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Developing Dynamic E-Learning Personas: An AI-Driven Approach Utilizing Online Survey and K-Means Clustering

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Abstract: - E-learning personas play a vital role in delivering customized educational experiences by providing pivotal insights that enable stakeholders (including designers, testers, and administrators) to make well-informed decisions that are in line with the requirements of the users. Nevertheless, the creation of these personas faces obstacles such as intricacy and the lack of a standardized approach. The existing research lacks sufficient participation from key stakeholders, including developers, testers, and system supervisors, in the evaluation of AI-driven e-learning personas and their development frameworks. This significant gap in the literature exacerbates the complexity of the situation. The present study suggests that artificial intelligence (AI), more specifically K-means clustering, be utilized to revolutionize the process of persona creation in the field of e-learning. Using both clustering analysis and survey data together will help make it easier to create e-learning personas that are representative of Omani Grade 10 students, a group that faces unique challenges and opportunities when it comes to e-learning. Additionally, a comprehensive framework is presented in this paper, which not only tackles the methodological obstacles but also advocates for the active participation of end-users and key stakeholders in the process of persona evaluation. It is expected that this active participation will greatly improve the precision, applicability, and relevance of the personas created, thereby providing more informed direction for the development of e-learning materials and interfaces.

Keywords: AI-driven e-learning persona, e-learning, k-means clustering, e-learning personas, human-computer interaction (HCI).

I. INTRODUCTION

The digital revolution has ushered in a transformative era for education, propelling e-learning to the forefront as a primary mode of instruction. This evolution has been facilitated by the proliferation of digital platforms, including learning management systems (LMS), websites, and mobile applications, offering learners unprecedented accessibility and flexibility[1]. Nevertheless, the wide range of learner preferences and requirements presents considerable obstacles when it comes to developing engaging and effective e-learning platforms[2]. A critical component in tackling these obstacles is the inventive implementation of e-learning personas[3]. Depicting unique learner archetypes, these data-driven constructs play a crucial role in informing the development of individualized and effective learning environments [4]. Developed from thorough research and analysis, they encompass a wide range of preferences, behaviors, and needs; their fixed structure frequently fails to adapt to the ever-changing dynamics of learner interactions and requirements in the digital educational environment [5].

The strategic implementation of personas in education through the adoption of persona methodology provides stakeholders and developers with a comprehensive representation of users, enabling them to make well-informed decisions. By employing personas as a reference, the process of customizing decisions to efficiently address user requirements is facilitated. The most recent publication, "Personas Characterizing Secondary School Mathematics Students: Development and Applications to Educational Technology," is proof that numerous studies have examined the effectiveness of personas in the field of education. This study investigates the utilization of personas in the field of education, demonstrating how they can improve educational technology through the provision of information regarding student preferences, behavior, and requirements[19].

The emergence of artificial intelligence (AI) offers an innovative strategy for overcoming these obstacles [6]. With its capabilities in data analysis and clustering techniques such as K-means, AI has the potential to adapt e-learning personas in a dynamic manner. AI can generate dynamic personas in real-time by utilizing comprehensive datasets obtained from online surveys and learner interactions. This enables the identification of complex learner profiles and the anticipation of changes in their requirements[6]. Moreover, during the implementation of AI in education, it is critical to prioritize ethical considerations such as data privacy, consent, and transparency. This research

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highlights the significant importance of ethical deliberations when employing AI for the creation of personas, guaranteeing confidentiality for learners, and openness regarding the utilization of data.

The K-means clustering algorithm is a fundamental unsupervised learning method that is extensively utilized in diverse fields for the purpose of data segmentation and analysis. Because of its straightforwardness, effectiveness, and effortless integration, it is an absolute necessity for persona development in e-learning [7]. K-means clusters observations according to their nearest means and refines these clusters iteratively until a stable solution is obtained. K-means is an optimal tool for analyzing large volumes of learner data due to its scalability and simplicity; it permits the identification of distinct learner segments. Segmentation is an essential process in the creation of personalized e-learning personas that effectively represent a wide range of learner types[8]. While K-means has some good points, it also has some problems. For example, it can be hard to figure out the right number of clusters (k) and it can be affected by initial centroid selections. With these limitations in mind, K-means' ability to divide learner data into meaningful chunks is a big step forward in making e-learning systems more customizable [8]. The utilization of machine learning algorithms and clustering in e-learning has created novel opportunities for the customization of instruction. A lot of research has been done on how AI can be used to improve the process of persona development, but most of the current applications are focused on adaptive learning paths and content recommendation. This gap underscores the unexplored capabilities of artificial intelligence in developing dynamically adaptable e-learning personas that more precisely mirror the ever-changing condition of the learner population[6].

