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EXPLORING FOREIGN LANGUAGE EDUCATION USING PERSONALIZED LEARNING ALGORITHMS AND DISTRIBUTED SYSTEMS BASED ON BIG DATA ANALYTICS

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Abstract. The limitations of traditional methods result in a lack of personalization and real-world immersion in language learning, particularly in foreign language learning skills. It leads to limited conversational practices and slower development. Also, traditional methods fail to adjust the respective needs of every individual learner and varying proficiency levels. To address these kinds of problems and to enhance foreign language education, the present study supports with its unique novel framework called the Cognitive Collaborative Language Optimizer (CCLO) model, which combines the benefits of collaborative filtering, fuzzy cognitive systems, and neighborhood-based recommendation algorithms based on distributed systems and big data analytics (BDA). By using real-time data based on every learner's performance, preferences, and progress, the CCLO framework adjusts learning experiences for each individual and provides an effective path for language development. While neighborhood-based algorithms form clusters of learners with shared learning paths, on the other hand, collaborative filtering identifies patterns in learner behavior. It suggests education materials that work well for learners with comparable backgrounds. This guarantees a personalized learning experience. Managing uncertainty is an important function in CCLO, and this was performed using fuzzy cognitive systems, where learners commonly prove their partial knowledge of learning. CCLO provides the best experience by adjusting every learner's needs and offers the benefit of vocabulary, grammar, and conversation practice at the correct time. Finally, the simulation of the suggested CCLO is conducted using a seven-week study based on the Chinese as a Foreign Language (CFL) dataset. The efficacy of the suggested model shows a notable improvement in conversation proficiency. The detailed illustrations and experiments are discussed in the following sections.

Key words: Cognitive systems, collaborative filtering, foreign language learning, personalized learning, fuzzy logic, recommendation algorithms, immersive learning and AI based education.

1. Background.

1.1. Challenges in Traditional Foreign Language Learning. The effectiveness and adaption are required for successful language development, these are limited due to the number of issues with traditional foreign language learning techniques. The inability to handle different learning methods and skill levels creates a major problem. A lot of traditional techniques take standard strategy that does not consider the needs of different learners, which commonly results in interest decrement and slower language gaining progress [10, 3]. Furthermore, learners find it challenging to practice traditional skills in real-world conditions and traditional settings due to a lack of real-world involvement [15, 6]. The limited use of technology limits the ability to design effective, attractive learning environments, which is another major obstacle. Traditional approaches commonly highlight textbook-based instruction, which cannot encourage recent advancements and does not promote critical thinking skills and active learning engagement [19]. Furthermore, the lack of effective learning pathways and personalized feedback makes it difficult for learners to concentrate on their areas of weakness (SpringerLink). Because of this, learners commonly find it difficult to become confident in everyday chats, particularly in situations involving other languages where cultural details are crucial [11]. Many of these issues are addressed by the move toward digital tools and customized algorithms, which helps to encourage flexibility and practical usage

In this era of globalization, knowledge of more than one foreign language has become a key skill that aids communication in personal, academic, and professional spheres. Conventional systems used in the teaching of the foreign languages are generally characteristic of a uniform model where all learners are treated the same regardless of their variations in learning styles and techniques. Such approaches often result in ineffective learning habits, disinterest, and poor performance in oral skills and pragmatics. In the same way, students

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are also unable to fully maximize their efforts because such forms of education are also void of feedback or possibilities of shifting the parameters and thus stimulating the students.

New technologies related to the active usage of big data and personalized learning algorithms bring radical improvement to the approaches taken in learning foreign languages. With the use of these technologies, processing a great deal of data and recognizing the features of the language learners and the concerns they are facing, enables each student to be provided with a learning plan that is tailor-made for him/her. The enhancement of the process consists in the connection of uniformly structured distributed systems for acquisition on-line, processing and returning the information about the learner‘s state.

The need to overcome the known disadvantages of conventional foreign language education systems is the motivation underlying this study. This study also examines and tries to identify how personalized learning algorithms coupled with big data and distributed systems can improve the process of language study. What is required is creating a modular and configurable system enabling the achievement of the stated objectives, where improving the speed and efficiency of the foreign language acquisition will not be the only goal, but enhancing a conversational experience, gaining cultural exposure, and improving comprehensively in order to meet the learners' demands as well.

