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PAPER

Empowering Teachers in E-Learning: A Case-Based Recommender System for Effective Learning Design

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ABSTRACT

In the rapidly evolving field of e-learning over the past decade, the learning design (LD) sector has emerged as a crucial determinant of success. It plays a vital role in ensuring effective instructional design, preserving best practices, enhancing educational quality, promoting personalization, and embracing technological innovation. However, the creation of effective LDs can be challenging due to the diverse range of learning methods, strategies, resources, learner profiles, evolving technologies, and communication platforms. This paper aims to address the research question of how to efficiently leverage recommender systems (RSs) and repurpose existing LD solutions to provide valuable support for teachers in the LD process. Specifically, this paper focuses on the implementation of case-based recommender system (CBRS) and presents the initial evaluation results. CBRS, which is a RS, assists teachers in locating and reusing pre-existing LDs. The initial evaluation results validate the system's effectiveness in supporting teachers throughout the LD process by offering reliable and useful LDs. Furthermore, additional findings pertaining to the overall user perception and the perceived value of CBRS are discussed.

KEYWORDS

e-learning, learning design (LD), teacher support, recommendation system

1 INTRODUCTION

Design for learning has been widely recognized as a significant challenge in the ever changing field of learning in the last decade. The evolution of technology, diverse learning methods, evolving pedagogical strategies, shifting learner profiles, rapid technological advancements, and dynamic communication platforms have all contributed to the complexity of designing effective learning designs (LDs). Numerous studies have highlighted the challenges and complexities involved in designing learning experiences that meet the needs of today's learners and leverage the potential of emerging technologies.

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Over the years, numerous studies have focused on the technique of LD. These works primarily aim to define methods, techniques, models, and theories associated with the design process [1] [2]. Many educators have embraced the LD process and are exploring various tools and methodologies to enhance their teaching practices.

Our work's main goal is to support teachers as designers throughout their LD process. To do this, we depend on the re-design via reuse concept to accomplish this goal, taking into consideration [3] what had to say "reuse can also be an act of design, if conceived in the right frame of mind." Adopting this tenet, we propose a case-based recommender system called CBRS, which makes recommendations for teachers by using preexisting LDs. In light of this, teachers redesign their peers' LDs by using recommendations and giving them careful thought rather than starting from scratch. Case-based reasoning (CBR) is an artificial intelligence (AI) method that takes into consideration all previous similar instances with their crucial traits, or "characteristics," and reuses them to respond to a new inquiry case [4]. The principle of supporting users by suggesting successful past experiences in similar situations has been successfully utilized in a variety of areas, as is apparent from [5] [6] [7]. This fact gave us the idea to investigate the possibilities of using case-based recommendations in the field of LD to assist teachers in the LD process.

1.1 The main contribution of this paper

1. We proposed CBRS for assisting teachers in the LD process.
2. We employed the affinity propagation algorithm for finding the best LDs in the search space to optimize the search phase of the CBR.
3. We performed an analysis of the results obtained from the experiment.

The following is how the paper has been set up: The relevant research in the field of recommender systems (RSs) in e-learning is described in Section 2. Part 3 explains the approach we suggest. In Section 4 of the paper, results and experimental analysis have been presented. The paper's conclusions are presented in Section 5, which also includes recommendations for more research.

