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A Case-Based Recommender System to Assist Teachers in the Learning Design Process for E-Learning

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Abstract

E-learning platforms are becoming more comfortable for both learners and teachers, enabling them to complete their academic requirements remotely, especially during time-sensitive situations like the recent Corona virus epidemic; they have become increasingly important in addressing the challenges posed by the pandemic by maintaining continuity of education and ensuring access to learning opportunities. One of these environments' biggest strengths is their capacity to tailor teaching to the needs of teachers and learners. The Learning Design (LD) process has become an essential practice, which constitutes a critical success factor, as it motivates teachers to adopt Learning Design (LD) activities as a way to foster education. It can be challenging for a teacher to conceive a Learning Design due to the variety of learning methods and strategies, the multitude of resources, the diversity of learners profiles and other contextual factors, the evolution of information and communication technologies, and the diversity of communication platforms. This paper proposes a case-based recommender system, which makes recommendations for teachers by using pre-existing LDs that adequately meet their requirements and preferences in order to redesign them. This research study details our system deployment and first assessment results. The findings of the first user-centric assessment experiment support the fundamental hypothesis that our system can assist teachers in the LD process and offer reliable and useful LDs. Additional findings about the teacher's view of the proposed system in general and its utility are presented. We also do a further offline study to evaluate our strategy to three baseline algorithms.

Keywords: Recommender system; Case-based reasoning; Learning design; E-learning

1 Introduction

The recent COVID-19 pandemic has highlighted the importance of e-learning platforms in a number of ways. During times of crisis, it is critical for education to continue in a safe and accessible manner. These environments play a critical role in ensuring that education continues during times of crisis, and offer a range of benefits to learners, educators, and institutions. One of these environments' major strengths is their ability to personalize learning in two ways. The first is to adapt teaching resources to the learning context, taking into account teachers' requirements and pedagogical habits, as well as the content of the learning for which the resources are being adapted. The second is to adapt learning and learning resources to the learners in such a way that each learner receives personalized learning based on their individual characteristics. Educational research emphasizes the teacher's position as a designer[1][2], and motivates teachers to adopt Learning Design (LD) activities as a way to foster education [3]. The Learning Design (LD) process is known as the entire process through which teachers are able to design, organize, and orchestrate the sequences of learning activities that make up a learning session; this activity is growing increasingly difficult and necessitates interdisciplinary expertise. This complexity is due to the variety of learning methods and strategies, the multitude of resources, the diversity of learners profile and other contextual factors, the evolution of information and communication technologies, and the diversity of communication platforms. For several years, many research works have focused on this technique of learning design. These works mainly aim to define methods, techniques, models and theories involved in the design process,[4][5] gather relevant research articles of the important ideas, concepts, resources for details on the underlying theory and practice in the subject. There are three key obstacles for LD situations, according to existing studies[6][7]: give flexibility, support all stages of the design process, and support teacher as designers. 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 what Mor et al. [7] 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. The case-based reasoning (CBR) is an artificial intelligence 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 [8]. It enables flexible knowledge representation and imitates the expert decision-making process. The basic tenet of the CBR method [9], is that similar problems require similar solutions. The case-based recommender system has already found use in a variety of areas more specifically: n the real estate domain, the authors of [10] propose a case-based reasoning approach based real estate recommender system which helps the clients find suitable property and make selections where they are needed. In the smart city domain, the authors integrate a case-based reasoning as an artificial intelligence approach, to construct a recommender system that will support smart city planning. In order to render cities smarter and more ecological, CBR offers recommendations for smart city dimensions that should be implemented by city decision-makers and planners [11]. Considering the CBR applications to the education domain, the authors propose a case-based reasoning approach to assist teachers in the LD process. It recommends the cases which are the most comparable to the teacher's enquiry [12]. In addition, Chaabouni et al. in [13] propose a case-based reasoning for determining similarities contextual tools for selecting and recommending relevant LDs for a target learning situation as an assistance for the reuse and capitalization of LDs. 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 the preceding. This fact gave us the idea to investigate the possibilities of using case-based recommendation in the field of LD to assist teachers in the LD process. We tackle the following research inquiries in this paper:

- Q1: Does the use of CBRS help teachers to satisfy their needs?
- Q2: Does CBRS offer reliable LDs?
    - Q3: Does CBRS help teachers and make the LD process easier?
- Q4: Does CBRS provide Useful LDs and resources?

The purpose of this study was to determine whether the suggested system's performance held the answers to the previously listed questions. Finally, this study measures the teacher's overall perception in order to evaluate the problem of the quality of user experience with the suggested system. We additionally do a further offline study to evaluate our strategy to the three baseline algorithms. perform a further offline study to evaluate our approach against three baseline algorithms.