1.2. Advancements in Personalized Learning Algorithms. By adapting learning opportunities for each learner, advanced personalized learning algorithms completely changed the nature of foreign language learning. These algorithms develop personalized learning ways that help support each learner's individual needs by analyzing massive volumes of data, such as learner behaviors, preferences, and progress [5, 7]. This approach guarantees that learners receive resources suitable for their current ability level and highlights the areas that need to be improved. By continuously adjusting student's growing vocabulary, these systems provide a more efficient and engaging way to learn a language. The main advantage of the personalized learning algorithm is its ability to provide real-time adjustments to the learning process [13]. While modern algorithms continuously adjust content, tempo, and difficulty according to the learner's development, traditional language learning methods commonly accept a static approach. For example, the system can highlight vocabulary or grammar rules that students find difficult and then offer exercises and materials that specifically target these areas and fill in their knowledge gaps. This makes learners by creating a highly engaged environment for learning [17, 12]. Furthermore, to improve communication skills, personalized learning systems include interactive components like dialogue simulations that imitate real-world language use. These characteristics allow learners to practice in reliable situations. The incorporation of adaptive learning technologies improves learners' language and cultural knowledge by allowing them to understand refinements that are important to learning a foreign language.

1.3. Suggested CCLO and its Contributions. By considering the impacts and benefits of the existing and current techniques, we present the advanced solution for improving foreign language proficiency, called CCLO, developed by using CF and fuzzy cognitive diagnosis and neighborhood recommendation algorithms [4, 18, 16]. With the help of various integrated, personalized learning approaches, the CCLO framework provides learners with customized, adaptive learning experiences that change in real time. CCLO guarantees that learners are guided through a customized path of language knowledge and focusing on areas that need to be improved. CCLO offers particular suggestions, which is one of its main contributions. It can leverage data from each learner's behavior and provide resources for their learning needs. For example, when a learner is strong in vocabulary but weak in sentence structure, CCLO modifies its recommendations to highlight sentence-building activities. Moreover, the problem of managing incomplete knowledge is addressed by CCLO. Learners commonly lack proficiency in specific areas of language learning, such as grammar or pronunciation. By handling this situation, we promote this suggested approach of CCLO.

2. Literature Discussions. This study [14] highlights using real materials and interactive exercises can help students become more proficient listeners in language learning environments. With the use of technology, educators can create personalized, interesting listening activities that meet each student's needs and help increase motivation and engagement. To improve English listening skills, a personalized learning path system is presented in [8], which adjusts learning paths according to the user's preferences and level of knowledge. The system recommends relevant listening materials, such as podcasts or audiobooks, using natural language processing (NLP) approaches. This dramatically improves expertise and student engagement. The study displays student satisfaction levels and the system's recommendation accuracy, from 85% to 92%. This study [9] compares collaborative filtering with content-based filtering algorithms to investigate how recommender systems are used to improve English language learning resources in higher education. The outcomes show the balance between recall and precision, with content-based methods providing more complete material coverage. The limitations of traditional e-learning systems, which commonly fail to adjust the unique needs of each learner, are clearly described in study [1]. The novel personalized recommender system NPR_eL is suggested to adapt learning materials according to a student's background, preferences, and memory capacity, which is introduced in this work. The study [2] introduces a customized intelligent mobile learning system (PIMS) that uses a learner's reading proficiency to suggest English news articles. Using a fuzzy item response theory, the system assesses learners' abilities and suggests new words to improve vocabulary acquisition.

3. Methodology.

3.1. Suggested CCLO design. The suggested CCLO structure is developed through three important key features: Fuzzy cognitive systems, neighborhood-based recommendation algorithms, and collaborative filtering.

The Learner Profile Module is the first module of the design, it helps to collects real-time data based on vocabulary, comprehension and conversational performance for every user. The Collaborative Filtering Engine uses this data to find trends and preferences between learners who are similar to the user and recommends learning resources such as vocabulary exercises or conversation scenarios, that are suitable for the user's level of proficiency.

At the same time, learners' confusing inputs are processed using the Fuzzy Cognitive System, which effectively modifies the difficult level and target areas of learning. For example, if the learner finds it difficult to understand grammar but performs well in vocabulary, the fuzzy system balances this by providing more grammar exercises and maintaining vocabulary at the same time. Neighborhood-Based Recommendation is the third component that helps cluster students regarding comparable performance courses. It generates a content recommendation based on how learners in the similar neighborhood are processed, and ensuring an improved learning path.

The AI Interaction Module also presents interactive conversational agents to make learners practice speaking, get real-time feedback, and modify their responses to real-world application. Finally, the Evaluation Module provides an exact outcome of suggested CCLO. Figure 3.1 displays the exact representation of suggested CCLO.

Further justification for the need for this method is the lack of any system that can efficiently customize language learning for individual students as this is always done in small magnitudes. Given that there are learners who have different command over the vocabulary or grammar, or even their conversational skills, the CCLO framework makes sure that each learner is taken along a unique, appropriate learning path that meets their needs. How the CCLO is implemented calls for the grouping of learners who have similar patterns of learning and through collaborative filtering, effective teaching aids are brought forth to ensure that the learning process is efficient. Fuzzy cognitive systems mitigate barriers arising from incomplete language learning by attending to spatial partial information and uncertain objectives.