This article presents an innovative framework that utilizes artificial intelligence to dynamically adjust e-learning personas, with an emphasis on K-means clustering analysis. By focusing on the particular requirements of 10th grade Omani students, this study not only fills a crucial void in personalized e-learning but also makes a substantial contribution to the conversation surrounding the role of artificial intelligence in educational design. By prioritizing ethical considerations and stakeholder engagement, it establishes a solid foundation for subsequent developments in the personalization of e-learning.

II. Motivation

Equivalent to numerous regions Globally, the task of optimizing e-learning platforms to correspond with student inclinations presents a substantial obstacle but also presents a vital prospect for the progression of education. Conventional methodologies frequently prove inadequate in comprehending and adjusting to the varied requirements of learners, underscoring the imperative for novel strategies. Introducing AI-powered e-learning personas, an innovative approach that harnesses the capabilities of artificial intelligence to continuously improve and develop learner profiles through data analysis and feedback. The primary objective of this research is to customize AI-generated personas to suit the distinctive technological, cultural, and educational environment of Oman. By looking at how well these methods can change to meet the needs of different students, we hope to create a framework that not only meets the needs of today's education but also shows flexibility for what's to come. This study signifies an advancement in the direction of more individualized, captivating, and efficient online learning encounters, establishing a novel benchmark for tailored education in Oman and, potentially, worldwide.

III. Materials And Methods

Utilizing an AI clustering technique and online surveys to generate dynamic e-learning personas requires the implementation of a framework for AI-driven e-learning personas. The process entails two primary stages: data collection and the implementation of k-means clustering.

3.1 Data Collection

In order to create AI-powered e-learning personas for tenth graders in Oman, we gathered a dataset that encompassed essential factors such as proficiencies, technological inclinations, learning styles, IT infrastructure, and e-learning platform evaluations. These insights are critical to customizing e-learning solutions to the needs of students and thereby enhancing the learning experience. To guarantee precise data collection, we administered a comprehensive online survey through school computer labs. An initial pilot study that evaluated the survey's relevance and understandability supported this endeavor. The reliability of the questionnaire was thoroughly assessed through the implementation of Cronbach's alpha, which guaranteed the responses' consistency. The requisite authorizations were obtained from the Ministry of Education of Oman in strict adherence to legal and ethical principles. This thorough methodology guaranteed dependable data, which aided in the successful development of dynamic e-learning personas.

The sample size for our research study was ascertained utilizing the Steven K. Thompson formula, which was selected due to its applicability to our research design and the distinct characteristics of our target demographic—tenth graders residing in Oman. Because it includes finite population correction, this formula works well for research projects with a small, well-defined population because it ensures statistical accuracy and representativeness while keeping the sample size from being too large.

$$\eta = \frac{N \times Z^2 \times P \times (1 - P)}{(N - 1) \times D^2 + Z^2 \times P \times (1 - P)}$$

The calculation gave a minimum sample size (η) of 380, taking into account the entire population (N) of 10th graders in Oman, which amounts to 33,495. A 95% confidence level was chosen, which is equivalent to a Z-value of 1.96. In addition, a 50% assumed proportion of the outcome of interest (P) and a 5% margin of error (D) were specified. This calculation was used for two reasons: first, to get a sample size that would give a high level of statistical confidence; and second, to see if the survey could actually be done, finding a balance between the study's practical limitations and its rigorous methodology.

3.2 AI-Driven Analysis

During the K-means clustering operation, data points are partitioned into a predetermined number of clusters (k). The centroids of these clusters, which stand for the points at which they converge in the multidimensional data space, serve as their definition. The algorithm iteratively assigns data points to the nearest centroid and recalculates the centroid's position until convergence is reached. The implementation flow of k-means clustering is described in detail in Table 1.

Table 1. Implementation of K-Means Clustering Steps.

No	Analyzing task	Description
1	Load Data & Data Cleaning and Data Preparation	The information collected must be imported into the analysis environment.
2	Data Scaling	Normalize or standardize the data to lessen the likelihood that the scale of measurements will distort the analysis [8,18].
3	Determining Cluster Quantity	Employ methodologies such as silhouette analysis or the elbow method to ascertain the ideal number of clusters (k) [12].
4	K-Means Clustering	Apply the K-means clustering algorithm to the preprocessed data to partition it into k distinct clusters [8,17].
5	Cluster Validation & Evaluation	Evaluate the significance and caliber of the generated clusters by employing validation indices including the silhouette score, Davies-Bouldin index, and Calinski-Harabasz index[17].
6	Cluster Analysis & Visualization	Perform a comprehensive analysis of each cluster in order to ascertain its distinct attributes and the similarities present among the data points comprising it [12].
7	Descriptive e-Learning Persona Synthesis	Employ the insights obtained from the cluster analysis in order to construct all-encompassing personas for online education.

