Fuzzy Logic Approach to Cold-Start Challenges in Deaf and Hard of Hearing Recommender Systems

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ABSTRACT

An adaptive e-learning environment faces significant challenges in offering personalized learning resources for Deaf and Hard-Hearing (DHH) learners. These learners exhibit diverse preferences in learning and communication, influenced by their characteristics related to deafness, highlighting the need for personalized educational content. A well-defined learning model is essential to map the characteristics of learners to suitable learning resources, enabling effective recommendations within an e-learning system. This study explores the development of a comprehensive DHH learner model, focusing on the presence of multiple learning preferences based on the VARK (Visual, Aural, Read/Write, and Kinesthetic) learning style model and the effectiveness of fuzzy clustering in capturing the diverse but overlapping preferences. Fuzzy-C-Means (FCM) successfully identified six different but overlapping clusters, indicating that most learners exhibit multimodal learning preferences rather than relying solely on a visual learning style. Cluster centroid analysis reveals that the visual learning style is the most preferred, while aural learning is the least favored among DHH learners. By calculating the overall learning style score based on the fuzzy membership value across all clusters on all four dimensions of VARK, learners' learning style preferences were validated against self-reported data. The evaluation involved a survey of 130 higher secondary DHH students from Kerala, India, yielding promising results (precision: 0.90, recall: 0.84, F1-score: 0.84) on the model's efficiency in identifying the dominant learning style. These findings emphasize the need for adaptive content delivery strategies that integrate text, visual, and interactive elements to enhance the engagement of DHH learners. However, the limited sample size, due to the unavailability of publicly accessible datasets, and the limited number of students in higher secondary education, further highlights the need for accessible and standardized DHH data to advance this research domain.

Keywords-DHH learner model; recommendation systems; cold-start; learning style; fuzzy clustering; adaptive e-learning

I. INTRODUCTION

E-learning solutions that recommend learning resources dynamically adjust difficulty levels and match and adapt to personalized learning and accessibility preferences. These solutions extend the flexibility of learning beyond the classroom and enhance autonomous learning for Deaf and Hard-Hearing (DHH) learners. Deaf individuals experience hearing loss in speech frequencies in both ears above 70 dB, whereas hard-hearing individuals typically experience hearing loss in 60 to 70 dB [1]. The influence of educational and family settings results in various preferences for communication and learning for DHH learners [2]. This diversity emphasizes the limitations of one-size-fits-all learning approaches for the DHH population and underscores the need for more flexible e-learning solutions for them [3].

E-learning content recommendation systems can effectively address the diversity among DHH learners by making personalized and adaptable recommendations. Recommendation systems use information filtering to predict a learner's interest based on historical data [4]. Here, the recommended objects are the learning resources, referred to as Learning Objects (LO). Adaptations and personalization are effective only when assigning the most appropriate LOs according to the learner's choice and knowledge, which is a tedious task in a personalized and adaptive e-learning environment [5-6]. Thus, the core idea of recommendation systems is to establish a mapping between the learner characteristics, such as choices and knowledge level, and the LOs, presented in various formats.

DHH learners have different accessibility and communication preferences influenced by deafness-related factors, which must be incorporated to obtain personalized learning experiences [7-8]. A well-defined learning model can effectively encapsulate these preferences and their deafness-related parameters. Therefore, a recommendation system that effectively interacts with the learner model can retrieve the most appropriate learning materials from the pool of resources. It is crucial to identify which learner features are primarily connected to learning resources and which are subsets of the other features that can further enhance recommendations at the individual level.

The learner model can help recommendation systems deal with cold-start problems when there is no interaction data available to identify a learner's preferred learning materials. The learning style is a vital characteristic that reflects preferences in the way individuals perceive information [8-11]. Mapping learning styles to learning objects is an effective way to offer recommendations. However, learning styles are often modeled as discrete categories, where, in reality, learners may exhibit a combination of preferences.

This study focuses on learning style computation as the basis for personalized recommendations to develop a DHH-specific content recommendation system. The computed probabilistic learning style scores serve as an essential input for an adaptive content recommendation framework. By linking these scores with accessibility needs and learning resource characteristics, this approach ensures that initial recommendations are more aligned with learners' needs and that the system can refine learning content suggestions based on real-time interactions. This study also collected profile data from 130 DHH learners to develop the learner model and evaluate the effectiveness of the fuzzy clustering-based approach in computing the probabilistic learning style.

II. BACKGROUND

A. Learner Modeling

Learner modeling is the process of understanding and representing learner characteristics that act as the basis for adaptation in recommendation systems. It is the continuous process of collecting and updating data on the learner, which involves the initial collection of learner characteristics, model construction, and updating the model by tracing learner activities in adaptive systems [12]. It is different from the learner profile, as the profile contains only static information, while the model continuously evolves to reflect their changing needs and preferences [13].

Knowledge level, cognitive characteristics such as learning style, social characteristics such as peer interactions, and engagement level are essential aspects of the learner model [12, 14]. A well-designed DHH learner model should adopt these characteristics to ensure meaningful adaptation. Additionally, for DHH learners, it is important to consider their deafness-related parameters and preferences in accessibility, communication, and learning styles alongside these general characteristics [3, 15]. Therefore, a comprehensive DHH learner model was developed, including both a static profile with personal data, deafness-related parameters, learning and communication, and accessibility preferences, and a dynamic profile that includes interaction data with resources. Although the self-reported profile may initially be static (e.g., accessibility, learning, and communication preferences), these preferences may evolve over time. As learners interact with resources, implicit feedback is used to dynamically update their profiles, ensuring more accurate and personalized recommendations.

B. Learning Style

Learning style refers to personalized approaches that learners employ to receive and process information [16]. This helps to understand the different ways in which learners interact, perceive, and make sense of learning materials. Learning style theories help tailor teaching resources to meet learners' preferences and needs by aligning their learning preferences with the most appropriate types of learning materials [17]. Fleming's VARK, a widely accepted sensory-based learning style model, defines learning style as an individual's characteristic and preferred way of gathering, organizing, and processing information [18]. The four dimensions of VARK are Visual (V), Aural (A), Read/Write (R), and Kinesthetic (K) [19].