Such efficacy of the CCLO framework is primarily due the focus on extending the boundaries of conversational capabilities as all language learners want to reach the goal. Due to the shift of focus in language learning towards the interactions over the internet, methods like CCLO are very crucial in opening up better and faster ways of learning that deal with the problem of difficulties each learner experiences.

3.2. Suggested CCLO Implementation.

3.2.1. Recommendation model for foreign language learning (CFL) based on fuzzy cognitive diagnosis. Binary scoring is mainly applicable to objective questions in traditional cognitive diagnostic models (CDMs), but it is not enough for foreign language learning, speaking, and writing. A fuzzy cognitive diagnostic model is presented to overcome these limitations. Fuzzy set theory is used mainly in CCLO to handle partial knowledge and inaccuracy. A learner's ability is denoted by a continuous value between 0 and 1, which indicates the student's partial or complete knowledge of particular language abilities rather than a binary approach. In CFL learning, every knowledge point k denotes each of the vocabulary, grammar, and syntax in a corresponding fuzzy set $(sl, \mu_k)$where μ_k is the membership function that specifies each learner's proficiency level, and sl is the

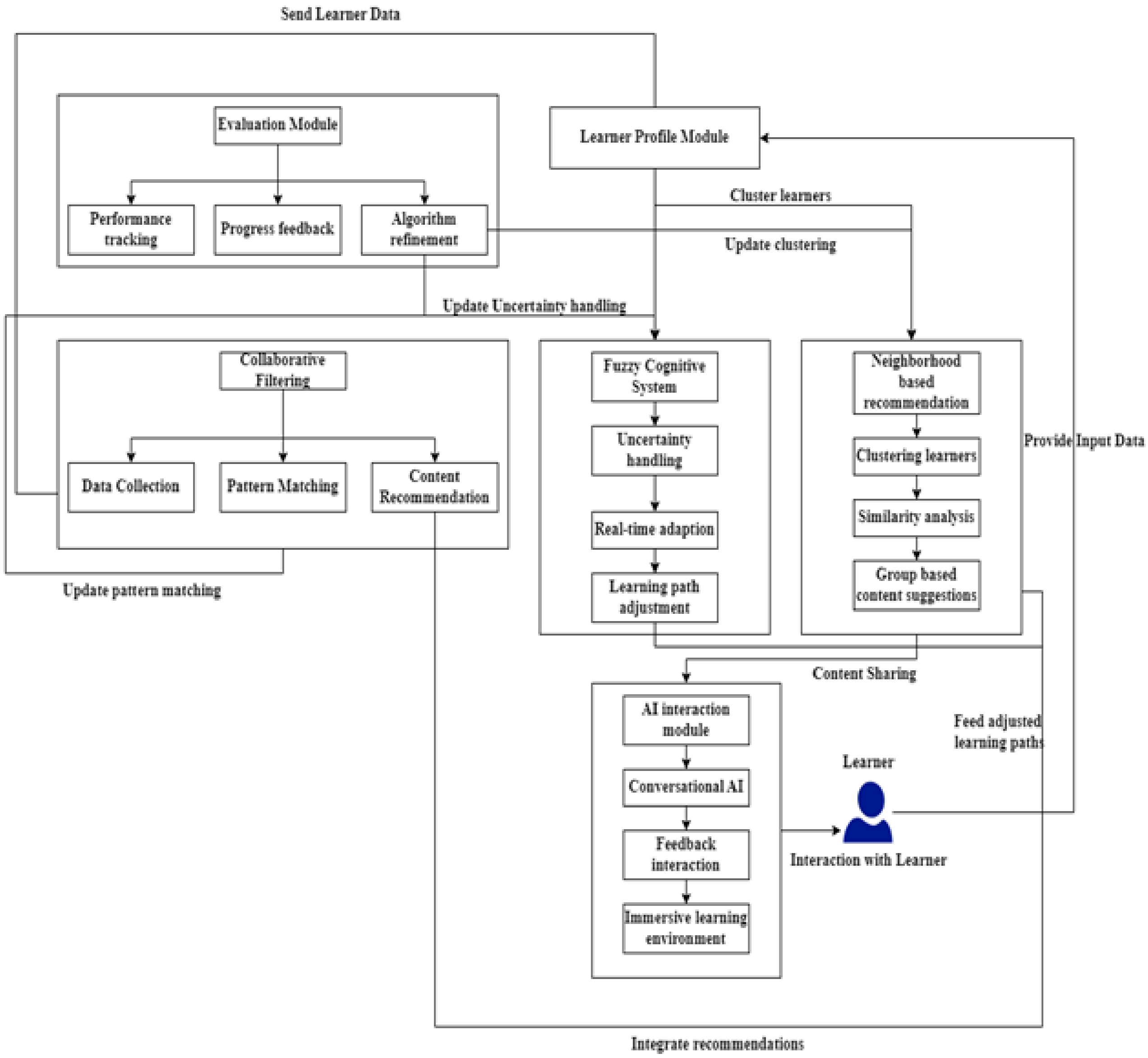

Fig. 3.1: Suggested CCLO Workflow

learner set. The logistic function is used to calculate the proficiency of the Fuzzy Cognitive Diagnosis Model pa_{slk}, which is comparable to the two-parameter logistic model in Item Response Theory (IRT).