2 RELATED WORKS

The majority of the RSs used in e-learning environments address the learners and seek to give them individualized learning content and learning activity sequences to help them achieve certain learning goals. The success of the learning process depends on various factors. Despite the fact that learners are the primary focus of learning processes, teachers are also essential to the teaching process. The last few years have seen the development of hundreds of RSs to support teachers in the LD process. According to our research, we performed a non-exhaustive literature study on RSs. This research presents ten systems that allowed us to identify characteristics of RSs (i.e., the activities they support, the methodologies they employ, and how they manage data) for teachers and how they can help with the LD process. A recommendation system architecture was presented by [8], which supports teacher designers in creating learning resources by bringing their preferences and profiles into consideration. The architecture was organized using four basic components: knowledge models, learning object (LO) models, learning object metasearchers, and recommendation models. In order to recommend the best instructional design technique, the authors used an ontological structure, taking into account teachers' profiles and course classification based on learners' knowledge, abilities, and behavior. Authors in [9] recommend teachers use learning objects retrieved from web repositories. Aiming to provide recommendations, they employ a hybrid strategy that combines a collaborative and content-based filtering technique by comprehending the following elements: (A) LO metadata based on the curricular context, which includes author, title, educational level, area, concept, unit, topic, and subject. (B) Teacher profile based on user similarity that comprehends the elements of educational level, subject, area, region, city, school type, and school. (C) Evaluations made by users that presents their satisfaction. (D) Statistics on the LOs usage, such as the number of downloads, evaluations made for the LO, the evaluation average, and the date of the last actualization. The research team of [10] presents a recommendation system that assists teachers in retrieving more appropriate learning objects from web repositories by grouping teachers with similar teaching styles (expert, personal model, formal authority, delegator, and facilitator). This classification uses the K-means clustering technique to divide teachers into four groups based on their teaching styles. Teachers' communities are formed as a result of this clustering, and recommendations are based on the preferences of teachers who share the same teaching attitudes. Based on the notion that users like to get suggestions from people they know and trust, the authors of [11] offer a trust-based recommendation system that helps teachers find learning resources that satisfy their requirements and preferences. In order to do this, the authors employed collaborative filtering based on user ratings and excluded teachers' profiles and activities on the system. It solves the sparsity problem when teachers do not have similar rating and when there are fewer available ratings by calculating the similarity of teacher profiles. The research team of [12] proposes a RS that assists teachers in selecting LOs from existing LOs for their LD process by taking into account individual teachers current ICT competence profile, elicited from their relevance feedback data (e.g., rating history, bookmarking history, learning object access history, and learning object creation history). To achieve this, the authors used Euclidean distance to identify the most appropriate group of neighbors for the active teacher based on the similarity of their ICT competence profile, and each teacher receives recommendations based on the opinions of peers with the same ICT competence profile. The authors in [13] propose an e-learning recommendation system called A3 that assists teachers in enhancing the learning process's educational content. The A3 recommendation system examines the learner's difficulties in comprehending the content by using opinion mining to identify the specific subtopic where the learners are having difficulties. It locates the concerned teachers who are working with the subject and generates recommendations for them that include subtopics that require greater clarification for learners by using content-based filtering. The teacher will update just those subtopics for which a recommendation has been made. In order to build teacher courses by enhancing the retrieval and reuse of LOs through the use of a full-text search algorithm, The authors in [14] present a recommendation system based on the tf-idf metric with the aim of calculating the similarity of other LOs used by colleagues with related interests and teaching styles. The study of [6] proposes Mentor, an integrated RS into the LD environment (LAMS), which assists teachers in the LD process by recommending pre-existing LDs to match their needs and preferences and making it simpler for them to create their own LDs. To enhance the teacher's perception of the recommendations, an explanatory mechanism has been included in the system. As a result, each proposal is accompanied by a text that explains how the recommended LD aligns with the teacher's preferences. The Mentor uses a CBR approach to recommend the cases that are the most comparable to the teacher's inquiry. In order to improve recommendations, the Mentor considers the teacher's evaluations of LDs as well as the historical information on the highly-rated LDs by using item-based collaborative approach. The goal of the research group [15] is to assist teachers in the process of selecting the teaching-learning techniques that should be used when designing teaching-learning activities. To achieve this, they presented a model of recommendation including a filtering and content-based method and an association rules mechanism for deducing probable teaching-learning technique combinations. This mechanism implies that teaching-learning activities include typical properties such as subject, learning goals, target population, and difficulty level that are fundamental to teaching-learning situations. MoodleREC is a hybrid recommendation system proposed by [16], which helps teachers create a new course that satisfies their needs. This system collects the most popular learning objects from existing learning objects and organizes them into a ranked list of recommendations. MoodleRec combines content filtering and collaborative filtering techniques. The first provides a ranked list of LOs to the user based on teacher model (the history of the teacher's choice and usage of LOs in their courses), the LOs in the rated list are ordered in the second stage of recommendation based on similarity between teachers who utilize that particular learning object.

2.1 Summary

None of these systems except [8] [13] use the information present in the profiles of learners to enhance the learning process. The study of [10] proposes to each group of teachers the same resources. Concerning the other RSs for teacher features, we found that they mostly either account for hybrid methods that combine content-based and collaborative filtering [9] [15] [16], or one technique alone.

Table 1 summarizes the key features of the ten provided e-learning recommendation systems which cover teachers learning need in order to assist them in their LD process. We mention attributes used in recommendations, techniques of recommendation, and items recommended to teachers for each of them. We can infer from these systems that:

1. Most of them do not take advantage of all the information available about learners to improve the design of the learning process.
2. Some of them do not customize their recommendations, giving all teachers the same resources.
3. Most of them do not incorporate the profile information and activities of the learners into the system.
4. Some of them do not integrate teachers profiles.
5. None of the aforementioned systems incorporate both the profiles of learners and teachers to enhance the recommendations.

Table 1. Summary of recommender systems for teachers

Paper	Attributes/Inputs	Technique of Recommendation	Item Recommended
[8]	Teacher profiles, student knowledge, abilities and behavior, knowledge models, learning object models, learning object meta searcher, recommendation model	Ontology method	Learning resources
[9]	Curricular context, teacher profile, evaluation and statistics on learning object usage	Collaborative and content filtering	Learning object
[10]	Teaching styles	K-means	Learning object
[11]	Ratings	Collaborative filtering	Learning resources
[12]	ICT competence profile	Euclidean distance	Learning object
[13]	Opinion mining	Content based filtering	Learning resources
[14]	interests and teaching styles	Full-text search algorithm	Learning object
[6]	Evaluations, historical information	Case-based reasoning Item based Filtering	Good learning design
[15]	Subject, learning goals, target population, and difficulty level	Content and collaborative filtering association rules	Teaching learning technique
[16]	Teacher model	Content and collaborative filtering	Learning object

3 PROPOSED CASE-BASED RECOMMENDATION APPROACH

This section provides our approach, which attempts to give teachers support on the LD process based on the concept of reusing preexisting LDs, as a potential response to the highlighted research topic.

The main goal of our contribution is to develop and operationalize CBRS, a hybrid recommendation system that uses existing LDs to recommend the most appropriate one for a given application domain in the form of templates to give teachers a head start rather than having to begin from the beginning and to facilitate the design of adaptive LDs for learners.

Each template can result in a new LD that meets specific requirements and preferences following teacher interaction. Our support framework is driven by case-based reasoning (see Figure 1). It operates by comparing a current teacher's problem or request to previous cases stored in its database. Besides, it looks for the most similar cases, then recommends the solution that was applied to that case; in other words, the system traits LDs as situations, which are specified by a set of specific characteristics, and recommends the situations that are the most similar to the teacher's inquiry.