Visual learners prefer to perceive information using visual content, such as videos, images, or presentations. Auditory learners learn best by listening and relying on verbal explanations. Read/write learners prefer text-based information and may benefit from textbooks, note-taking, etc. Kinesthetic learners prefer to learn things by doing, being experimental learners, and can benefit from exercise, quizzes, simulations, etc. Table I details the key characteristics of the VARK learning style model and examples of adapted learning materials [18-19].

TABLE I. VARK LEARNING STYLE MODEL AND ITS KEY CHARACTERISTICS

	Learning style	Key characteristics	Preferred learning resources
1	Visual (V)	Learners prefer videos, images, or different spatial arrangements	{animated explainers, screencasts, tutorials, lecture recordings, demos, micro-learning videos, documentary videos, interactive videos, diagrams, charts, graphs, infographics, slideshows}
2	Aural (A)	Learning occurs best through verbal discussions and listening	{audio-lectures, podcasts, text-to-speech tools, debates, video with audio}
3	Read/Write (R)	Learners prefer reading and writing to process information	{articles, e-books, documents, transcripts}
4	Kinesthetic (K)	Learning happens through experiments and movements	{Simulations, games, exercises, quizzes, virtual labs}

There is no fixed number of combinations for these learning styles; instead, all possible preference profiles are considered as: single modality, where the highest score is in one category and lower in others, multimodal, where two or more categories have high scores, and dominant modality, where in a multimodal profile, the category with the highest score is considered a dominant one.

Previous studies have shown that DHH learners exhibit various learning preferences beyond visual learning [10, 19, 20]. Therefore, identifying their VARK learning styles, mapping them accurately to learning resources, and ranking them based on the diversity of accessibility preferences can serve as an effective starting point for recommendation systems to avoid the cold-start problem. The cold-start problem refers to the challenge faced by the recommendation system in making accurate recommendations when there are insufficient interaction data [21-23]. The learning style is a suitable characteristic for this purpose, as it reflects how a learner prefers to perceive and process information. Therefore, identifying DHH learners' preferences in learning and mapping those styles to appropriate learning resources can serve as an effective approach to providing initial recommendations [24].

C. Fuzzy Clustering

Clustering, an unsupervised learning technique, acknowledges diversity while reducing the complexity of individual variations by organizing data into manageable subgroups, revealing underlying patterns [25]. In clustering, there are two types of data assignment: hard and soft. In hard clustering, each object is forced to belong to a single cluster, even if it shares attributes with multiple clusters, resulting in non-overlapping groups [4]. However, real-world data, such as learning style preferences, are often fuzzy in nature, with varying degrees of membership in different clusters [9]. This makes soft clustering techniques, such as Fuzzy C-Means (FCM), a better choice, as they allow partial membership in multiple clusters rather than strictly assigning each data point to one cluster. This approach effectively captures diverse learning style preferences across different modalities.

Most existing recommendation systems are designed for hearing learners and often do not meet the unique needs of DHH learners when engaging with digital learning resources. The lack of adaptation to accessibility requirements, limited consideration of multimodal learning styles, and challenges in mapping learning resources to individual learning preferences, as well as the scarcity of DHH-specific datasets for model training emphasize the necessity of a DHH-specific recommendation system [26]. This gap limits the effectiveness of current e-learning solutions for DHH learners [27-28]. This study aims to address this gap by developing a DHH-specific recommendation system to improve learning engagement in online education. The following research question was formulated: "Can developing a learner model and a fuzzy learning style model help address the cold-start issue in e-learning content recommendations for DHH learners?" To answer this, the following objectives were defined:

- Develop a DHH learner model that incorporates deafness-related parameters, Personal Needs and Preferences (PNP) profile, knowledge level, and interaction data.
- Convert self-reported learning style preferences based on the VARK model into probabilistic values using fuzzy clustering that serves as an essential input for an adaptive content recommendation framework.

III. METHODOLOGY

A. Data Collection

The lack of open datasets related to DHH students, including their deafness-related features, learning preferences, communication styles, accessibility needs, and prior knowledge, poses a significant research challenge in adaptive content recommendation systems [29-31]. Data for this study were collected by the researchers from higher secondary schools across four districts in the state of Kerala, India. Data were collected by offline survey using a questionnaire related to socioeconomic, deafness-related, personal needs and learning preferences, and accessibility, as well as prior knowledge features [10, 32]. In line with the future enhancements outlined in [4], the questionnaire was enhanced by adding items related to capturing the preferences in learning style based on the VARK model, accessibility, and prior background knowledge. The revised instrument was then validated through expert review with four teachers of DHH students and two specialists in deaf education.

Table II provides a structured overview of the questionnaire items, grouped into major feature categories used to collect information on demographics, deafness profile, knowledge profile, and learning and communication preferences of the

DHH learners. Tables III and IV provide a more detailed breakdown of the key features assessed under the deafness profile and learning and communication preferences, respectively. This compact representation captures the essential variables required for learner modeling, which are subsequently used to enable personalization in the adaptive learning environment. Data were collected by interpreting the questions for the students with the help of their teachers and specially created Indian Sign Language (ISL) videos of the questionnaire to ensure accessibility.

TABLE I. CATEGORIES AND LIST OF FEATURES IN THE DATA

	Category	Features
1	Demographic details	{age, gender, grade, subject, instruction medium, type of schooling}
2	Deafness profile	{percentage of disability, degree of hearing loss, type of hearing loss, reception of speech therapy, hearing aid user, undergone cochlear implant, preferred communication mode, lip reading proficiency}
3	Prior knowledge profile	{English proficiency, computer proficiency marks in grade 10, and 11}
4	Learning and accessibility profile	{Preferred learning style, preferred accessibility feature, challenges in online learning}

TABLE II. DEAFNESS PROFILE

	Category	Features
1	Percentage of disability	Ranges from 0 to 100
2	Degree of hearing loss	{mild (<40), moderate (40-60), severe (61-80), profound (>80)}
3	Type of hearing loss	{conductive, sensorineural, mixed}
4	Reception of speech therapy above or below the age of 5	{yes, no}
5	Hearing aid user and cochlear implant	{yes, no}
6	Preferred communication mode	{sign, sign supported speech, speech}
7	Lip reading proficiency	Ranges from 0 to 5

TABLE III. PREFERENCES IN LEARNING STYLE AND ACCESSIBILITY (PNP PROFILE)

	Features	Values
1	Learning style	{visual, aural, read/write, kinesthetic}
2	Accessibility	{sign language, audio description, captions/subtitle, transcripts. text-to-speech, speech-to-text}

Ethical considerations were carefully addressed to ensure the rights and well-being of DHH participants. Informed consent was obtained from all participants, ensuring they fully understood the study's purpose, procedures, and their right to withdraw at any time. Furthermore, data privacy and anonymity were prioritized, ensuring that no personally identifiable information was stored or shared.