$$pa_{slk} = \frac{1}{1 + \exp[-1.7\,(pa_{slk}\,(\vartheta_m - db_{slk}))]} \tag{3.1}$$

Here, pa_{slk} is the proficiency of the learner, ϑ_{sl} denotes the learner latent ability and db_{slk} highlights the difficulty of knowledge point k.

In the fuzzy cognitive model, we consider the objective and subjective questions. Students must observe all relevant data points to answer objective questions, whether they are correct or incorrect. We apply the linkage-type concept for this, where the student's minimum proficiency in each assessed knowledge point is used to calculate the proficiency $p\eta_{sln}$ of question n by learner sl.

$$p\eta_{sln} = \min_{1\leq k\leq K}(\mu_{sl}(k)) \tag{3.2}$$

According to subjective questions, speaking and writing are examples of scores that depend on partial knowledge. The adequate assumption is applicable in this situation, and the maximal proficiency across knowledge points is used to calculate the level of proficiency $p\eta_{sln}$.

$$p\eta_{sln} = \max_{1\leq k\leq K}(\mu_{sl}(k)) \tag{3.3}$$

The approach additionally handles guessing and errors students make when answering subjective and objective questions. The probability that a learner sl will correctly respond to question n in an objective question which is expressed as

$$pr(r_{sln} = 1) = gp_n + (1 - gp_n)p\eta_{sln} \tag{3.4}$$

Here gp_n is the guessing parameter and $p\eta_{sln}$ is the learner's knowledge of the question. In subjective questions, a Gaussian distribution is used to simulate the probability distribution of learner scores.

$$pr(r_{mn} = s) = N + (s|p\eta_{mn}, \sigma^2) \tag{3.5}$$

$N + (s|p\eta_{sln}, \sigma^2)$ is a normal distribution centered at $p\eta_{sln}$ with variance σ^2, sl is the learner score on the subjective question.

The CCLO system incorporates several real-time information and enhances the learning by making it more personal for the users. In the case of performance data, it may consist of results of quizzes and exercises as well the time and accuracy of responses during language activities. Other measures focus on the behavioral data, such as how much idle time users have on the task and which specific areas they seem to perform less well, and the duration of utility of the platform. Learning data consists of how learners interact with other people by way of role plays, conversations, and responses to feedback given by the trainer in person or electronically. In effect, the system demands preference data from users and in this case, learners outline style of learning they are comfortable with, content they will require and feedback they expect. It might also entail gathering social and collaborative data by performing group activities and group tasks and as for the uncertainty facet, this relates to fuzzy cognitive systems that recognize partial understanding and areas of confusion that learners encounter.

After the information is collected, several algorithms are undertaken to process the information in the database. Collaborative filtering establishes associations among the learners to suggest suitable learning resources. Fuzzy cognitive systems work in situations of uncertainty by modifying task difficulty depending on the performance of the learner. Learner progress and preferences are used in neighbourhood recommendation systems to enrol learners with such characteristics who would benefit from learning materials and peer interaction. The system embeds feedback in the form of continuous updating of the learning trajectory as the learner progresses with an aim of enhancing the learning experience actively rather than passively.

3.2.2. Neighborhood-Based Recommendation Algorithms. Based on their performance and proficiency levels, the neighborhood-based recommendation algorithm identifies similar learners and suggests individualized learning materials. Calculating the similarity between learners based on their proficiency between knowledge points is an essential step.

The similarity between two learners sl_1 and sl_2 based on the proficiency in knowledge points can be calculated using

$$sim(sl_1, sl_2) = \frac{\sum_k a_{sl_1k} \bullet a_{sl_2k}}{\sqrt{\sum_k a_{sl_1k}^2} \bullet \sqrt{\sum_k a_{sl_2k}^2}} \tag{3.6}$$

where a_{sl_1k} and a_{sl_2k} are the proficiency of learners sl_1 and sl_2 on knowledge point k.