At this level, the search phase for appropriate situations has been optimized by using a technique for clustering LDs using affinity propagation that orients the search, reduces the search time, and constricts the search space. The system only needs to search within the cluster of similar cases instead of the entire case base, which allows for a more efficient search process.

In order to provide adaptive LDs to teachers, the proposed framework is composed of five components: generating learners' models and teachers' preferences; selection and recommendation of appropriate LDs; reuse and adaptation; execution; and evaluation. Each component processes the data output from the previous layer and then transmits it to the next layer until reaching the final output, as shown in Figure 1.

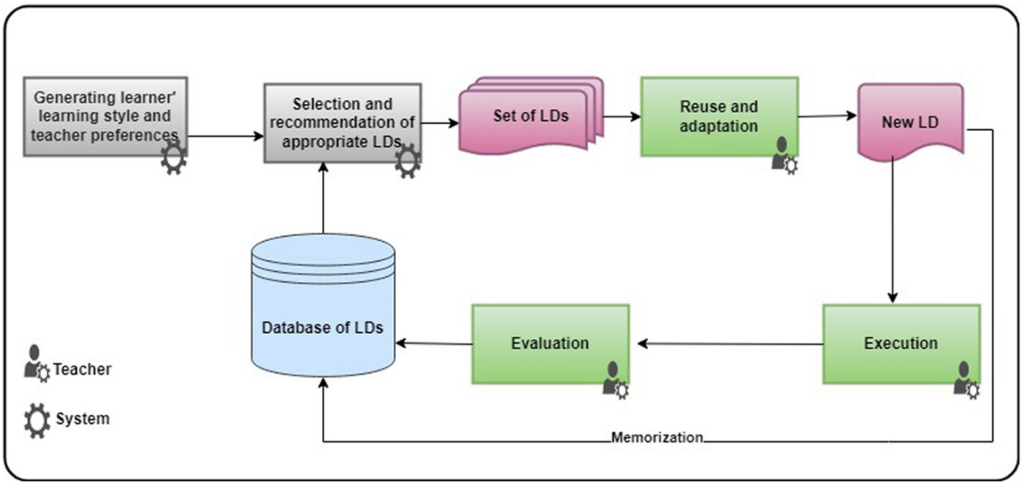

Fig. 1. The general principle of the proposed approach

3.1 Generating teachers and learners preferences

This section deals with step 1 of the process shown in Figure 1, which is "generating the learning style of learners and teachers' preferences." At first, the system tries to find out the teacher's preferences and the learners' learning styles. This module takes the resultant data submitted by teachers and learners into the questionnaire as input. Once they complete this task, the framework retrieves the result of the questionnaire they conducted to estimate their preferences and stores it in the database. A learner's learning style refers to the way in which a particular learner prefers to process and retain information. Different people have different learning styles, which can include visual, auditory, kinesthetic, and other modalities. Understanding a learner's preferred learning style can help educators' present information in a way that is most effective for that individual, leading to better retention and understanding of the content.

To do this, the system uses Fleming's visual, auditory, or kinesthetic (VAK) model [17], where learners are divided into three categories according to their preferred learning styles. This model was chosen since it makes it very straightforward and easy to identify learning preferences and helps teachers enhance their approach to better meet the needs of individual learners. The VAK learning style model is a pedagogical theory that identifies the best teaching strategy for each learner. This concept is founded on the notion that those who learn best visually prefer visual tools such as diagrams, illustrations, overhead slideshows, and handouts to help them see or think. The auditory learner only acquires knowledge by hearing; hence, information should be presented to them through auditory techniques such as debates, lectures, and audios. The paradigm also emphasizes the idea that readers are the only ones who can teach visual learners. The model also argues that kinesthetic learners should be given the opportunity to engage with their learning environment through hands-on techniques such as touching, doing, and moving, as they can only learn by doing. This information will be saved in the learner's profile and then presented to teachers during each LD process to be used, besides facilitating the design of adaptive LDs for learners. Recognizing and utilizing the preferred learning style of learners is very important because it enhances their understanding and retention of information. When learners are taught in a way that aligns with their learning style, they are often more engaged and motivated in the learning process [17].

3.2 Selection and recommendation

The recommendation process uses the aforementioned information to select and generate appropriate recommendations that are personalized for each teacher in the e-learning environment. The proposed method works in two phases, which are offline and online. The offline phase of the proposed CBRS begins with two distinct processes; similarity calculation and clustering. To accelerate the implementation of recommendations and reduce the running time, the procedures in this phase are carried out in offline mode. In order to go on to the next stage, we first calculate the similarity between the various LDs included in the dataset. To do this, a similarity matrix of LDs is generated using "DICE similarity" [18], and then it is loaded into the affinity propagation algorithm for clustering [19]. Once the clusters are formed, they can be used to generate recommendations.

$$S(LDi, LDj) = \frac{2\sum_{i=1}^{N} LDi.LDj}{\sum_{i=1}^{N} LDi + \sum_{i=1}^{N} LDj} \tag{1}$$

In the second stage, which focuses on generating recommendations for teachers, a similarity metric is employed to identify the cluster of LDs that most closely aligns with the preferences of the active teacher. Many techniques are available for calculating similarities, such as the Euclidean distance metric, the dice similarity measure, and Pearson correlation. We employed dice similarity [18] to compare the present model's LD to each cluster's existing experiences in order to choose the most appropriate clusters for the generation of recommendations; in other words, the system delivers to teachers the LDs most suitable for reuse that have been run in contexts that are similar to the target context.