1.1 The main contributions of our paper

1. We proposed CBRS, a case-based recommender system for assisting teachers in the learning design 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 the 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 RSs in elearning 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 recommendation systems (RSs) used in e-learning environments addresses the learners and seeks to give them individualized learning content and learning activity sequences to help them achieve certain learning goals. The successful of learning process depends on a variety of actors, despite the fact that learners are the primary focus of learning processes, teachers also are essential to the teaching process. The last years have seen the development of hundreds of recommendations systems 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 [14], which supports teachers designers in creating learning resources by bringing their preferences and profiles into consideration. The architecture was organized using four basic components, namely knowledge models, learning object models, learning object meta searcher and recommendation model. 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 [15] recommend teachers 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) Learning objects (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 as educational level, subject, area, region, city, school type and school. (C) evaluations made by users that presents their satisfaction. (D) Statistics on the learning objects usage such as the number of downloads, evaluations made for the LO, the evaluations average and the date of the last actualization. The research team of [16] presents a recommendation system that assists teachers in retrieving more appropriate learning objects from web repository by grouping teachers with similar teaching styles (expert, personal model, formal authority, delegator, and facilitator). This classification use 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 sharing the same teaching attitudes. Based on the notion that users like to get suggestions from people they know and trust, the authors of [17] 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 set of rating and when there are fewer available ratings by calculating the similarity of teacher profiles. The research team of [18] proposes a recommendation system that assists teachers in selecting learning object from existing LOs for their learning design process by taking into account individual teacher's current (ICT) competence profile elicited from their relevance feedback data (e.g. rating history, bookmarking history, learning object access history, 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 [19] 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 teachers courses by enhancing the retrieval and reuse of LOs through the use of a full-text search algorithm, The authors in [20] present a recommendation system, which based on the tf-idf metric, in the aim of calculating similarity of other LOs used by colleagues in related interests and teaching styles . The study of [12] propose Mentor, an integrated recommendation system into the LD environment LAMS, which assists teachers in the learning design process by recommending pre-existing learning designs to match their needs and preferences and making it simpler for them to create his/her own LDs. to enhance the teacher's perception of the recommendations, an explanatory mechanism has been included into the system. As a result, each proposal is accompanied with a text that explains how the recommended learning design aligns with the teacher's preferences. Mentor uses case-based reasoning approach to recommend the cases which are the most comparable to the teacher's enquiry. In order to improve recommendations, Mentor considers the teacher's evaluations of learning designs as well as the historical information on the highly rated learning designs by using item based collaborative approach. The goal of the research group at [21] 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 techniques combinations, this mechanism implies that teaching-learning activities include typical properties like subject, learning goals, target population, and difficulty level that are fundamental to teaching-learning situations. MoodleREC is a hybrid recommendation system proposed by [22],which helps teachers to create a new course that satisfies their needs, this system collects the most popular learning object from existing learning object and organizes them into a ranked list of recommendations. MoodleRec combines content filtering and collaborative filtering technique. 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 her/his courses), the LOs in the rated list are ordered in the second stage of recommendation based on similarity between teachers who utilize that particular LO.

2.1 Summary

None of these systems except [14][19] use the information present in the profiles of learners to enhance the learning process. The study of [16] proposes to each group of teachers the same resources. Concerning the other RSs for teachers features, we found that they mostly either account for hybrid methods that combine contentbased and collaborative filtering [15][21][22], 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 learning design process. We mention attributes used in recommendations, technique 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 learning process design.
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 teacher's profiles.
5. None of the aforementioned systems incorporate both the profile of learners and teachers to enhance the recommendations.

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 work is to develop and operationalise CBRS, a hybrid recommendation system that uses existing LDs to recommend the most appropriate one for a given application domain in the shape of templates to give teachers a head start rather than having to begin from the beginning and to facilitate the designing of adaptative LDs to learners. Each template can result in a new LD that meets with specific requirements and preferences following teacher interaction. Our support framework is driven by case-based reasoning (see Fig. 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, it 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, reducing the search time and constricts the search space. The system only needs to search within the cluster of similar cases instead of the entire cases base that allows for a more

Table 1: Summary of recommender systems for teachers

Paper	Attributes/Inputs	Technique of recommendation	Item recommended
[14]	Teacher profiles Student knowledge, abilities and behavior, knowledge models, learning object models, learning object meta searcher, recommendation model	Ontology method	Learning resources
[15]	Curricular context, teacher profile, evaluation and statistics on learning object usage	Collaborative and content filtering	Learning object
[16]	Teaching styles	K-means	Learning object
[17]	Ratings	Collaborative filtering	Learning resources
[18]	ICT competence profile	Euclidean distance	Learning object
[19]	Opinion mining	Content based filtering	Learning resources
[20]	interests and teaching styles	Full-text search algorithm	Learning object
[12]	Evaluations, historical information	Case-based reasoning Item based filtering	Good learning design
[21]	Subject, learning goals, target population, and difficulty level	Content and collaborative filtering Association rules	Teaching learning technique
[22]	Teacher model	Content and collaborative filtering	Learning object

efficient search process. In order to provide the adaptative LDs to teachers, the proposed framework is composed of five components, which are generating learners' model 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 Fig. 1.