According to Pearson's correlation coefficient-based similarity calculation, it considers the mean proficiency of students across all knowledge points, was expressed as

$$sim\,(sl_1, sl_2) = \frac{\sum_k \left(a_{sl_1k} - \overline{a}_{sl_1}\right)\left(a_{sl_2k} - \overline{a}_{sl_2}\right)}{\sqrt{\sum_k \left(a_{sl_1k}^2 - \overline{a}_{sl_1}\right)^2} \bullet \sqrt{\sum_k \left(a_{sl_2k}^2 - \overline{a}_{sl_2}\right)^2}} \tag{3.7}$$

Here $\overline{a}_{sl_1}$ and $\overline{a}_{sl_2}$are the mean proficiency of students sl_1 and sl_2 across all knowledge points.

3.2.3. Fuzzy cognitive and neighborhood-based learning model for CFL. Once the student similarity has been identified, the model uses proficiency and similar learner performance to select questions and learning resources for each student.

For each learner, sl, the system suggests the knowledge points of k based on their current proficiency and the difficulty of learning materials. The cosine similarity between learners' proficiency and difficulty of the test question is calculated by

$$dist\,(sl, n) = \frac{\sum_k \emptyset_{slk} \bullet \leftthreetimes_{nk}}{\sqrt{\sum_k \emptyset_{slk}^2} \bullet \sqrt{\sum_k \leftthreetimes_{slk}^2}} \tag{3.8}$$

Here $\emptyset_{slk}$ denotes the student proficiency of knowledge point k and $\leftthreetimes_{slk}^2$ denotes the difficulty of knowledge point k in the recommended content n.

Fuzzy cognitive systems (FCS) are excellent when it comes to overcoming the problems of uncertainty in language learning, those are appropriate for working with undefined or uncertain, incomplete information typical for such situations as education. In language learning, students do not have absolute knowledge of the different aspects of grammar, vocabularies, and conversation, and can therefore have different fluency levels. This partial understanding may originate from the fact that the learner does not recall a specific grammar rule or cannot remember when a given word seems contextually appropriate. Binary or deterministic (this is right or this is wrong) approaches to the problem do not comprehend such insights whereas however, this is where fuzzy systems come into its consideration and treatment of such vagueness.

FCS does this by treating the different variables as belonging to certain degrees of membership as opposed to simply categorizing them as either true or false. For instance, with regard to learning a language, rather than using a flip chart with a straight indication of right and wrong for a learner's grasp of a certain concept, a fuzzy logic diagram would show how much a learner has mastered the concept probably on a scale of between 0 and 1. Thus learning system determines such optimal responses or exercises that are not overboard difficult or so easy for that matter but are just right basing on his/her current level of competence.

Fuzzy systems resolve this by permitting the learner to possess or be assessed to have a "good understanding" or "needs improvement" range of language proficiency allowing partial membership in different language knowledge categories. It is also true that learners might not have a full-fledged picture of things all the time. Fuzzy systems are designed to use part of information thereby making their application conducive when giving feedback based on the level of knowledge and performance of the learner which is often in a state of flux hence bridging the existing learning gaps more efficiently.

Personalization and Adaptation. In contrast to a more rigid approach, fuzzy systems facilitate the treatment of the learners' learning behaviors and performance with some leeway allowing for relative decomposition of the learning structure. Just as it is typical with all learners, there are various levels of mastery over grammar, praction, or vocabulary among learners which often times are fuzzy logical developmental and hence improveover time.

Understanding how a human thinks. The human logic or reasoning is complex and is followed up with some degree of uncertainty or consistent with incomplete data and so fuzzy systems are built around this concept. Thus, they are particularly useful in teaching situations as students usually have partial information about the right answer and tend to be confused.

3.3. Hybrid Collaborative Filtering (HCF) Algorithm under CCLO. Collaborative filtering technique, which helps to continuously monitor learner behavior and generate recommendations based on similarities across users and resources, is one of the most popular recommendation approaches, particularly in personalized learning platforms.

Following the execution of Neighborhood-Based Recommendation Systems and Fuzzy Cognitive Diagnostic Models, CF algorithms are the additional advantage contributed by CCLO. The neighborhood-based and fuzzy cognitive models evaluate each learner's proficiency and recommend resources according to their observation of certain knowledge points. Again, the CF algorithm adds another level of personalization by considering similar learners' more general learning habits, which is a further effective refinement process performed under CCLO. The hybrid CF depends on the integration of two classifications of filtering. User-based filtering and item-based filtering.

Real time data accessibility for working with learners in a learning environment is one of the elements within the Cognitive Collaborative Language Optimizer (CCLO) framework that makes the learning process more personalized. The system utilizes big data analytics in a distributed fashion and captures, processes and analyzes learner engagement with the language learning activities in real-time.