3.3 Framework for AI-Driven E-Learning Personas:

Through the ongoing process of refining and updating e-learning personas in response to emerging data and insights, Dynamic Persona Adaptation guarantees their sustained effectiveness and relevance. Comprehensive guidelines for the implementation of dynamic persona adaptation utilizing artificial intelligence, focusing on the analysis of online surveys and questionnaires and clustering techniques such as K-means:

A. Framework Design:

Dynamic persona adaptation is an ongoing, cyclical process. By implementing artificial intelligence (AI) and clustering methods, systematically collecting and analyzing data, and integrating findings into the creation of e-learning resources, it is possible to ensure that personas remain relevant to the changing needs of learners. This enhances the effectiveness and personalization of e-learning experiences. The constituent elements of the Framework for AI-Driven E-Learning Personas are depicted in Figure 2.

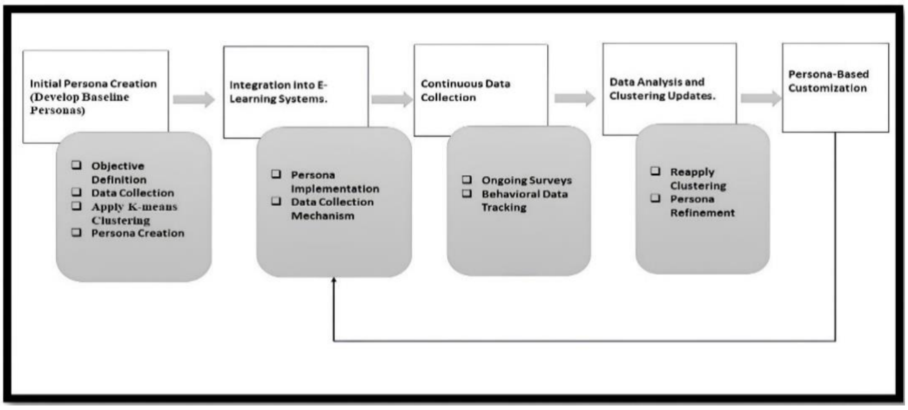

Fig. 1. Framework for AI-Driven E-Learning Personas.

B. Implementation of Framework for AI-Driven E-Learning Personas:

By employing AI and clustering algorithms such as K-means in particular, this framework delineates a methodical strategy for constructing and implementing dynamic, data-driven e-learning personas. These personas are generated from insights extracted from online questionnaires and surveys.

Initial Persona Creation (Develop Baseline Personas):

- *Objective Definition:*

The primary aim of integrating artificial intelligence (AI) into the e-learning persona development and refinement process is to achieve an unparalleled level of customization in educational experiences relative to traditional methods. The purpose of this effort is to utilize the predictive capabilities of artificial intelligence in order to analyze and interpret intricate learner data. The resulting actionable insights will have a substantial impact on the development and distribution of e-learning materials. More precisely, the integration is designed to *Enhance Personalization , Improve Learner Engagement, Educational Outcomes Improvement. Moreover,* The integration of artificial intelligence (AI) assistance offers a prospect of shifting from intuition-driven decision-making to a more empirical approach in the design and delivery of educational programs.[16].

- *Collected Data:*

The gathered data is predicated on the objective definition delineated in the preceding stage of the AI-Driven E-Learning Personas Framework. Its purpose is to gather information that contributes to the goals outlined in this framework. The survey attracted a total of 380 student responses, which exceeded the anticipated sample size and strengthened the reliability of the study. In order to maintain the demographic integrity of the dataset, participants were chosen using a stratified sampling technique that ensured the gender distribution of Grade 10 students in Omani public schools was accurately reflected. Additional information regarding the process of data collection can be located in the Materials and Methods section.

- *Applying k-mean clustering:*

This research substantially enhances the process of developing personas for e-learning through the application of k-means clustering for data analysis. Implementing this approach is crucial for transforming unprocessed data into actionable insights that inform the intricate development of persona profiles. The process of data analysis is methodically carried out in a sequential fashion.:

1. Load Data & Data Cleaning and Data Preparation:

The process of data preparation prior to analysis involves several key steps: removing extraneous entries, duplicates, and inconsistencies; ensuring the dataset's integrity; and addressing missing values through the implementation of diverse imputation strategies, as shown in Listing 1.

```
# Import necessary libraries
import pandas as pd
```

```
import numpy as np
# Load the dataset
df = pd.read_csv('C:\\learning_data.csv')
# Function to clean the dataframe:
def clean_data(dataframe):
# Remove duplicate rows
    dataframe = dataframe.drop_duplicates()
# Handle missing values (example: fill with the mean of the column)
    dataframe = dataframe.fillna(dataframe.mean())
    return dataframe
# Clean the data
cleaned_df = clean_data(df)
# Display the first 5 rows of the cleaned data
print(cleaned_df.head())
```

Listing 1: Load Data & Data Cleaning and Data Preparation.