3.1 Generating teachers and learners preferences

This section deals with step 1 of the process shown in Fig. 1 which is "generating learning style of learners and teachers preferences". At first, the system tries to find out the teacher preferences and learners' learning style. This module takes the result data submitted by teachers and learners into the questionnaire as input. Once they complete this task, the framework retrieves the result of the questionnaire conducted by them to estimate their preferences and stores it in the database. 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 to present information in a way that is most effective for that individual, leading to better retention and understanding of the content

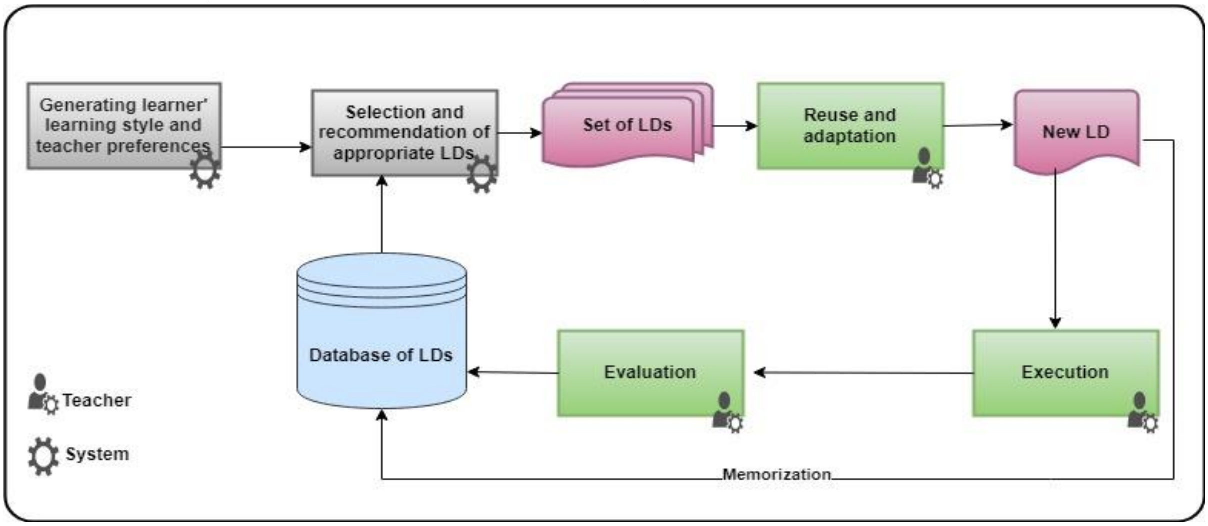

Figure 1: The general principle of the proposed approach

To do this the system uses fleming VAK model [23] (visual, auditory or kinesthetic), 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 help teachers to 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 like 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 like 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 then presented to teachers during each learning design process to be used, besides to facilitate the designing of adaptative LDs for learners. Recognizing and utilizing the preferred learning style of learners is very important because it enhance 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 [23].

3.2 Selection and recommendation

The recommendation process uses the aforementioned information to select and generate appropriate recommendations that are personalized for each teacher of 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"[24], and then it is loaded into the affinity propagation algorithm for clustering. Once the clusters are formed it can be used for generating recommendations. The main benefits of utilizing Dice similarity over other similarity metrics are:

1. In Natural Language Processing and information retrieval, the Dice similarity measure is frequently used to assess how similar two collections of data, such as text documents.