All these activities go on in a real time environment while the system collects and captures data as learners work on completing exercises, partaking in discussions, working with learning content and providing as well as receiving feedback and comments. The content of the learning path and the tasks being faced by the learner are monitored so that changes are made actively and timely based on the so that the particular content and tasks suited for the learners are appropriate relative to their current state of progression in learning.

In the CCLO framework collaborative filtering and fuzzy cognitive systems are applied using this real time data as a way of individualizing the learning process. These algorithms work hand in hand to make accurate predictions on what materials and activities will be most suitable for the learner and the same algorithms will reposition with respect to the learners' proficiency level.

3.3.1. User-based filtering. Based on the performance and interactions with learning materials, similar learners are identified by the User-Based CF algorithm. By comparing students' results from a variety of tasks, such as grammar, vocabulary, and listening comprehension, the algorithm can calculate the similarity between learners. To predict the interest of learners in a specific source it can be expressed as

$$pr_{u,j} = \overline{ar}_u + \frac{\sum_{v \in knn(u)} siml(u,v) \bullet (ar_{v,j} - \overline{ar}_v)}{\sum_{v \in knn(u)} siml(u,v)} \tag{3.9}$$

Here $pr_{u,j}$ is the predicted score of learners u for resource j, whereas $\overline{ar}_u$ and $\overline{ar}_v$ are the average ratings of learners u and v and $ar_{v,j}$ is the actual ratings of resource j by learner v. $siml(u,v)$ highlights the similarity between learners u and v based Pearson's.

3.3.2. Item-based CF algorithm. The calculation of similarity between various learning resources such as vocabulary tests and reading comprehension activities is done by item-based CF. For learners who have showed proficiency in a particular exercise, this is helpful because it allows the system to suggest similar materials that have assisted other learners to improve. The similarity between two resource i and j is expressed as

$$siml\,(i,j) = \frac{\sum_u ar_{u,i} \bullet ar_{u,j}}{\sqrt{\sum_u ar_{u,i}^2} \bullet \sqrt{\sum_u ar_{u,i}^2}} \tag{3.10}$$

With the use of this technique, instructors can provide recommendations for activities or courses which are effective for other learners with similar learning needs.

4. Evaluation and Experiments.

4.1. Experimental Setup. The present study is evaluated based on CFL dataset, inspired from [4]. According to the features, we perform evaluation for the suggested CCLO model. Table 4.1 presents the important details about dataset features.

Table 4.1: Dataset Details

Category	Details
Participants	10 students, aged 18-22, no prior experience with Chinese
Participant Information	Level-1 Chinese course, minimal outside exposure
	Lesson on shopping (32 vocab words, 6 sentences)
Learning Session	4 sessions in Panoramic Scenes and Virtual World
	Vocabulary and conversation via task-based teaching
	AI role-play for listening, comprehension, speaking

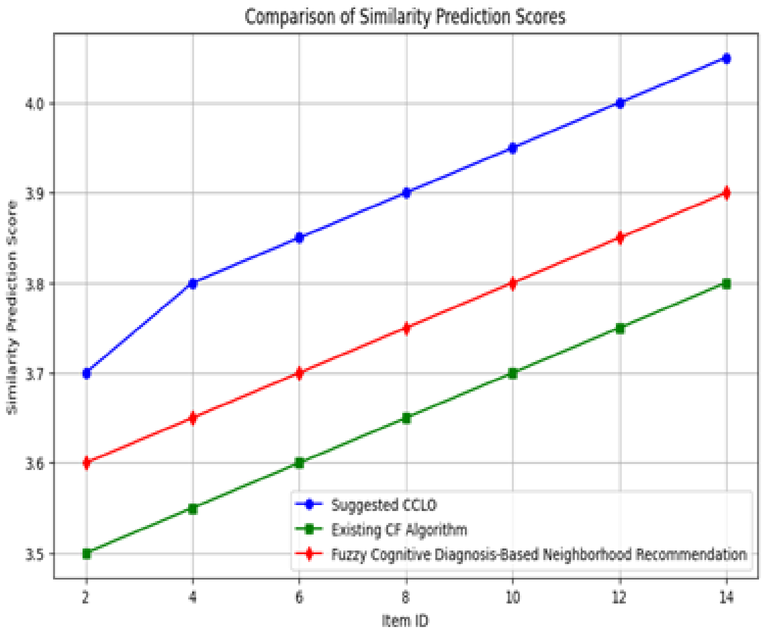

Fig. 4.1: Similarity Prediction Comparison

4.2. Evaluation Criteria. Figure 4.1 presents the efficacy of suggested CCLO in terms of similarity prediction scores across different item id. Due to the combining strength of both CF and fuzzy logic, which considers the partial knowledge and learning gaps, this efficacy is possible. The suggested model provides more effective learning experience by perfectly adjusting to the user behavior and individual performance. As a result, CCLO achieves best scores when compared with existing techniques in maintaining the prediction stability and improving overall recommendation accuracy.