B. Dataset Description

Since the research focuses on DHH students in higher secondary education, the survey was conducted exclusively in special schools for such students in Kerala. This includes students from regular school settings who completed their prior schooling before entering higher secondary education, as well as those who studied exclusively in special schools. According to the latest list of the Higher Secondary Education Department in Kerala, there are 16 special higher secondary schools for DHH students in 12 districts, one of which caters to blind, deaf, and hard-hearing students. These schools include aided, vocational, and government institutions. A total of 334 students were admitted to grade 11 for the current academic year (2024-2025), according to statistics from the Kerala Higher Secondary Education Department [33].

During the initial round of data collection, a total of 130 students from 4 districts gave their consent to participate in the survey. Figure 1 shows the data distribution by district. The dataset comprises 53.8% male and 46.2% female students between the ages of 15 and 24. Most students (63.1%) choose sign-supported speech as their preferred mode of communication, while 26.2% prefer American Sign Language (ASL). Only 10.8% of students opt for speech. The dataset consists of 60.8% profound DHH learners, 23.8% severe DHH learners, 13.1% in the moderate category, and only 2.3% with mild hearing loss. Most students (83.1%) received speech therapy after the age of 5, indicating that they primarily accessed intervention programs in schools, while only 16.9% had no exposure to such programs. Additionally, 55.4% of the learners received speech therapy before age 5, whereas 44.6% did not benefit from early speech training intervention. 69.2% of students use hearing aids, while 30.8% do not. Students who do not have mixed schooling experience come mainly from special school backgrounds, whereas those who have experienced both mainstream and special school settings are almost equally divided.

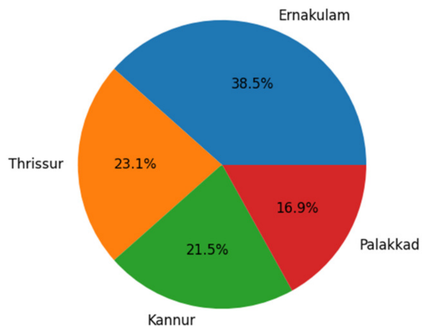

Fig. 1. District-wise sample distribution.

C. Learner Modeling

Learner modeling is a way of representing a learner's characteristics, including demographics, deafness-related parameters and personal preferences in learning and accessibility needs, and knowledge profile in an adaptive e-learning platform. A comprehensive learner profile helps the recommendation system suggest suitable learning materials, especially in cold-start scenarios.

1) Demographic Profile

This includes basic details such as age, gender, main subject stream, medium of instruction, current grade level, and prior type of schooling. The prior type of schooling experience helps to understand the different teaching methods that students might be interested in. This feature helps refine learning resource recommendations in an adaptive environment.

2) Deafness-Related Parameters

This includes the degree and type of hearing loss, whether they received speech therapy before or after age 5, the use of hearing aids or cochlear implants, preferred communication mode, and proficiency in lip-reading. Table II details this profile. These features also help refine learning resource recommendations by ensuring that the recommended resources are both accessible and effective for learners.

The level of hearing loss determines whether auditory content is useful for learners, while the type of hearing loss provides an indication of whether they can process speech information effectively, even with the use of hearing aids. Hearing aid usage amplifies sounds, but speech clarity depends on speech discrimination and noise cancellation abilities. Learners can benefit from auditory materials if speech clarity is sufficient. Early intervention programs, such as speech therapy, improve spoken communication skills, making captioned speech-based learning resources beneficial. They also enhance lip-reading skills, allowing recommendations for videos with clear facial visibility based on the learner's proficiency in lip reading. The primary communication mode directly affects the type of content of learning resources they interact with. Sign language users benefit from sign-integrated content, including text and video/audio, as well as lip-readable video resources. Sign-supported speech users can also benefit from spoken lectures and podcasts, as can speech users.

Notably, a significant number of individuals in the profound hearing loss category received early intervention programs before age 5, which may have helped them develop lip reading and speech skills. This, in turn, could have influenced their communication mode, as many students rely on sign-supported speech.

3) Learning and Accessibility Preferences (PNP Profile)

This includes preferences for learning styles and the accessibility of digital learning resources. Learning style preferences are based on the VARK model, defining how learners engage with educational content. Being a multimodal learner means preferring two or more of the four VARK learning modalities. These preferences were self-reported during data collection, where learners were allowed to select multiple modalities, indicating their flexibility in interacting with content across different formats. To accurately capture the multimodal learning preferences of DHH learners, a learning style preference question was used, allowing them to select multiple preferred modalities among the VARK rather than being restricted to a single choice. Table IV describes the PNP profile of learners.

A three-step validation process was employed to enhance the reliability of self-reported preferences. First, clear communication with ISL support ensured that each learning style preference was explained using real-time learning scenarios, allowing learners to fully understand their options. Second, encouraging authentic responses helped learners make informed choices by explicitly stating that they could select multiple preferences based on their actual learning experiences, avoiding forced selections. Finally, instructor cross-validation was performed, as the survey was offline, to ensure consistency between reported preferences and observed learning behaviors as cross-validated by the instructors.

Figure 2, which represents the x-axis as the number of learning style combinations, reinforces that most learners prefer more than two learning styles. This indicates that most learners are multimodal, meaning they benefit from content delivered in multiple formats. The most frequently reported learning style combinations in the data are kinesthetic, read/write, and visual, as shown in Figure 3. In addition, visual is the leading style, and aural is the least preferred. Understanding learning style preferences defines engagement with learning resources, while accessibility determines their usability.