2. Data Scaling:

The StandardScaler from scikit-learn was utilized in our research to normalize the data, eliminate mean bias, and scale features to unit variance; this was an ideal fit for our dataset and analysis. Although min-max scaling and Z-score normalization were alternatives at our disposal, StandardScaler was selected due to its pertinence to our goals, as evidenced by our preprocessing code. Furthermore, principal component analysis (PCA) was implemented to reduce the dimensionality of high-dimensional datasets. This process aimed to simplify the data without compromising essential attributes that were critical for the algorithms we selected, as elaborated in the program code[18].

```
from sklearn.decomposition import PCA
scaler = StandardScaler()
scaled_data = scaler.fit_transform(selected_columns)
# Apply PCA
pca = PCA(n_components=2)
data_pca = pca.fit_transform(scaled_data)
```

Listing 2: Data Scaling.

3. Determining Cluster Quantity:.

Before proceeding with the implementation of a clustering algorithm such as K-Means, it is critical to ascertain the optimal number of clusters. In this manual, the Davies-Bouldin index is employed in combination with the Elbow Method to determine the ideal number of clusters. The 'elbow point,' as shown in Figure 2 and Listing 3, which indicates diminishing returns with an increase in cluster count, is established by the Elbow Method through the graphing of the within-cluster sum of squares (WCSS) against the number of clusters, as shown in Table 2. Furthermore, the silhouette score and the number of students in each clustering are utilized to validate the selected number of clusters.

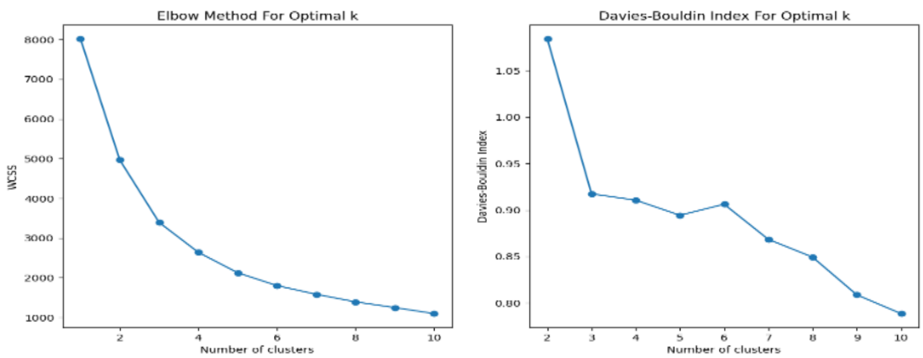

Fig. 2. Elbow Method with the Davies–Bouldin index.

```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
# Determine number of clusters using Elbow Method and Davies-Bouldin Index
wcss = []
db_index = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=0)
    kmeans.fit(data_pca)
    wcss.append(kmeans.inertia_)
    db_index.append(davies_bouldin_score(data_pca, kmeans.labels_))
# Plot Elbow Method and Davies-Bouldin Index values
plt.figure(figsize=(12, 6))
plt.subplot(121)
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Elbow Method For Optimal k')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.subplot(122)
plt.plot(range(1, 11), db_index, marker='o')
plt.title('Davies-Bouldin Index For Optimal k')
plt.xlabel('Number of clusters')
plt.ylabel('Davies-Bouldin Index')
plt.show()
```

Listing 3: Determining Cluster Quantity.

3. K-Means Clustering Implementation. :

Once the optimal cluster count has been determined, the data is segmented utilizing the KMeans algorithm, as illustrated in Listing 4. In addition, the distribution of clustering is depicted in Figure 3, and the quantity of students belonging to each cluster is detailed in Table 2.

```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
# Apply K-Means clustering based on the determined number of clusters
num_clusters = 4  # Update with the number determined
kmeans = KMeans(n_clusters=num_clusters)
kmeans.fit(data_pca)
# Analyze and visualize the results
cluster_assignments = kmeans.labels_
data['Cluster'] = cluster_assignments
```

Listing 4: K-Means Clustering Implementation.