The score of similarity of features related for new case and exemplar of each cluster is obtained by "DICE similarity":

$$S(fnld, fexp) = \frac{2\sum_{i=1}^{N} fnld.fexp}{\sum_{i=1}^{N} fnld + \sum_{i=1}^{N} fexp} \tag{2}$$

Where *fnId* and *fexp* are values of features related for new case and exemplar of cluster. The steps involved in the selection and recommendation process can be summarized in Algorithm 1 (see Figure 2).

Algorithm 1 Case-Based Affinity Propagation

Input: Database of LDs, Database of Teacher Preferences
Output: List of recommended LDs
1. Calculate the similarity matrix S(i,j) using DICE similarity measure between all pairs of LDs i and j.
2. Initialize $A(i,j) = 0, R(i,j) = 0$.
3. Use the preference form filled out by the teacher to determine their preferences in terms of Title, pedagogical profiles of learners, target learner, objectives, and evaluation.
4. Initialize the preference matrix $P(i,j) = -max(S(i,j))$
5. **repeat**
6. Update the responsibility matrix R(i,j)
7. Update the availability matrix $A(i,j)$
8. Update $P(i,j)$
9. Check for convergence by comparing the number of clusters in the previous iteration to the current iteration. If the number of clusters has not changed, stop the algorithm.
10. **until** convergence
11. Assign each LD to its corresponding cluster based on the availability matrix A
12. Determine the degree of similarity between the present modeled LD and that of prior cases of each cluster
13. Display to the present teacher a listing of LDs belonging to a specific cluster

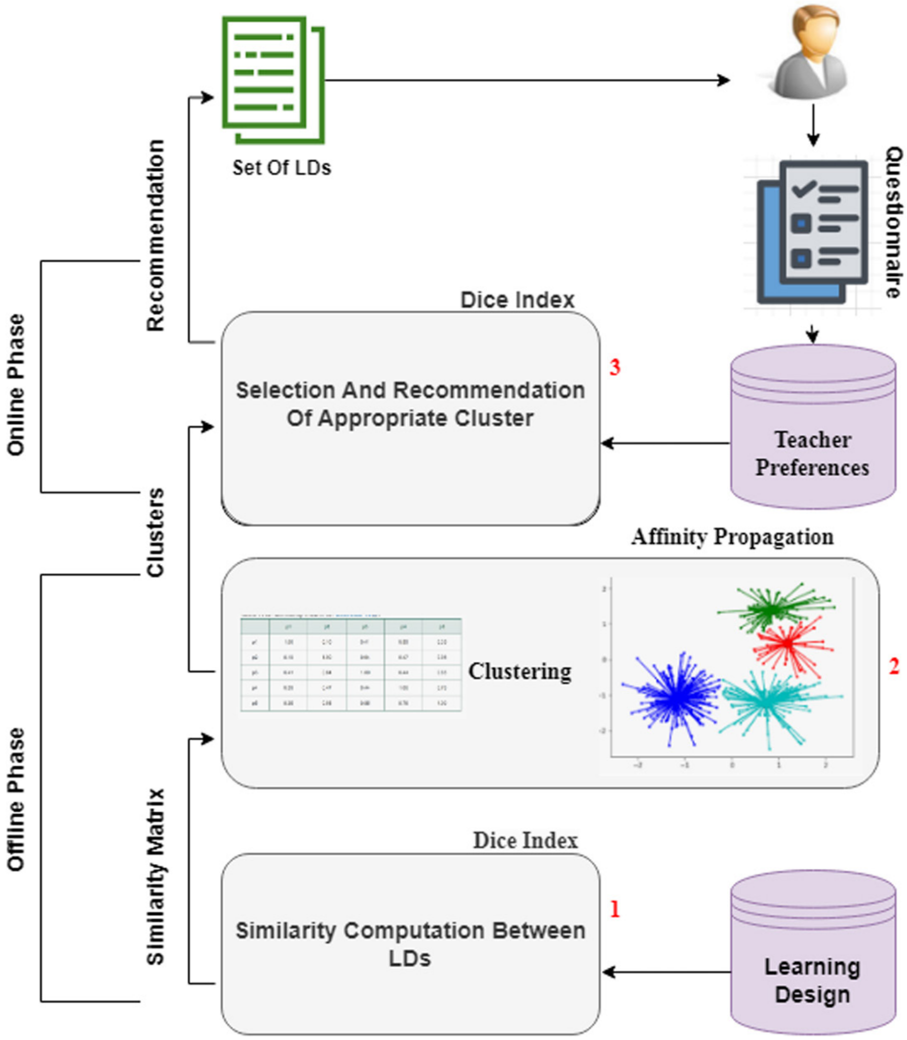

Fig. 2. The process of selection and recommendation

3.3 Reuse and adaptation

This phase involves the use of retrieved LDs that provide possible solutions to teachers, where they use the system's assistance to construct their LD by reusing the recommended LDs and modifying them to meet specific learning needs and contexts. They may either reuse a LD completely as it is without changes, or they can modify it to suit their needs and/or reuse only specific activities or sequences of activities to create a new LD for improvement of the recommended solution. Our system assists the teacher in adapting and reusing the source LD to solve their current problem.