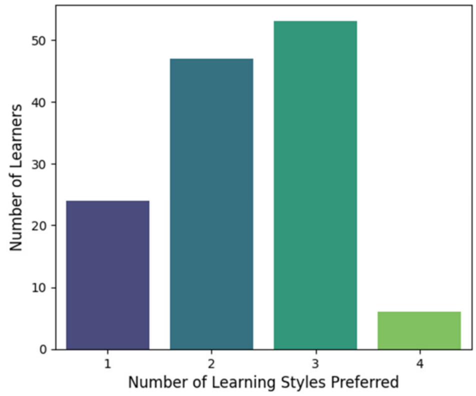

Fig. 2. Distribution of learners by number of learning style preferences.

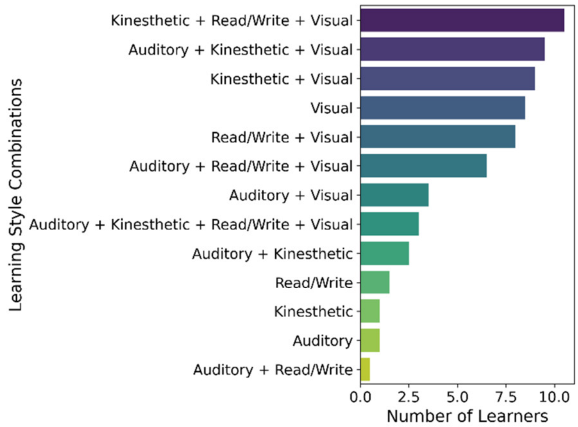

Fig. 3. Distribution of learning style combinations.

Figure 4 illustrates the accessibility options based on learning style preferences. The results indicate that captions/subtitles, along with ISL and voice, are the most preferred accessibility options across all learning styles. Learners with a read/write preference slightly favor captions/subtitles, whereas aural learners show a high preference for ISL with voice. This suggests that auditory learners within the DHH population are not purely audio-based, but their preferred mode of communication is sign-supported speech, as illustrated in Figure 5. This suggests they rely on a combination of lip-reading, residual hearing, and sign language for learning.

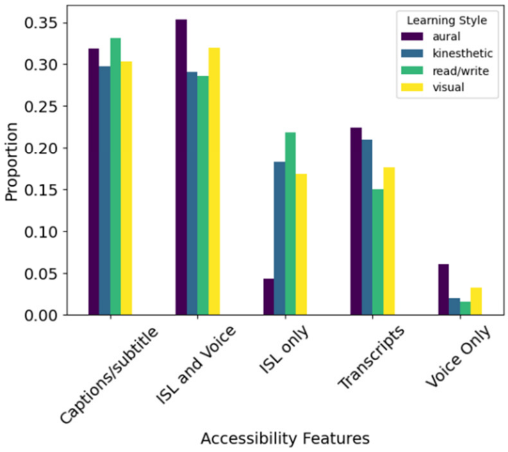

Fig. 4. Most preferred accessibility feature by learning style.

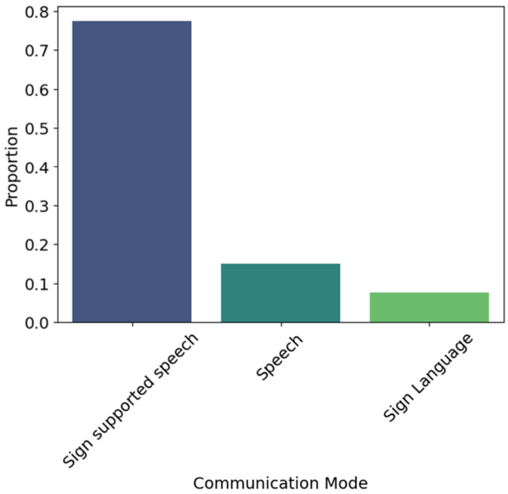

Fig. 5. Preferred communication mode among aural learners.

It was also observed that kinesthetic and read/write learners exhibit a high preference for ISL-only content. Voice-only content is the least preferred across all learning styles. The strong preference for multimodal accessibility features aligns with the fact that most learners in the dataset demonstrate multimodal learning styles, reinforcing the need for flexible content delivery strategies that accommodate their accessibility choices. These findings motivated the adaptation of the traditional VARK model for DHH learners, as summarized in Table V, to better suit their needs.

4) Knowledge Profile

Initially, the learner's knowledge profile was set to beginner, and as he progresses through the system, it gradually updates to intermediate and then advanced. Likewise, the model also collects learner interaction data to track their progress, offering real-time personalization in e-learning. Cloud-based servers can process real-time interaction data from learners, while edge devices, such as local servers, enhance response time by reducing latency, ensuring a real-time, adaptive, and personalized e-learning experience.

TABLE IV. DHH ADAPTED VARK LEARNING STYLE MODEL

	Learning style	Key characteristics	Preferred learning resources
1	Visual (V)	Learners prefer videos, images, or different spatial arrangements	{Sign-supported videos, images, concept maps, captioned/subtitled animated videos, transcripts}
2	Aural (A)	Learning occurs best through visual-auditory alternatives	{captioned videos, audio-lectures with transcripts, podcasts, text-to-speech tools, debates, ISL video with audio, lip-readable video materials}
3	Read/Write (R)	Learners prefer text-based learning materials, reading, and note-taking	{articles, e-books, documents, sign-language glossaries, captioned online courses, written assignments, transcripts}
4	Kinesthetic (K)	Learning occurs through hands-on activities and real-world examples	{Simulations, games, exercises, quizzes, virtual labs, sign-based demos, hands-on project}

D. Resource Tagging

To ensure that the recommended learning resources are personalized and accessible for all DHH learners, digital learning materials are tailored to various learning styles and accessibility needs, thus enhancing their online learning experience. Each resource is tagged and scored based on its alignment with the VARK modalities by analyzing its content components. For instance, a high visual score is assigned to materials that include videos, animations, webinar recordings, or slideshows. A medium visual score is given to resources with images, conceptual diagrams, and infographics, while a low visual score is assigned to text-heavy content with few images. Similarly, scores are calculated for Aural, Read/Write, and Kinesthetic dimensions according to the nature of the content. To ensure accessibility, the system incorporates accessibility-aware content tagging, where each learning resource is labeled with its accessibility attributes, such as captions, sign language support, transcripts, or voice-based narration, along with sign support.