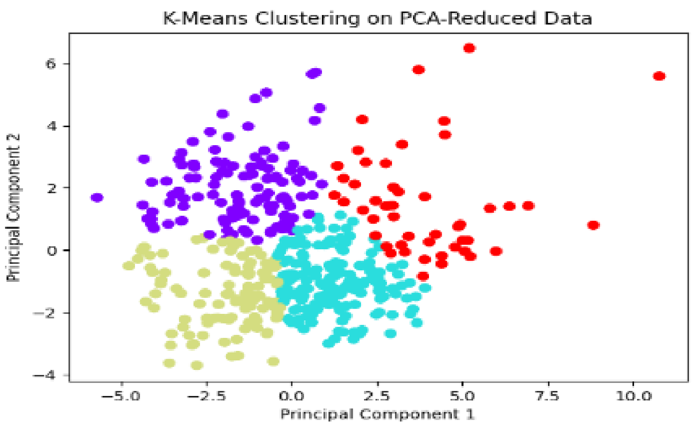

Fig. 3. Distribution Clustering.

Table 2. Number of students in each cluster.

Cluster no	Number of students each cluster
0	90
1	100
2	122
3	78

4. Cluster Validation & Evaluation:

The silhouette score is a measure employed to assess the efficacy of clustering by quantifying the degree of separation and cohesion among clusters.

```
silhouette_avg = silhouette_score(data_pca, cluster_assignments)
print(f"Silhouette Score: {silhouette_avg:.2f}")
```

Listing 5: Applying cluster validation using siloutte score.

The silhouette score of 0.80 that we got from our analysis shows strong cluster cohesion and distinctiveness. This proves that our method works for creating e-learning personas for Oman 10th graders.

Fig. 4. The Silhouette Score.

5. Descriptive e-Learning Persona Synthesis:

With each cluster representing a distinct e-learning persona, a comprehensive analysis is conducted, encompassing the following:

A) Mapping Categorical Features: Categorical data evaluation includes the analysis of binary, Likert scale, spatial, and average value distributions, as shown in Listing 6.

```
for cluster_num in range(num_clusters):
    cluster_data = data[data['Cluster'] == cluster_num]
    print(f"Persona {cluster_num + 1} Analysis:")
    mapping_dict = {
        'UsingTwitter': {1: 'Active', 0: 'Inactive'},
        'ConstantlyUpdatedOnSmartphone': {5: 'SA', 4: 'A', 3: 'N', 2: 'D', 1: 'SDA'},
    for column in cluster_data.columns:
        if column in mapping_dict:
            mode_val = cluster_data[column].mode()[0]
            print(f"{column}: {mapping_dict[column][mode_val]}")
        else:
            print(f"\n- Feature '{column}' is not binary and may require special handling.\n")
```

Listing 6: The analysis of binary, Likert scale, spatial, and average value distributions.

B) Feature Distribution Analysis:

As illustrated in Listing 7, this section provides assessments of feature prevalence in each cluster in a variety of formats, including graphical and percentage-based representations, as well as top-ranked and average-based data.

```
# Add mappings for other features
avg_daily_time = cluster_data['DailyTimeOnSocialNetworkSites'].mean()
print(f"Average Daily Time on Social Network Sites: {avg_daily_time:.2f} hours")
for feature in mapping_dict.keys():
    mode_val = cluster_data[feature].mode()[0]
    print(f"{feature.replace('_', ' ')}: {mapping_dict[feature][mode_val]}")
```

Listing 7: *Feature Distribution Analysis*.

6. Persona Drafting:

Following an analysis of cluster attributes, preliminary e-learning personas are constructed and enhanced through input from stakeholders. The finalized personas address the concerns of stakeholders, which facilitates decisions regarding student requirements. Figure 13 illustrates the methodology, emphasizing the distinctive characteristics of each persona within the context of e-learning.