In our system, the LD is not fixed; it is adaptable according to the needs of the teachers by modifying the LD taking into account the learners preferences presented by the system as well as the text messages to direct them in tailoring the information to the learning styles of the learners, or they can move on to adding their own activity resources. Adaptation can also be done after the execution of the LD, which adapts it according to the feedback obtained.

3.4 Execution and evaluation

This section covers "Execution and Evaluation," steps 4 and 5 of the process shown in Figure 1. Once the LD has been created, it is put into practice in a genuine learning situation, where it produces outcomes and leaves traces of use. At this point, the teacher evaluates the results of the LD's development, including the traces of the activity of learners, their productions, and their interactions during a learning session.

This task is carried out through indicators on the actual progress of the activities of the LD. For this type of indicator, we can cite: success rate, from which the LD is considered to be successful in a specific context or not; if the indicator for this test's success rate hits the number 80%, the teacher will consider the exam to have successfully passed. This phase takes as inputs traces providing information on the outcomes of the evaluation's responses. The following formula is used to determine a learner's (x) success rate ($SR(x)$) in a subject (i):

$$SR(x)i = \frac{Number\ of\ good\ responses}{Total\ number\ of\ questions} \tag{3}$$

The formula used to determine the learner's (x) success rate in each topic is as follows:

$$SR(x) = \frac{\sum_{i}^{n} SR(x)}{N} \tag{4}$$

Where, N is the total number of evaluations.

4 EVALUATION

4.1 Live user experiment

To be able to validate the proposed approach, an experiment was conducted with the collaboration of computer science teachers and students from the University of Chadli Ben Djdid-El-Taref (Algeria) and the University of Badji Mokhtar Annaba

(Algeria). Our goal is to test the teacher's perception of relevance of recommendations given by CBRS that adopted the proposed approach.

The latter was utilized to validate our strategy in a practical learning environment. 421 participants from the computer science departments of the two universities were concerned by the experiment, including 389 learners and 32 teachers.

The experiment was conducted for six months, from September 2022 to February 2023. Teachers were invited to create their LDs, post their course materials, and engage with the learners on the CBRS platform in accordance with the present learners' preferred learning styles. With a total study load of 140 hours, the 32 engaged teachers created 123 LDs and 120 learning resources throughout six learning units.

Learners were asked to complete exams, download resources, answer questions about their learning preferences, and consult the platform's resources. Figure 3 presents screenshots from the 'CBRS' system that show "Teacher space," in which they can:

- Re-design their own LD according to learning preferences and to the text message proposed by the system; consult and reuse the recommended LDs, as well as other functionalities proposed by the system.
- Share a learning object and tests.
- Conduct teaching programs.