E. Data Preprocessing

The collected data was preprocessed in the following ways: (i) data cleaning involved handling missing values, (ii) data discretization transformed continuous variables into categorical bins, (iii) feature encoding converted categorical variables into numerical representations, (iv) feature scaling normalized the numerical values for consistency, and (v) a user-feature matrix was created to prepare the data for clustering [13]. Missing values were filled using average values, while the column "Type of Hearing Loss", which had a majority of missing data, was ignored. Categorical features were encoded into numerical values using label encoding and multilabel binarization. A min-max scaler was employed to normalize the numerical values. The required features, including learning style, accessibility preferences, hearing loss level, usage of hearing aids, lip-reading proficiency, and communication mode, were structured into a user-feature matrix.

F. Learner Clustering

For clustering, only the learning style features were used, which include four categories: Aural, Visual, Kinesthetic, and Read/Write. Learners can select more than one category based on their preferences. Since this is a multilabel feature, multilabel binarization encoding was applied to represent the preferences across the four categories. The selected preferences were encoded as a binary matrix, where 1 indicates a chosen preference, and 0 denotes no interest, as shown in Table VI. The remaining features in the feature matrix are used to dynamically filter and refine content recommendations.

TABLE V. BINARY REPRESENTATION OF THE LEARNER'S SELECTED LEARNING STYLES

LearnerID	Aural	Read/Write	Kinesthetics	Visual
1	0	1	1	1
2	1	0	0	1
3	1	0	0	1
4	0	0	1	1
5	1	1	0	0
6	1	1	0	1
7	0	0	0	1
8	0	0	1	1
9	0	0	1	1
10	1	1	0	1

1) Fuzzy C-Means (FCM)

This is a centroid-based unsupervised learning algorithm that extends hard clustering methods by assigning a data point to multiple clusters with varying degrees of membership [34]. This is a reasonable choice in this context where learners exhibit overlapping preferences in the different learning styles. Instead of assigning a learner to a single cluster, it provides membership values across multiple clusters, making the results more interpretable for adaptive and diverse recommendations. The aim is to minimize the value of the objective function of FCM [25]:

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^{m} \, .d\left(x_i, c_j\right)^2 \quad (1)$$

where u_{ij} is the membership value of the data point x_i in the cluster c_j, m is the fuzziness parameter that controls the degree of overlap, $d\left(x_i, c_j\right)$ is the Euclidean distance between the data point x_i and cluster centroid c_j, n is the number of data points, and c is the number of clusters. The membership value for each data point is calculated using (2), and the sum of all membership values across the clusters is 1 [25].

$$u_{i,j} = \frac{1}{\sum_{k=1}^{c}\left(\frac{||x_i - c_j||}{||x_i - c_k||}\right)^{2/(m-1)}} \quad (2)$$

The algorithm begins by initializing random centroids according to the predefined number of clusters. Next, the membership values for each data point across the clusters are calculated using the fuzziness parameter, and the cluster centers are updated. These steps continue until the changes in the centroids are minimal. The output will consist of soft membership values for each data point across the specified number of clusters.

2) FCM on Learner-Feature Matrix

Choosing the optimal number of clusters c and the fuzziness parameter m plays a crucial role in FCM. In this study, c was set at 6 and m was set at 1.4, considering the top 6 combinations of VARK learning styles that appear in the data. However, to reinforce the choice of $c = 6$, the Xie-Beni Index (XBI) was calculated, which measures the compactness of clusters (where the within-cluster distance is minimized) and the separation of clusters (where the inter-cluster distance is maximized) [27, 35]. A lower XBI value indicates better clustering performance and the optimal combination of m and c is determined by the lowest XBI value. Figure 6 shows the line plot of the XBI across different values of c and m. The results show that XBI is minimized at 0.1471 when $m = 1.4$ or 1.5, as these values yield the lowest XBI values and smoother behavior. XBI steadily decreases as c increases, and the elbow point appears around $c = 6$ or 7, which reinforces the choice of c.

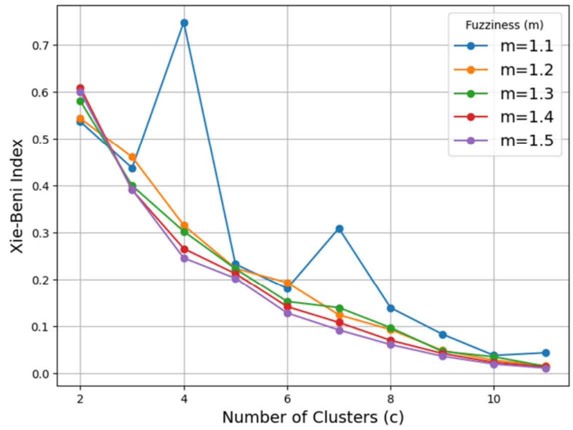

Fig. 6. XBI for different (m,c).

In FCM clustering, the centroids are initialized randomly. However, once the clustering process converges, the centroids remain stable and consistently represent the underlying distributions of the learning styles. The centroids:

- Define Representative Learner Profiles: Each centroid captures a distinct blend of VARK preferences that define a group of learners. This helps in understanding the prevalent multimodal learning behaviors among DHH learners.
- Enable Personalized Learning Recommendations: The calculated probabilistic learning style scores enable the system to connect new learners with the nearest centroid, ensuring they receive relevant learning materials.
- Support Adaptive Learning: Since centroids are derived from fuzzy clustering, learners are not confined to a single VARK category. As learners engage with the content, their learning style profiles may change, allowing the system to recalculate centroids and improve recommendations.

Running the FCM algorithm with the chosen parameters provides the membership matrix u_{ij} that includes the membership values of each learner in each cluster. These values indicate the degree to which each learner i belongs to each cluster j. It also returns the centroid matrix $Centr_{kj}$ that represents the average preference strength for learning styles in each cluster, showing how cluster k relates to learning style j.