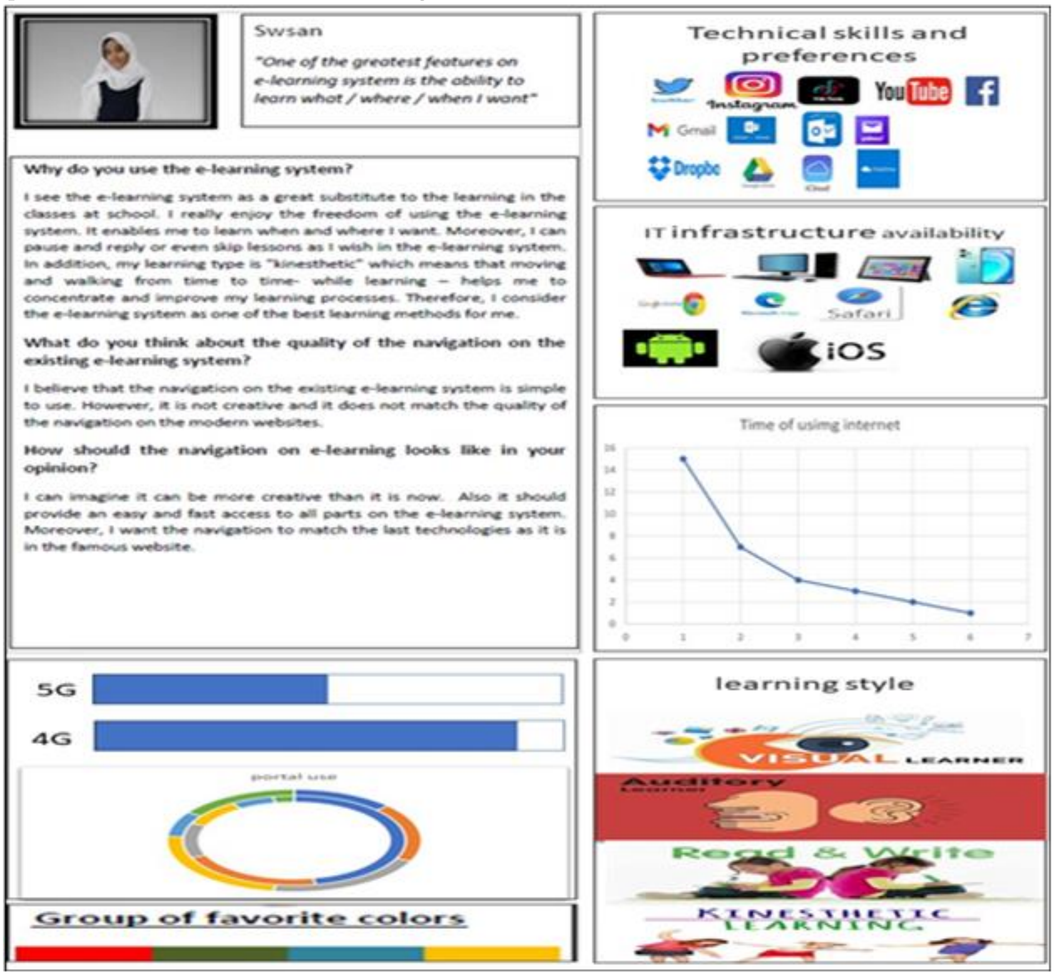

Fig. 5. Persona Drafting.

Continuous Data Collection

A crucial, cyclical procedure that is an integral part of the development of the Dynamic E-Learning Personas Framework is dynamic persona adaptation. By ensuring that e-learning personas continue to reflect the changing needs and behaviors of learners, this continuous process is crucial for the development and decision-making of e-learning systems.

Ongoing Surveys: In order to ensure that e-learning personas remain accurate and pertinent, periodic online surveys are employed. By adopting this methodology, it is guaranteed that the dataset will be consistently revised to incorporate newfound understandings of the preferences, behaviors, and requirements of learners. The surveys are strategically implemented at regular intervals in order to document the evolution of the learner population. This enables the continuous improvement of personas using up-to-date data.

Behavior Tracking: For the purpose of this research, we employ an advanced indicator system that was previously implemented in the educational portal of Oman to oversee and assess the interactions of learners. By gathering vital information regarding user engagement, this system informs the determination to enhance or create fresh e-learning personas. Such insights are crucial for comprehending user behavior and recognizing emerging trends that may necessitate persona modifications.

Implementing behavior tracking and periodic surveys to gather ongoing data is critical for comprehending the requirements of learners and facilitating the development of a flexible and dynamic e-learning environment. Implementing this methodology guarantees that the Dynamic E-Learning Personas Framework will continue to be adaptable and receptive to the needs of learners in the present and future.

Data Analysis and Clustering Updates:

The data collected during the ongoing data collection phase serves as the foundation for the revision and assessment of our clustering model in the future. We are currently adding the new datasets to the K-means clustering framework, which was first used to create basic e-learning personas. Our goal is to make these persona clusters better and bigger.

Persona-Based Customization:

By creating comprehensive personas, persona-based customization adapts e-learning experiences to the specific requirements and preferences of each user. By conducting dynamic analysis of these personas, we guarantee that the learning interfaces, instructional materials, and learning paths closely correspond to the unique attributes and learning inclinations of every user group.

IV. Results And Discussion

This study looked into a new way to use dynamic e-learning personas by using "An AI-Driven Approach Utilizing Online Surveys and K-Means Clustering." This made a lot of progress toward making e-learning environments more personalized. In order to collect a wide range of information regarding the learning preferences, IT proficiencies, technical capacities, and resource accessibility of 10th graders in public schools in Oman, we initiated the process with an all-encompassing survey.