Fig 4.2 presents the CCLO in improving the personalization recommendations by considering both the previous interactions and partial understanding of learners. Here the modified cosine similarity indicates the similar recommended resources. Through the maintenance of uncertainty and effective adaption of learners, performance the suggested CCLO obtains better language proficiency outcomes.

Figure 4.3 indicates the MAE scores of nearest neighbors n. According to the figure, suggested CCLO shows the low MAE scores, which highlights that the CCLO prediction of learner's performance or learning progress are more accurate. Similarly, Figure 4.4 shows the RMSE scores comparison of various models. Based on the figure we observe that, the suggested CCLO predicts few large errors, which means it provides more reliable outcomes of learning item effectiveness for learners.

Figure 4.5 presents the index comparison scores. The suggested CCLO considerably outperforms the existing CF, and fuzzy models. It shows its effectiveness in terms of high precision, recall, coverage and

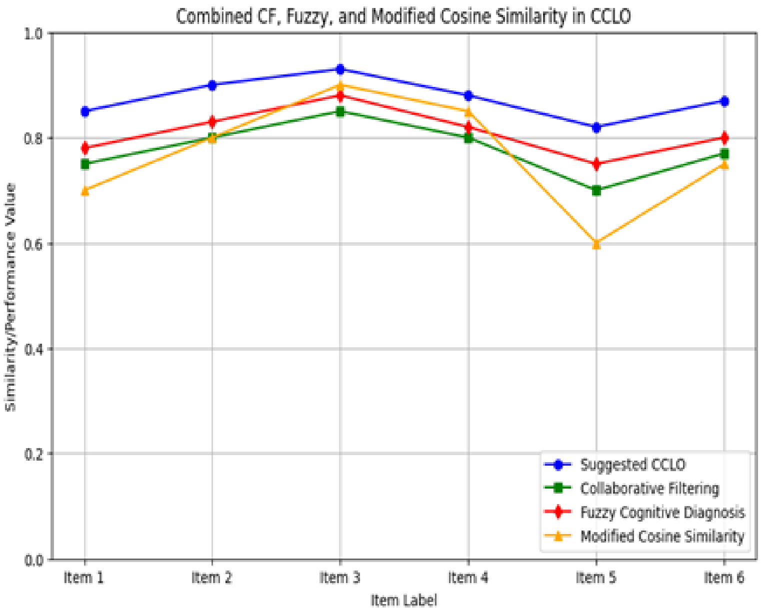

Fig. 4.2: Cosine Similarity Value

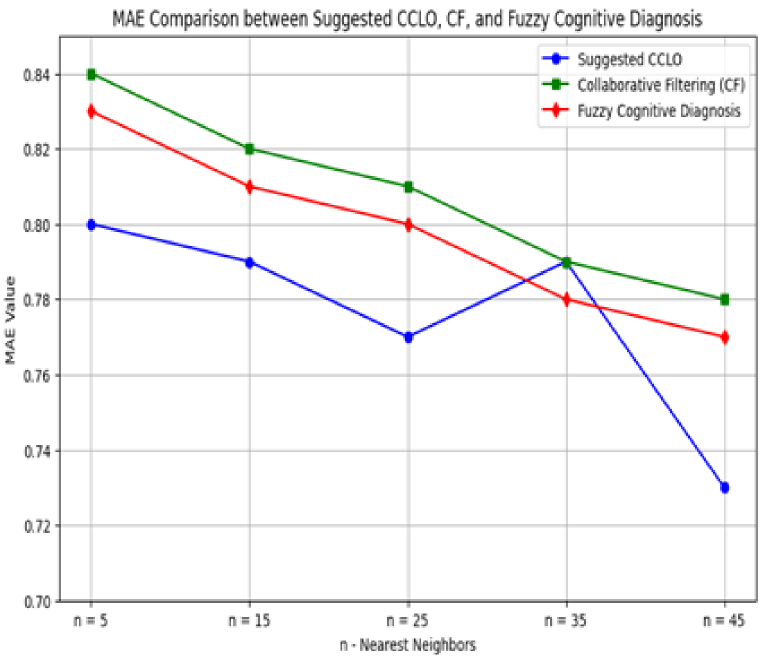

Fig. 4.3: MAE Comparison Scores

popularity.

