, supporting their relevance for targeted adaptation strategies.

Table 1. Comparison of Clustering Methods

Method	Key Characteristics	Visual Clarity	Silhouette Score	Suitability for UX Clustering	Notes
KMeans	Assumes equal-sized, spherical clusters; fast convergence; easy interpretation	High	0.157	High	Best separability and cluster meaning
Agglomerative	Builds hierarchy; supports non-spherical shapes; linkage-sensitive	Moderate	0.146	Moderate	Useful, but less compact clusters
DBSCAN	Density-based; detects noise; no need for k	Low	-0.017	Low	Failed to form meaningful clusters

To bridge clustering results with the 4C learning framework, each identified UX segment was mapped to a pedagogical support strategy that emphasizes different competencies. Cluster 0 (high comprehension) aligns with Critical Thinking, as these users benefit from tools that promote analysis, synthesis, and autonomy. Cluster 1 (moderate comprehension) is supported through Communication-oriented enhancements, including guided prompts and clearer interface feedback. Cluster 2 (low comprehension) demands Creativity and Collaboration-focused interventions, such as multimodal tutorials, peer-assisted navigation, and visual explanation aids. This mapping operationalizes the 4C model by matching system interventions to users' cognitive and behavioral needs, rather than treating the framework as a static reference.

4.1. Microservices Adaptation by Cluster

Each user cluster played a crucial role in shaping the design of adaptive services within the system. Users in Cluster 0, characterized by high proficiency, were granted enhanced opportunities for autonomous exploration with minimal guidance, supporting their capacity for independent navigation and problem-solving. Cluster 1 users, representing moderate proficiency, benefited from semi-automated assistance and structured prompts that offered a balanced level of support without undermining their growing autonomy. Meanwhile, Cluster 2, comprising users with lower proficiency, was provided with simplified interfaces, intuitive visual aids, and proactive human support to ensure accessibility and ease of interaction, thereby reducing potential friction in their learning experience.

4.2. Visualizing Architecture and Flow

The end-to-end design is shown logically in Figure X. The Clustering Engine assigns a cluster label to each user; this label guides the Adaptation Service, which then decides the individualized interface and content. Through gRPC communication, the microservices architecture lets users dynamically, real-time customize themselves.

4.3. Microservices Adaptation by Cluster

To maximize the pedagogical impact of the e-learning system, each user cluster identified through the KMeans algorithm was aligned with specific 4C competencies—Critical Thinking, Communication, Collaboration, and Creativity. This mapping allowed for tailored microservices delivery based on the users' comprehension profiles, ensuring that system resources were optimally allocated to support meaningful learning outcomes.

Cluster 0, which predominantly consisted of users with higher comprehension levels, was directed toward enhancing critical thinking and collaborative problem-solving. The microservices serving this group were configured to deliver advanced assignments, case-based learning modules, and peer coaching environments. These services encouraged learners to engage in analysis, evaluation, and joint decision-making, enabling them to apply their skills in real-world simulations.

Cluster 1 comprised consumers with intermediate knowledge. Enhancement of the communication competency helped these consumers most at all. Microservices were developed to enable them by means of organized scaffolding elements including guided conversations, automated feedback loops, and integrated help prompts. Along with frequent formative evaluations to track development and promote reflective learning, learning materials were offered at an intermediary difficulty level.

Meanwhile, Cluster 2 consisted of users with lower comprehension scores. Their learning experience was oriented around creativity and exploration. Microservices for this group emphasized the use of visual aids, interactive simulations, storytelling tools, and exploratory learning paths. These features were designed to lower cognitive barriers and stimulate engagement through creative expression and intuitive understanding, rather than abstract logic or heavy textual material. Through this cluster-based adaptation, the microservice architecture not only supported scalability and modularity but also enabled personalized educational pathways. This alignment with the 4C framework ensured that each learner group received the type of support most relevant to their developmental needs, ultimately enhancing the system's pedagogical responsiveness.

4.4. Discussion

The results of this work show the great possibilities for intelligent, adaptive learning platforms by means of UX clustering combined with microservice-based system design. Unsupervised machine learning techniques allowed users to be segmented into separate groups, each indicating varying degrees of system comprehension and interaction ability. Through a modular microservices architecture, these clusters—mapped as high, medium, and poor UX proficiency—formed the basis for providing individualized digital experiences.