An Examination of Innovative Persona Development Employing K-Means Clustering The foundation of our approach was the application of K-means clustering, a method chosen for its efficacy in partitioning the dataset into numerous distinct clusters based on shared characteristics. The segmentation process made it easier to create discrete clusters, each of which represented a cohesive learner profile with distinguishing characteristics and educational prerequisites.

Creation of Dynamic E-Learning Personas: The study successfully produced a multitude of dynamic e-learning personas by leveraging the clusters that were identified. Empirical data support the personas as archetypes that represent the various technological engagement levels and learning preferences of the student population under investigation. The analytical capabilities of K-means clustering served as a guide for the persona development process, ensuring that each representation was accurate and applicable.

Determining the ideal quantity of clusters is critical in the process of creating e-learning personas. By employing the elbow method to determine the threshold at which further clusters provide diminishing returns and coupling this with silhouette score analysis, the distinctiveness and pertinence of each cluster are guaranteed. By making sure there are the right number of clusters based on the balanced distribution of students and high silhouette scores, this method creates unique personas that can be used in targeted teaching methods. This approach improves comprehension of learner data, which in turn simplifies the development of personas that are representative.

Practical Applications and Implications: The creation of these dynamic e-learning personas facilitates the innovative implementation of personalized e-learning solutions. By integrating these personas during the stages of decision-making and development for e-learning systems, educators and technologists can improve the tailoring of learning experiences to meet the varied needs of students in a more effective manner.

Limitations: During the process of creating e-learning personas, we came across a number of elements that, for a variety of reasons, might produce unforeseen outcomes. The complexity of IT terminology may be confusing to students of this age, which makes it difficult to communicate with them effectively. Such a misunderstanding could compromise the faithfulness of e-learning personas to the real experiences of students. Furthermore, the determination of the ideal quantity of e-learning personas continues to be a formidable task, notwithstanding the implementation of the methodologies delineated in our development framework. Furthermore, although conducting surveys in academic classrooms guarantees adequate participant involvement and support when required, this methodology necessitates substantial investments of time, money, and labor.

In order to implement AI-driven persona development in education, its viability and scalability must be thoroughly assessed. This methodology necessitates substantial financial investments for initial implementation, continuous enhancements, and upkeep. In order for these systems to be managed effectively, IT personnel and educators must possess or acquire the requisite expertise. In addition, a dependable internet connection and the required hardware and software infrastructure are essential for the integration of AI technologies. Notwithstanding these obstacles, the incremental integration of AI-driven persona development, training investment, and strategic planning presents a feasible approach to augmenting personalized learning experiences.

In summary, the present study illustrates that the integration of conventional survey methods with AI analytics substantially enhances our comprehension and assistance towards heterogeneous student populations. The results regarding dynamic e-learning personas establish a strong basis for enhancing the usability and engagement of e-learning platforms, with a particular focus on the educational environment in Oman. This approach not only customizes learning experiences to suit the specific requirements of each individual but also sets standards for subsequent investigations in the field of educational technology. This research's contribution to the advancement of persona development fills in numerous empirical gaps and limitations that have been identified in the literature on persona creation.

V. Conclusion And Further Study

The current study endeavored to address the multifaceted nature of e-learning platform development by employing "An AI-Driven Approach Utilizing Online Surveys and K-Means Clustering" to surmount a variety of obstacles. Finding a new standard for creating dynamic e-learning personas was made possible by using K-means clustering strategically. This method grouped learner responses into meaningful personas.

Critical Contributions: The findings of our investigation revealed the critical importance of integrating sophisticated AI analysis, including K-means clustering, and learning style considerations into the persona development process. Through the implementation of this approach, a thorough understanding of the inclinations and actions of students was attained, resulting in the creation of e-learning personas that accurately represent the diverse academic needs of tenth-grade students in Oman.

Enhancing the Practicality of E-Learning Personas: The findings of our study underscore significant domains that warrant further investigation in order to improve e-learning personas. Active user engagement is critical in order to evaluate the efficacy of the personas and guarantee that they strongly resonate with the learners. In addition, it is imperative to perform comprehensive ethical and privacy evaluations in order to safeguard learner data, particularly when AI and data analytics are employed.

The Consequences Resulting from K-Means Clustering: It has been demonstrated that K-means clustering has a substantial amount of potential for generating effective and representative e-learning personas. By employing a methodology that categorizes students based on shared characteristics and preferred modes of learning, we have been able to offer Omani pupils a more captivating and personalized educational experience that is tailored to their unique needs.