3) Learner's Learning Style Profile Calculation

For each learner, the final learner profile computation is performed by calculating the weighted average of the cluster centroids, where the learner's fuzzy membership value in the cluster serves as the weight. This approach helps in combining the characteristics of each cluster and the individual learner membership in each cluster, resulting in a better representation of their learning style preferences, as given below.

```
Algorithm 1: Computing the learner's
learning style profile
Input:
  u_ij: membership matrix of size n*c, where
  n is the number of learners and c is the
  number of clusters
  cntr_jk: centroid matrix of size c*d where
  c is the number of clusters and d is the
  number of learning style dimensions
  lsNew: Learning style feature matrix of
  a new learner.
Output:
  Learner's learning style profile.
Steps:
1. Compute the membership values for the
  new learner by comparing the new
  learner's feature matrix against
  existing cluster centroids.
2. Calculate the weighted average of the
  centroids:
2.1. Multiply the membership values u_ij by
     the centroid values cntr_jk for each
     cluster.
2.2. Sum the weighted centroids to
     calculate the final preference
     profile across all VARK learning
     dimensions
```

$$P_i = \sum_{j=1}^{c} u_{i,j} \cdot cntr_{j,k} \quad (2)$$

```
    where P_i is the learner's learning
    style profile.
    Return the learning style profile list
    based on their rank.
```

For example, consider a learner profile (ID:96) and six clusters ($c = 6$). The learner's membership values for each cluster, given by the FCM algorithm, are {cluster 1: 0.04, cluster 2: 0.02, cluster 3: 0.26, cluster 4: 0.31, cluster 5: 0.04, and cluster 6: 0.33}.

This indicates that the particular learner has 33% membership in Cluster 6, 31% in Cluster 4, 26% in Cluster 3, and very low membership in the other clusters. So, the final learning style profile is calculated using step 2 as described in the algorithm by multiplying each cluster's centroid value for that style by the learner's membership values for that respective cluster and then summing up these products across all the clusters. The calculation for the Read/Write dimension across all clusters is shown below.

$$\frac{Read}{Write}: (0.04 * 0.99) + (0.02 * 0.01) + (0.26 * 0.04) + (0.31 * 0.99) + (0.04 * 0.01) + (0.33 * 0.88) = 0.6294 \approx 0.63$$

So, the final scores for the learner will be like Aural: ≈0.52, Kinesthetic: ≈0.55, Read/Write: ≈0.62, Visual ≈0.91.

Based on this, it is identified that this learner has a strong learning preference for visual, followed by read/write, and, lastly, aural. Therefore, the weighted average approach allows us to capture a more personalized learning style profile that reflects each learner's varying degree of association with multiple, potentially overlapping learning style clusters. This allows us to rank the resources according to the content type and recommend them accordingly.

The calculated preference scores, given by the FCM, are then used to recommend learning resources that align with the learner's dominant modalities while ensuring accessibility through captions, transcripts, and sign language interpretation. This means that if a learner has a strong visual preference, most recommendations (e.g., 6-7 out of 10) will include visual materials such as videos and animations, while the remaining suggestions may include text-based materials with images or hands-on activities. As learners interact with the system, their preferences are continuously updated, refining recommendations to better match their evolving multimodal learning needs.

4) Learning Resource Recommendation in Cold-Start Scenario

The proposed method primarily focuses on how FCM clustering is used to compute the learning style profile of DHH learners by capturing their overlapping preferences. These computed profiles serve as the initial input to the recommendation system, which matches personalized learning resources according to these values. Each learning resource is also tagged with its content-accessibility features and learning style values based on the VARK model.

When a new learner logs into the system, his VARK-based profile and accessibility preferences are collected. The system then computes his learning style profile by entering his self-reported learning style preferences into an FCM clustering model, which generates probabilistic values for each modality (e.g., Visual = 0.91, Read/Write = 0.62). This approach ensures that learners are not strictly assigned to a single category but instead exhibit overlapping learning preferences. The calculated learning style values and accessibility preferences are then sent to the recommendation engine, which retrieves pre-tagged learning resources that correspond to both learning styles and accessibility requirements. These resources are sourced from a database, where each learning object has been pre-scored with VARK-aligned values and accessibility features (e.g., captions, ISL support).

In future work, the recommendation engine could further utilize fuzzy logic to enhance resource suggestions. For instance, a fuzzy logic-based system could implement adaptive rules, such as recommending visually engaging learning materials (e.g., animations, videos, slideshows) for learners whose visual preference score surpasses a specified threshold. The detailed implementation of fuzzy logic for recommendation decision-making is planned as an extension of this work.

Initially, the learner receives recommendations based on his learning profile. However, as he interacts with the system, behavioral data are collected, such as engagement time, quiz performance, and resource completion rates. As the system accumulates sufficient interaction data, it recomputes the learner's learning style profile using adaptive learning mechanisms. This refined profile allows the recommendation engine to provide more personalized and accurate suggestions over time, enhancing the learning experience. Unsupervised learning techniques, such as autoencoders, can further enhance this process by learning compressed representations of learner behavior, allowing for the extraction of meaningful patterns that improve accuracy and personalization [36, 37].

IV. RESULTS AND DISCUSSION

This section details the cluster analysis and evaluates how well the fuzzy clustering identifies the learner's self-reported learning preferences.

A. Cluster Analysis

As discussed previously, the FCM algorithm was applied to the self-reported learning style preference data of DHH learners, resulting in 6 clusters and a fuzziness parameter (m) of 1.4. These values were selected based on the XBI, which measures the compactness of the clusters. The analysis is based on four learning style dimensions: Aural, Read/Write, Kinesthetic, and Visual. The heatmap in Figure 7 represents the centroid values of the 6 fuzzy learning style clusters, showing how strongly each one is associated with a particular learning style. The radar plot in Figure 8 provides the leading learning dimensions of each cluster. The cluster descriptions are as follows.

1) Cluster 1: Read/Write - Visual Learners

This cluster is characterized by extremely strong preferences for the Read/Write (0.99) and Visual (0.89) dimensions of VARK. This cluster has a very low preference for Aural and Kinesthetic learning styles. The learners in this cluster may prefer text-based explanations and visual-type learning materials.