A major realization from the clustering study was the obvious variation in user behavior and support requirements. Cluster 0 users showed great autonomy, good problem-solving ability, and platform contentment, therefore indicating less system intervention needed. On the other hand, Cluster 2 users indicated the requirement of proactive advice since they battled with fundamental interface features and usually relied on outside help. By allowing the implementation of tiered assistance strategies directly into system functionality, this stratification helped to operationalize personalizing on a scalable basis.

Translating these ideas into real-time system behavior proved much aided by the microservices architecture. Every service—adaptation, content delivery, user profiling—was separately in charge of meeting the needs of a certain user group. By allowing asynchronous service updates, autonomous scalability, and targeted improvements without upsetting the whole system, this division of concerns fits best standards in distributed design. Moreover, by low-latency, high-throughput interactions, essential for real-time personalization in high-demand contexts, gRPC communication improved system performance.

Crucially, the alignment of this architecture with the 4C framework defines its teaching value. Every cluster was mapped to one or more fundamental competencies—critical thinking, communication, collaboration, and creativity—such that system adjustments not only enhanced usability but also strengthened teaching goals. Users in Cluster 0, for example, were urged to engage in group projects and critical problem-solving exercises; users in Cluster 2 received multimodal, creative help to develop confidence and digital fluency.

Taken together, these results support the fundamental argument of the research: intelligent learning systems have to be pedagogically ethical as well as technologically sensitive. The system shows a new paradigm for adaptive e-learning design—one that is user-centered, data-informed, and competency-aligned—by combining UX analytics, machine learning, and educational theory into a coherent microservices-based architecture. This double attention guarantees not only functional efficiency but also educational impact, so providing a strong basis for next intelligent applications in industry and beyond.

5. Conclusion

This work offers a fresh fusion of microservices architecture with UX clustering to support intelligent, adaptive learning systems. We showed how methodically designed personalized, pedagogy-aligned digital environments could be by using unsupervised machine learning on UX data and mapping the resulting user segments to the 21st-century 4C educational framework (critical thinking, communication, collaboration, creativity). This method closes the distance between technical scalability and instructional relevance by allowing systems to change in real time to meet various student needs.

Based on their interaction patterns, KMeans turned out to be the most successful of the clustering techniques examined in terms of meaningful category division of users. Every cluster—representing high, medium, and low proficiency users—was assigned customized microservices with differing degrees of complexity, autonomy, and support systems. High-proficient users interacted with little intervention; medium-proficient users were guided through contextual support; low-proficient users received proactive, simplified help. This difference shows how data-driven UX design can be practically applied in an educational setting.

Underlying gRPC communication, the suggested microservices architecture guaranteed that service interactions stayed scalable, quick, and lightweight. Along with supporting system extension and autonomous service evolution, this design helps to integrate dynamic clustering upgrades and customized content delivery pipelines. Future-proofing digital learning systems in fast changing educational environments depends on such adaptability.

Most importantly, the congruence with the 4C framework guarantees that every adaptive intervention strengthens important skills needed in modern education. The system fosters learner development by including instructional goals into every level of system interaction, hence transcending mere response to UX problems.

Looking ahead, the application of reinforcement learning could create constant feedback loops for model improvement, therefore enabling the system to grow with user behavior. While long-term behavioral analytics may provide greater understanding of learning paths, future installations in real Learning Management Systems (LMS) will evaluate the efficacy of the approach at scale. Moreover, applying this strategy to other fields, such e-government or healthcare, can confirm its adaptability and social influence.

Future development will focus on deploying the system in an actual e-learning environment using an open-source platform such as Moodle. The adaptive microservices will be integrated via RESTful APIs and gRPC layers, and clustering updates will be evaluated in real-time using Apache Kafka as a message broker. In the next phase, reinforcement learning (e.g., Q-learning or contextual bandits) will be explored to continuously adapt UX delivery strategies based on real-time learner feedback. Evaluation metrics will include learning performance, system latency, and user engagement.

In future work, the system will be validated in a production-grade learning environment, such as Moodle or OpenEdX, to examine its impact on user engagement, system performance, and scalability under real-world loads. Quantitative benchmarking will also be incorporated to refine the adaptive logic based on actual user dynamics.

6. Declarations

6.1. Author Contributions

Conceptualization: P.L.L., S.P.; Methodology: P.L.L., M.A.; Software: P.L.L.; Validation: S.P., F.K.; Formal Analysis: P.L.L.; Investigation: P.L.L.; Resources: G.K.; Data Curation: P.L.L.; Writing – Original Draft Preparation: P.L.L.; Writing – Review and Editing: S.P., M.A., F.K., G.K.; Visualization: P.L.L.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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