Progressive perspectives: This research establishes the foundation for furthering the development of e-learning personas, emphasizing the significance of investigating novel approaches and technologies to facilitate personalized learning. Its substantial contribution to educational technology showcases the potential of artificial intelligence in developing e-learning environments that are more adaptable and efficient.

Further investigation in the field of persona development, with a specific focus on e-learning, may expand upon this study's findings by examining supplementary data sources such as social media activity or user login patterns. By integrating avatar technologies powered by AI, e-learning personas could be rendered more interactive and captivating. In addition to prioritizing resource efficiency, it is crucial to streamline the persona development process through the implementation of scalable frameworks and automated tools that can be modified to suit a variety of educational environments. Furthermore, it will be imperative to identify economical methods of incorporating personas into established educational technologies in order to deliver learning experiences that are both dynamic and personalized.

Acknowledgments

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References

[1] Flores-Chacón, E., et al., Educational innovation: the architecture of digital technologies as a catalyst for change in university teacher training. Scientific Reports, 2023. **13**(1): p. 20991.

[2] Anvari, F., H.M.T. Tran, and D. Richards. *Effectiveness of peer review in teaching and learning user centered conceptual design among large cohorts of information technology students*. in *2021 IEEE/ACM 43rd International Conference on Software Engineering: Software Engineering Education and Training (ICSE-SEET)*. 2021. IEEE.

[3] Li, L. and J. Xiao, *Persona profiling: a multi-dimensional model to study learner subgroups in Massive Open Online Courses.* Education and Information Technologies, 2022: p. 1-29.
[4] Lilley, M., A. Pyper, and S. Attwood, *Understanding the student experience through the use of personas.* Innovation in Teaching and Learning in Information and Computer Sciences, 2012. **11**(1): p. 4-13.
[5] Derr, K., R. Hübl, and M.Z. Ahmed. *Using test data for successive refinement of an online pre-course in mathematics*. in *14th European Conference on e-Learning ECEL*. 2015.
[6] Kim, E.-S., S.-J. Eun, and K.-H. Kim, *Artificial intelligence-based patient monitoring system for medical support.* International Neurourology Journal, 2023. **27**(4): p. 280.
[7] Wang, Y. and Q. Wu. *Research on Online Learning User Profile Based on K-means Algorithm*. in *2021 IEEE 4th International Conference on Electronics and Communication Engineering (ICECE)*. 2021. IEEE.
[8] Sinaga, K.P. and M.-S. Yang, *Unsupervised K-means clustering algorithm.* IEEE access, 2020. **8**: p. 80716-80727.
[9] Jansen, B.J., et al., *How to Create Personas: Three Persona Creation Methodologies with Implications for Practical Employment.* Pacific Asia Journal of the Association for Information Systems, 2022. **14**(3): p. 1.
[10] Jung, S.-g., et al. *Automatic Persona Generation (APG) A Rationale and Demonstration*. in *Proceedings of the 2018 conference on human information interaction & retrieval*. 2018.
[11] Li, Y.-J., et al. *Design and Evaluation of a Healthcare Management Terminology Mobile Learning Application*. in *2019 IEEE International Conference on Healthcare Informatics (ICHI)*. 2019. IEEE.
[12] Wang, X. and Y. Bai, *The global Minmax k-means algorithm.* SpringerPlus, 2016. **5**(1): p. 1-15.
[13] Stanca, L., et al., *Determining IT Student Profile Using Data Mining and Social Network Analysis.* International Journal of Computers, Communications and Control, 2020. **15**(5).
[14] Ali Amer Jid Almahri, F., D. Bell, and M. Arzoky. *Personas design for conversational systems in education*. in *Informatics*. 2019. Multidisciplinary Digital Publishing Institute.
[15] Anvari, F., et al. *Teaching user centered conceptual design using cross-cultural personas and peer reviews for a large cohort of students*. in *2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering Education and Training (ICSE-SEET)*. 2019. IEEE.
[16] Salminen, J., et al. *A literature review of quantitative persona creation*. in *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 2020.
[17] Ikotun, A.M., et al., K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. Information Sciences, 2023. **622**: p. 178-210.
[18] Festa, D., et al., *Unsupervised detection of InSAR time series patterns based on PCA and K-means clustering.* International Journal of Applied Earth Observation and Geoinformation, 2023. **118**: p. 103276.
[19] Weinhandl, R.; Mayerhofer, M.; Houghton, T.; Lavicza, Z.; Eichmair, M.; Hohenwarter, M. Personas Characterising Secondary School Mathematics Students: Development and Applications to Educational Technology. Educ. Sci. 2022, 12, 447. https://doi.org/10.3390/educsci1207044