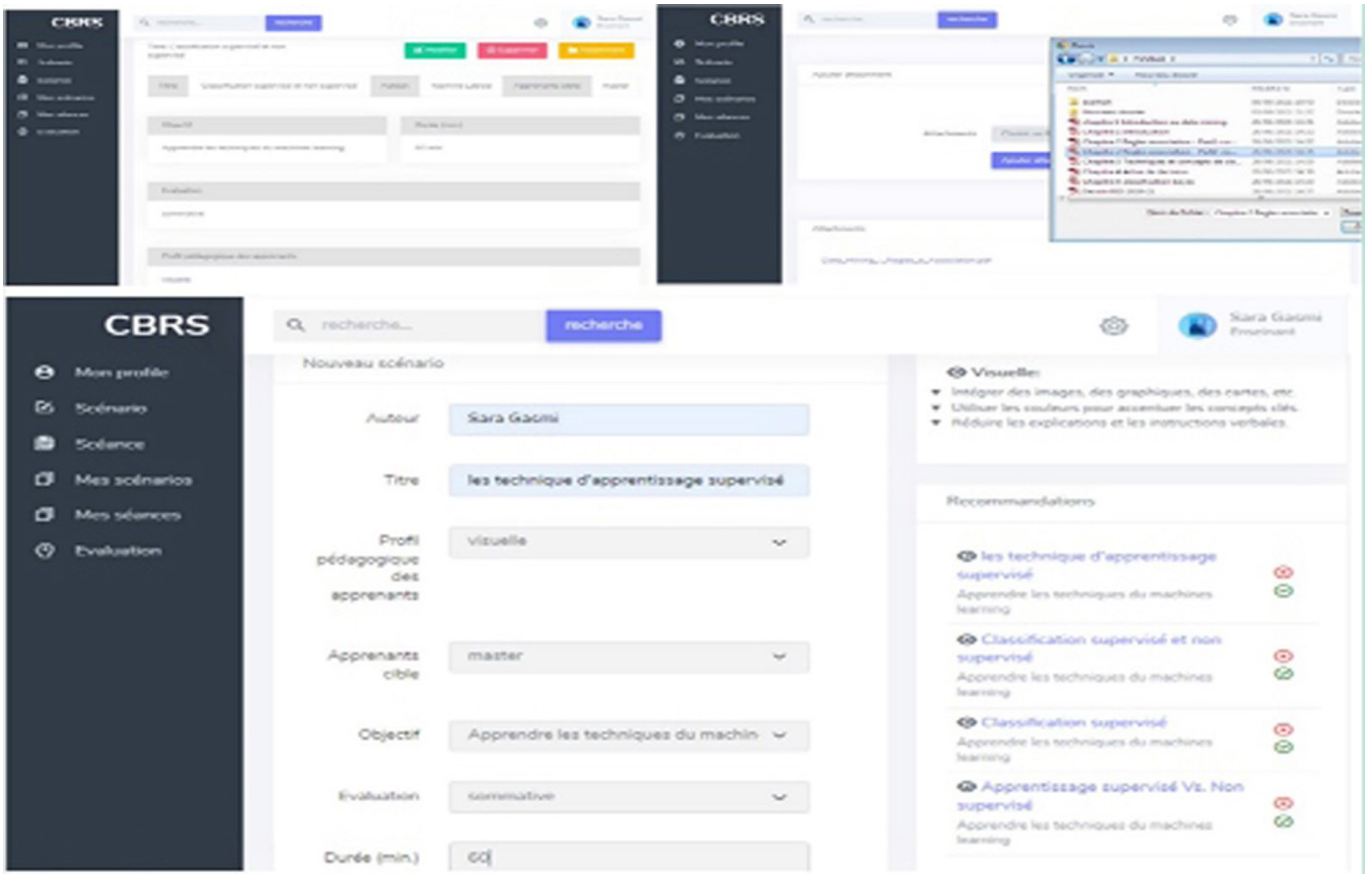

Fig. 3. Screenshots of 'CBRS' system

In the first phase of the experiment, a questionnaire is given to evaluate whether the RS proposed by our approach is effective and acceptable from the teacher's point of view. We have decided to employ ResQue (Recommender systems' Quality of user experience) [20], a unified evaluation framework for RSs. In order to assess the qualities of the recommended items, the system's usability, usefulness, interface, and interaction qualities, users' satisfaction with the system, and the impact of these qualities on users' behavioral intentions.

The questionnaire was composed of four components: 1. User perceived quality, 2. User beliefs, 3. User attitudes, and 4. Behavioral intention. In order to verify the suggested approach, we have selected 18 questions from the ResQue questionnaire and added two additional questions that are consistent with that we wish to validate (indicated with an asterisk (*) in Table 2).

Teachers are asked to complete questionnaires made up of 20 questions, in order to characterize the teachers' responses, we utilized a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Using ResQue as a framework for evaluating RSs provides several benefits compared to other evaluation methods [21].

In comparison, other evaluation frameworks for RSs may focus primarily on technical metrics such as accuracy and relevance rather than the user experience. This may not provide a complete view of the effectiveness of the RS. This might not give a full picture of how well the RS works from the viewpoint of the user [21].

Table 2. Questionnaire

Construct	Question
Attitudes (Q1) 1	Overall, I am satisfied with the recommender? I am convinced of the resources recommended to me? I am confident I will like the LDs recommended to me? The recommender can be trusted? What level of satisfaction do you have with the LDs you designed using the system?* How satisfied are you with the overall use of the system?*
Quality of recommended items (Q2)	The LDs recommended to me matched my interests? The recommendation I received better fits my interests than what I may receive from a friend? The LDs recommended to me are novel and interesting? The recommender system helps me discover new LDs?
Interface adequacy Perceived ease of use (Q3)	The recommender's interface provides sufficient information? The layout of the recommender interface is attractive and adequate? I became familiar with the recommender system very quickly? I found it easy to make the system recommend different things to me? It is easy for me to inform the system if I dislike/like the recommended item?
Perceived usefulness (Q4)	The recommended LDs effectively helped me find the ideal resource? I feel supported to find what I like with the help of the recommender?
Behavioural intentions	I will use this recommender again? I will tell my friends about this recommender? I would visit the LDs recommended, given the opportunity?

Results of questionnaire. The results of the questionnaire are shown below. Figure 4 displays the average values for the questionnaire's 20 items. These mean values vary from 3 to 4.88, which indicates that the questions' responses are favorable.

The overall findings' standard deviation ranges from 0.4 to 1.11, as illustrated in Figure 5. These questions' responses indicated that teachers agree that CBRS can simplify the LD process; additionally, it provides useful and reliable resources, as illustrated in Figure 6 (mean value for Q1 = 4.41, Q2 = 4.06, Q3 = 4.59, and Q4 = 4.36). Finally, we determined the Cronbach´s alpha to assess the questionnaire's reliability [22]. It provides a straightforward and widely accepted measure of internal consistency. This information is used to make decisions about the validity of the questionnaire and to determine whether the questionnaire is a reliable tool.

A high Alpha Cronbach score indicates that the questions in the questionnaire are highly correlated with each other. Obtaining a value of = 0.914 for our questionnaire indicates that the questionnaire was highly reliable and had a high level of internal consistency.