2) Cluster 2: Visual Learners

This cluster shows preference only in the Visual dimension of the VARK learning style. So, these learners prefer strong visual content.

3) Cluster 3: Aural- Kinesthetic Learners

This cluster exhibits a strong preference for the learning styles Aural (1.00) and Kinesthetic (0.95) but a moderate preference for Visual (0.88). This cluster has less interest in text materials. Therefore, learners with a strong membership in this cluster may benefit from audio-based explanations, hands-on activities, or lip-readable video materials.

4) Cluster 4: Multimodal Learners

These learners can adapt to any format, making them highly flexible. For this cluster, all the learning style preferences are equally important except aural. These learners can enjoy the combination of text, visual, and interactive learning activities.

5) Cluster 5: Kinesthetic-Visual Learners

This cluster has a strong preference for Kinesthetic (0.99) and Visual (0.93). Learners in this cluster have extremely low preference for read/write and aural-based learning. So, they will not benefit from heavy text-based content and audio descriptions. They prefer hands-on activities, demonstrations, and visual explanations.

6) Cluster 6: Aural-Visual Learners

These learners have a strong preference for the Aural (0.99) and Visual (0.94) dimensions of VARK. They are very weak in the kinesthetic dimension but exhibit a moderate preference for read/write style. They will benefit from lectures supplemented with text and visual aids.

The radar plot in Figure 8 visualizes the cluster centroids across the four different dimensions of VARK, showing how each cluster differs in terms of learning style preferences. The shape of the polygon indicates the dominant traits of each cluster. Figures 7 and 8 reveal that visual learning preference is prevalent across all clusters, closely followed by kinesthetic learning. A significant number of learners also prefer the read/write learning style, whereas the aural one is the least preferred among DHH learners.

The analysis of learning style distribution, as shown in Figure 3, underscores this finding, indicating that most learners exhibit multiple learning style preferences rather than fitting strictly into one category. Since most learners exhibit multiple learning styles, the FCM model efficiently captures this overlap by assigning a degree of membership to multiple clusters. This capability allows for a more flexible and realistic representation compared to traditional hard clustering methods.

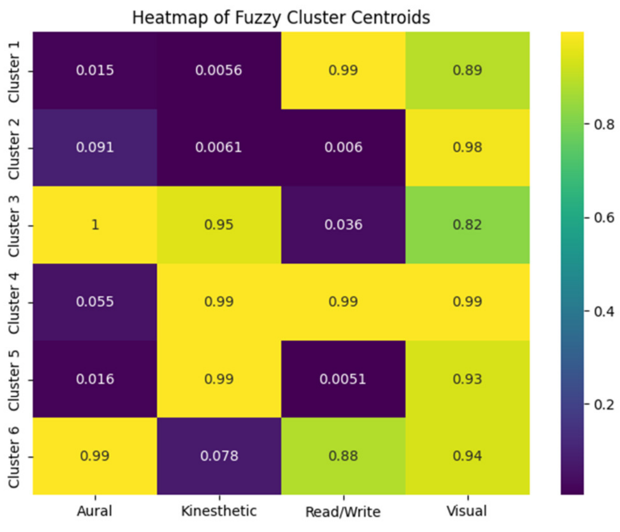

Fig. 7. Heatmap of fuzzy learning style cluster centroids.

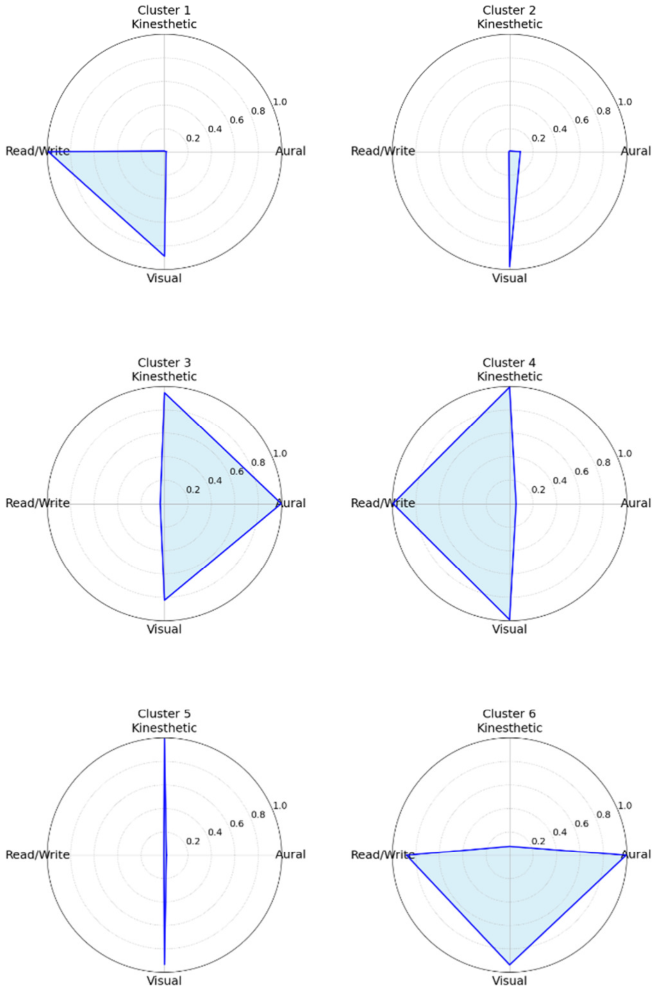

Fig. 8. Radar plot for fuzzy learning style cluster centroids.

B. Validation of Computed Fuzzy Learning Style Profiles Against Self-reported Styles

The clustering results were validated against self-reported learning styles using multiple evaluation methods. Since the learners selected multiple VARK preferences in the questionnaire, it was examined whether the clustering outcomes aligned with their choices. The computed weighted learning style profiles, derived using FCM, were compared with the learners' explicitly reported preferences. Precision, recall, and F1-score were used to measure agreement between the computed clusters and self-reported preferences, ensuring that the assigned cluster membership accurately reflected the learners' dominant learning modalities.