5. Conclusion. The suggested study presents the effective fusion model called CCLO which combines fuzzy cognitive diagnosis and neighborhood recommendation algorithm with collaborative filtering algorithm

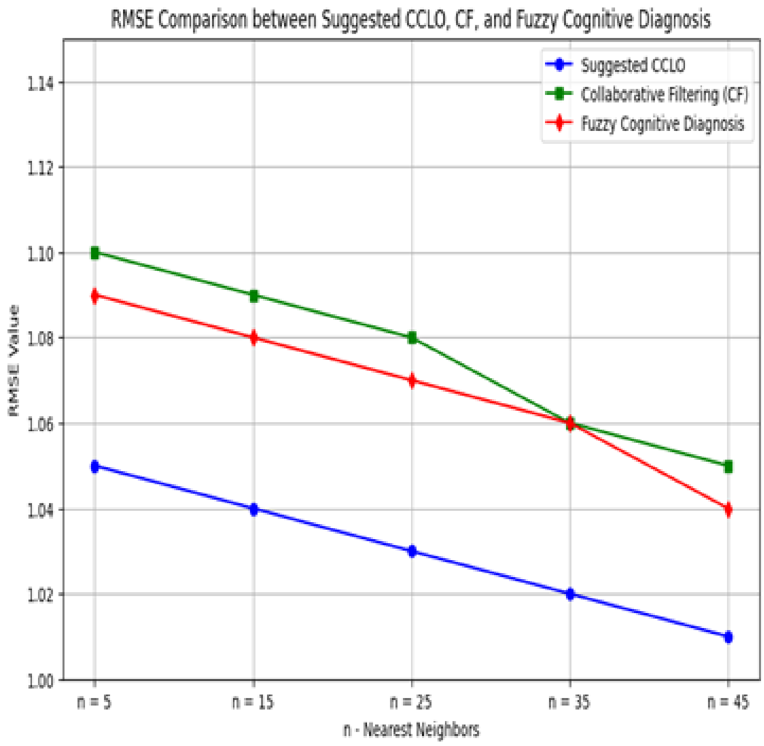

Fig. 4.4: RMSE Comparison

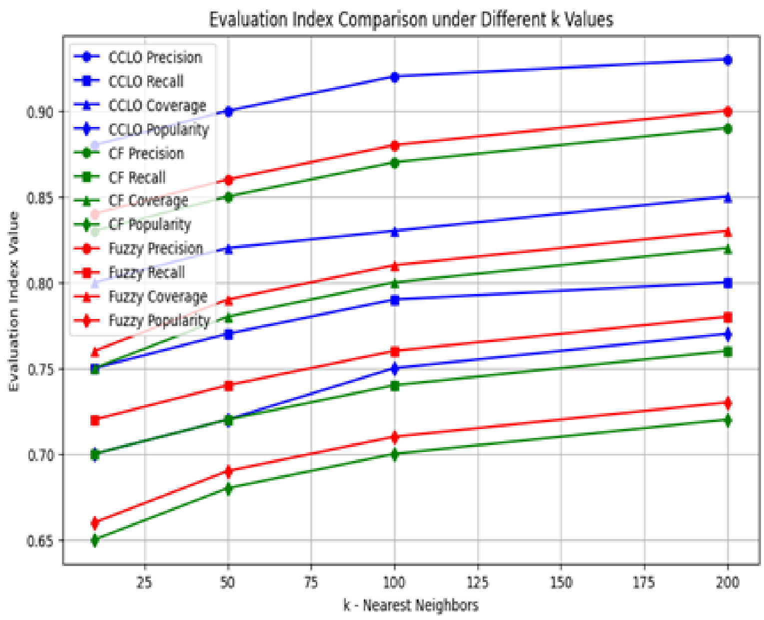

Fig. 4.5: Evaluation Index Scores Comparison

for improving foreign language education. According to this, we use CFL dataset to evaluate the suggested CCLO. The present model is a combination of both fuzzy and CF algorithms, so the results of the suggested model is effectively compared with both CF and fuzzy models. The experiments proves that the effectiveness of proposed model in improving the expectable proficiency of learners. But however, this type of effective fusion also leads to some common drawbacks, such as the fusion model is just a novel term; to implement this in real world application, we need more refined algorithms and the adaption of advanced techniques to execute. During the language processing the system feels more complexity to process this due to the advanced filtering and recommendation combinations. Apart from that, it is a most powerful contribution to the field of language learning and personalized recommendation systems. Future research is most necessary to rectify the limitation of this suggested model.

Major limitation of CCLO framework is forming appropriate learner clusters using neighborhood-based recommendation algorithms. In those cases when a dataset was sparse or learners had different styles and level of progress, it was difficult to group learners into cliques. Because of this, the particular learning paths created for these clusters were sometimes ineffective, causing lesser engagement or slower progress of these learners. In future research, Given these obstacles, it may prove worthwhile to examine new clustering techniques in subsequent studies, including, for example, deep learning methods or k m-hybrid designs, which practice several clustering strategies together. That would increase the efficiency of grouping learners and provide for more targeted and successful learning environments.

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