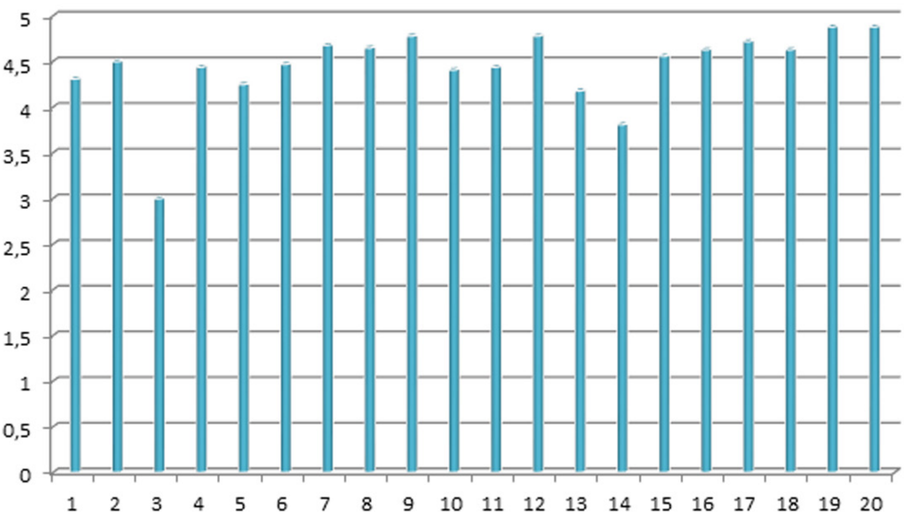

Fig. 4. Mean Likert scale teachers ratings

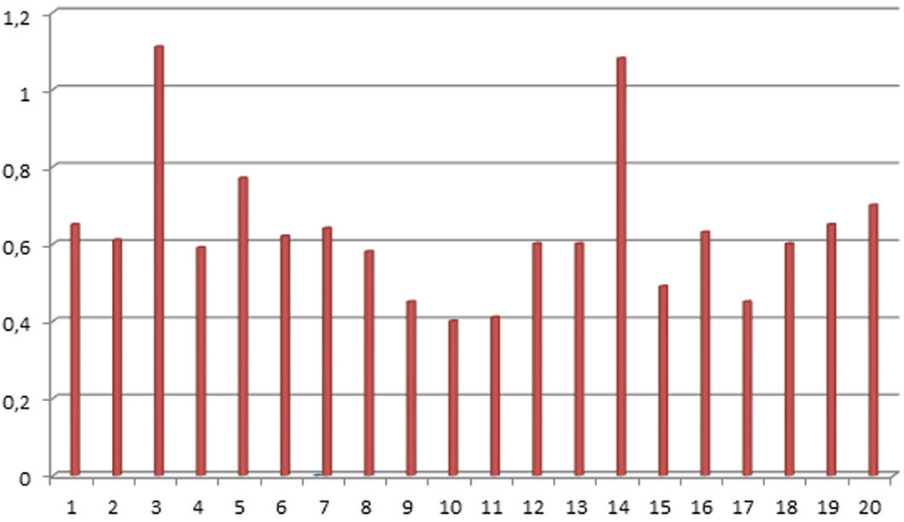

Fig. 5. Standard deviation of teachers Likert ratings

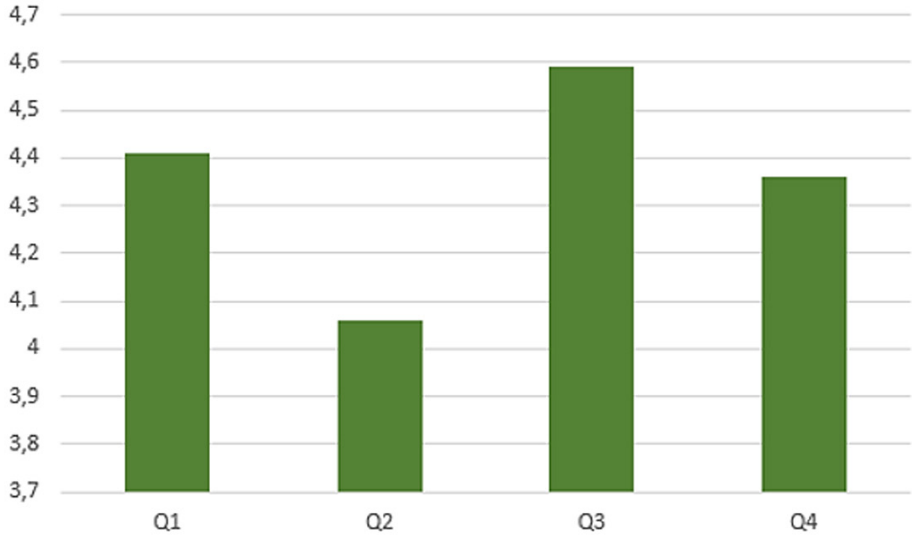

Fig. 6. Average Likert scale teacher ratings

Discussion. The results show that teachers strongly agree that utilizing CBRS will improve their performance in the LD process and that it is considered to be very valuable. The suggested approach has been validated using questionnaire results. Teachers who use CBRS express satisfaction with it. About 90% of the questionnaire questions had results that were better than average (average mean 4).

This is a promising sign for the teachers' adoption of CBRS and its potential future use. Thus, results show that most teachers found the recommendations they were given appropriate. We may come to the conclusion that the suggested approach's recommendations for LDs are relevant and satisfy our initial expectations. Another benefit of CBRS is that it incorporates both the preferences of learners and teachers to enhance the LD process since it takes into account users needs when opposed to the aforementioned similar studies [10] [11] [12], which put a greater emphasis on collaborative filtering techniques that use only teacher profiles. Essentially, the overall results of the evaluation seem to indicate that the recommender is helpful and essential for providing teachers with support.

4.2 Offline study

Experiment. The aim of this offline study is to evaluate the performance of the proposed recommendation approach compared to other existing approaches. The performance of the RS is evaluated on a dataset that has been collected from CBRS for almost six months.

This study provides a useful way to identify the strengths and weaknesses of the RS and determine how well it performs relative to other systems. It also helps to identify weak points for improvement and inform future development and refinement.

How accurate is the proposed RS in comparison to other systems? This question can be answered by comparing a recommendation system with others. The accuracy of the proposed approach will be compared only with three baseline algorithms, namely content-based filtering, random and popularity-based recommendation, as it is challenging to compare a RS without a user rating matrix with any standard recommendation method. The first recommends items that are similar in content to items the user has interacted with in the past and in the properties of the items themselves. The recommendations are made by calculating the similarity between items and recommending the most similar items to a user.