Each learner provided his explicit preferences across the VARK dimensions, which were then converted to a binary feature vector. Then the probabilistic learning style profile was computed for each learner using FCM. To assess the correctness of this computed profile, self-reported preferences were compared with computed top-k learning styles [9]. A learner may exhibit multiple preferred styles, making partial matching crucial. In this context, precision, recall, and F1-score are appropriate metrics, as they effectively measure the agreement between the computed styles and self-reported styles. Precision (3) indicates the proportion of computed top-k learning styles that match the learner's self-reported style. Recall (4) is used to measure the proportion of the learner's self-reported styles that are successfully captured in the computed top-k preferences. The F1-score (5) balances precision and recall to measure how well the computed styles match the self-reported styles. A high F1 score shows that the algorithm effectively captures the preferred preferences.

$$Precision = \frac{1}{N}\sum_{i=1}^{n}\frac{|TopK\ computed\ styles \cap selfreported\ styles|}{TopK\ computed\ styles} \quad (3)$$

$$Recall = \frac{1}{N}\sum_{i=1}^{n}\frac{|Topk\ computed\ styles \cap selfreported\ styles\ |}{Selfreported\ styles} \quad (4)$$

$$F1-score = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (5)$$

The overall evaluation of learning style computation using fuzzy clustering, compared against self-reported preferences, demonstrates that the model's performance is reliable. The FCM model effectively identifies learners' dominant learning styles, achieving a precision of 0.90, indicating that the model is highly reliable in predicting learning style preferences with minimal false positives. The 0.84 recall indicates that the model accurately identifies 84% of the actual dominant styles, although some cases remained unrecognized. The balanced F1-score of 0.84 further underscores the model's effectiveness in maintaining a strong trade-off between precision and recall, ensuring reliability. Figure 9 presents the evaluation results.

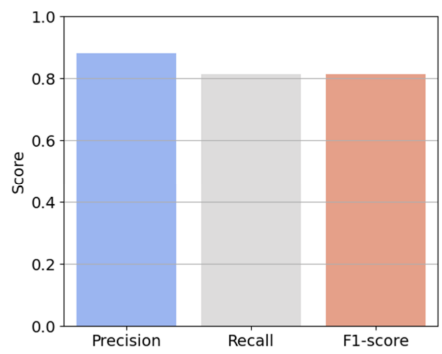

Fig. 9. Evaluation metrics.

Additionally, the XBI was applied to assess the compactness and separation of clusters, verifying the effectiveness of the fuzzy clustering approach. As a further validation step, it was examined whether learners assigned to a particular cluster had their preferences aligned with the leading modality of that cluster. Future work will extend this validation by implementing the recommendation system and evaluating its effectiveness in providing personalized learning content. Moreover, the lack of existing DHH-specific learning style datasets and the absence of benchmark datasets prevented direct comparisons of the computed learning style profiles with prior research.

Although existing studies have explored the adaptation and accessibility of e-learning content for DHH learners, they focused primarily on improving comprehension through sign language support, visual enhancements, and bilingual information rather than personalized recommendation systems. Some works have categorized DHH learners according to learning styles but did not integrate these preferences into a recommendation framework. Unlike these approaches, this one introduces FCM clustering to compute probabilistic learning style scores across VARK modalities, enabling a more flexible and multimodal approach. This ensures that learners receive personalized content recommendations that align with both their learning styles and accessibility needs, an area that has not been extensively explored in previous studies.

V. CONCLUSION AND FUTURE SCOPE

This study primarily explored the development of a DHH learner model, examining whether there are multiple learning style preferences and how FCM clustering captures these diverse yet overlapping preferences. It also demonstrated how the overall learning style profile can be computed from overlapping cluster memberships and validated against self-reported data. The computed learning style profiles, along with accessibility preferences, serve as input to the fuzzy logic-based decision-making system. This approach ensures that learning content is tailored to the learner's preferences and accessibility needs, making e-learning more inclusive for DHH learners. The findings highlight the importance of integrating adaptive multimodal learning style computation and accessibility-aware content tagging. Thus, this research contributes to the design of more inclusive e-learning platforms.

The findings of this study highlight the need for DHH learners to engage with digital learning materials through multiple modalities that meet their accessibility needs, ensuring a more inclusive and effective learning experience. This has direct implications for policymakers, including special educators, school administrators, and instructional designers, reinforcing the importance of inclusive learning resource design. Additionally, incorporating adaptive learning recommendations into institutional Learning Management Systems (LMS) can significantly enhance student engagement and reduce dropout rates among DHH learners. This directly supports Sustainable Development Goal 4 (SDG 4: Quality Education), which advocates for equitable access to education and inclusive learning environments for people with disabilities.

Despite its contributions, this study has certain limitations, including a relatively small sample size and variations in ISL, which may have introduced communication barriers during data collection. To mitigate this, local interpreters, including educators from the respective schools, assisted in the process. Another limitation was ensuring a diverse dataset that accurately represents different learning behaviors, accessibility needs, and educational backgrounds. Furthermore, the reliability of self-reported learning and accessibility preferences poses a challenge. To minimize reporting bias, self-reported preferences were validated against those of instructors.

Currently, clustering is based on self-reported data regarding VARK preferences. Future improvements could integrate behavioral data, engagement patterns, and performance metrics of DHH learners to make a dynamic and continuous learning adaptation. Future work will involve the practical implementation and evaluation of the proposed model in real-world educational settings, as follows:

- Development of an Integrated Learning Platform: A dedicated learning website that integrates the FCM clustering model and the recommendation system.
- Content Tagging and Accessibility Enhancements: Digital learning materials should be precalculated and tagged with VARK-based attributes and accessibility features (e.g., captions, sign language interpretation, transcripts).
- Initial Learner Profiling and Continuous Adaptation: During registration, the learners specify their VARK and accessibility preferences, which are processed using fuzzy clustering to generate an initial learning profile. As learners interact with resources, engagement data is used to refine their profiles and dynamically update recommendations.

By implementing these improvements, this research aims to develop a fully adaptive, accessibility-aware recommendation system that enhances the digital learning experience for DHH learners.

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