The second algorithm suggests items to users at random, without taking into account their preferences or any other information about them, and the third recommends the most popular items to all users, regardless of their individual preferences.

The accuracy of each algorithm is evaluated in this experiment using the F1 score [23]. The F1 score is the harmonic mean of precision and recall, which are two important evaluation metrics for RSs. Precision measures the proportion of recommended items that the user found relevant, while recall measures the proportion of relevant items that were successfully recommended to the user. A relevant recommendation is one that is deemed to be of interest to the user based on their past behavior or explicit feedback.

Results. Table 3 shows the results of the offline study. This table represents the four algorithms' average F1 scores.

Table 3. Illustrates a comparison of the accuracy results of our proposed method and the three baseline methods

Method	Precision	Recall	F1 Score
Content-based filtering	0.63	0.43	0.51
Random	0.40	0.45	0.42
Popularity-based recommendation	0.41	0.49	0.45
Proposed method	0.98	0.97	0.97

We found that the performance of the proposed approach exceeds the performance of the three baseline methods by carefully examining the results of the precision and recall shown in Table 2. This is a positive result, as it indicates that CBRS is providing more accurate and personalized recommendations to teachers, as shown in Figure 7.

The results demonstrated that the proposed technique outperforms the three baseline algorithms of recommendations in terms of performance by a large margin. In this study, we suggested applying the case-based recommendation technique to enhance the effectiveness of recommendations. The decision to choose this strategy offers various advantages over other recommendation techniques:

1. Provide more personalized recommendations to users by taking into account their individual preferences. In contrast, baseline methods often provide generic recommendations based on popular items or items that have been frequently viewed.
2. Take into account the context in which a user is making a recommendation request by incorporating contextual information.
3. Better handling of cold start problems by identifying similar cases or items and making recommendations. In contrast, baseline methods may struggle to provide recommendations in the absence of historical data.
4. It is designed to adapt to changes in user preferences and item availability over time. For example, if a user's preferences change, it can modify the recommendations accordingly. Baseline techniques, on the other hand, are often static and need regular modifications to stay current.

Overall, our proposed approach outperforms baseline methods because it provides more personalized recommendations, is more adaptable to teacher preferences, and can handle cold start problems more effectively.

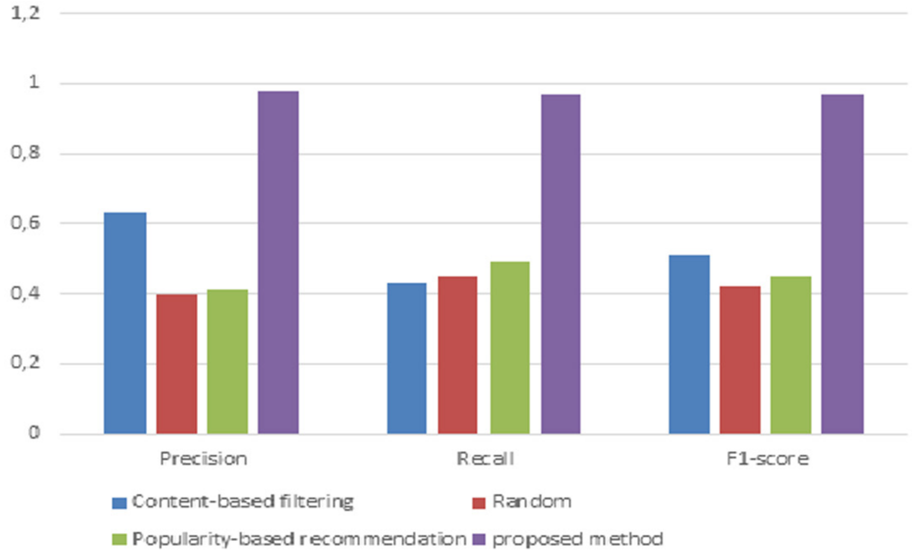

Fig. 7. Average Likert scale teacher ratings categorized by hypotheses

5 CONCLUSION

This paper has presented CBRS, which has been developed, put into use, and assessed in light of the need for teacher help during the LD process. For a specific application domain defined by the teachers individually, CBRS recommends a collection of LDs, where the teacher can select a recommended LD and customize it taking into account learners' learning styles presented by the system. We tested this system with actual users in order to assess our contribution by completing a first assessment experiment and taking into consideration teachers' experiences and opinions on CBRS, the answers to the research question provided at the beginning of this paper were obtained. Generally, the experiment produced fruitful outcomes and showed that the responses to research questions were positive due to teachers' affirmation that the CBRS simplified the LD procedure. The results of the offline study demonstrate that our proposed approach performs better than baseline techniques because it offers more customized recommendations, is more adaptable to user preferences, and is more adept at dealing with cold start issues. An exciting area for future research is the enhancement of the recommendation approach described in this paper by adding social data, such as social interactions and activities of users from the e-learning platform or social networks. In terms of future works, we intend to enhance the recommendation approach described in this paper by adding social data, such as social interactions and activities of users, from the e-learning platforms or social networks. In addition, to optimize the recommendation process by integrating new factors such as the success rate of LDs and the evaluation of LDs by peer teachers, favor the most relevant LDs or prioritize the most frequent of them in terms of reuse. Finally, other similarity metrics can be incorporated and evaluated, such as COSINE or JACCARD similarities, in order to be compared with our recommendation results.

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