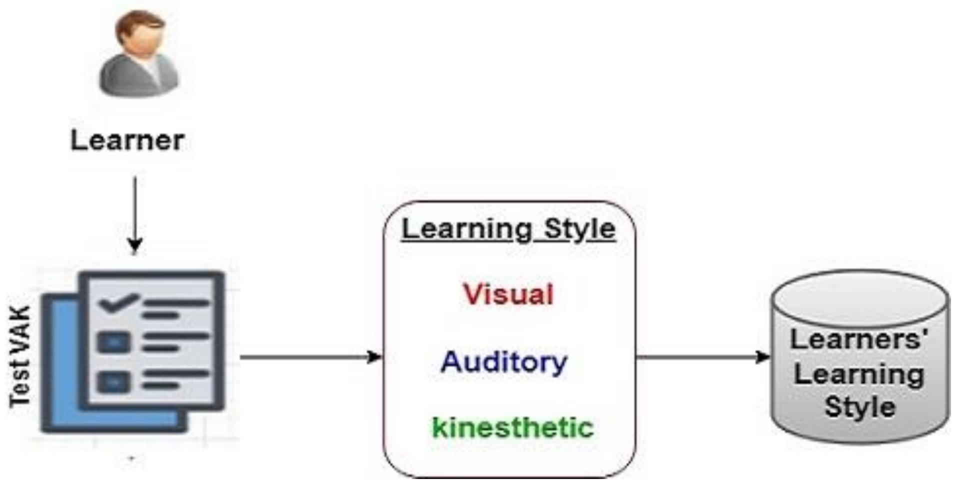

Figure 2: Learners' learning style

2. Compared to other similarity metrics like Jaccard similarity, dice similarity is less susceptible to variations in set size.
3. As dice similarity is symmetric, the degree of similarity between any two sets is the same regardless of how they are presented.
4. Compared to other metrics, dice similarity is less susceptible to the sparsity of the data

The DICE similarity between two vectors LDi and LDj is defined as follows:

$$S(LD_i, LD_j) = \frac{2\sum_{i=1}^{N} LD_i.LD_j}{\sum_{i=1}^{N} LD_i + 2\sum_{j=1}^{N} LD_j} \quad (1)$$

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 the dice similarity[24] to compare the present model's LD to each cluster's existing experiences in order to choose the most appropriate clusters for selecting appropriate clusters for the generation of recommendations, in other word 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":

$$S(LD_i, LD_j) = \frac{2\sum_{i=1}^{N} fnId.fexp}{\sum_{i=1}^{N} fnId + 2\sum_{j=1}^{N}} \quad (2)$$

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 are as follows: (shown in Fig. 3):

1. Firstly, the system calculate similarity between LDs of the database using DICE similarity
2. The system groups together similar LDs into clusters. It used affinity propagation algorithm presented in section 3.2.1
3. Teachers fill out a preference form, which has the following fields: Title, pedagogical profiles of learners, target learner, objectives and evaluation.
4. The system determines the degree of similarity between the present modeled LD and that of prior cases of each cluster.
5. Finally, the system then displays to the present teacher a listing of LDs belonging to a specific cluster where he can make action and develop his own LD. It is tailored to each teacher and exclusively concentrates on teachers rather than learners.

These steps are summarized in Algorithm 1.

Algorithm 1 Case-based affinity propagation

Input: Database of Learning Designs (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

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3.2.1 Affinity propagation

Affinity propagation is a revolutionary semi supervised machine learning technique used for clustering, it is a very popular algorithm based on a graph representation[25]. Affinity propagation does not need the number of clusters to be known or approximated before starting the algorithm, unlike clustering methods like k-means or k-medoids. Compared to other methods, it uncovers pertinent information clusters quickly and with a great deal less failures. The Affinity Propagation Algorithm was employed to find LDs clusters; it takes into account all LDs from the database as potential cluster centers (exemplars) by considering each LD as a network node. This method sends real-valued messages in a recursive manner along network edges until a useful set of exemplars and matching clusters appear. Affinity propagation considers every LD to have a probability of being selected as an example and serving as a message-sending node in the system. Each message's value reveals the current affinity of one LD for selecting another LD as its exemplar. A set of real-valued similarities among LDs is used as the input for the algorithm. This method takes as input a matrix NxN such that s(i,j) represents the similarity between LDi and LDj. The similarity between two points, denoted by s(i, j), shows how similar two points are to one another, by computing a negative Euclidean distance between them:

$$s(i,j) = -xi - xj^2 \qquad (3)$$

where $i \neq j$

Affinity propagation uses a numerical value s(i, i) to measure how similar one data point is to the others, and points with higher values have a greater probability of becoming exemplars. ”Preferences” refers to this numerical value. The communications transmitted between the data points are divided into two categories which are responsibility and availability[25].The ”responsibility” matrix R's values r(i, k) indicate how well-suited xk is to act as the exemplar according to other potential exemplars for xi. The”availability” matrix A includes values a(i, k) that show how ”suitable” it would be for xi to choose xk as its exemplar, taking into consideration other

points' preference for xk as an exemplar. Both matrices start out with zero values. After that, the algorithm iteratively makes the following updates: First, responsibility updates are sent around

$$r(i,k) = s(i,k) - a(i,k') + s(i,k') \qquad (4)$$

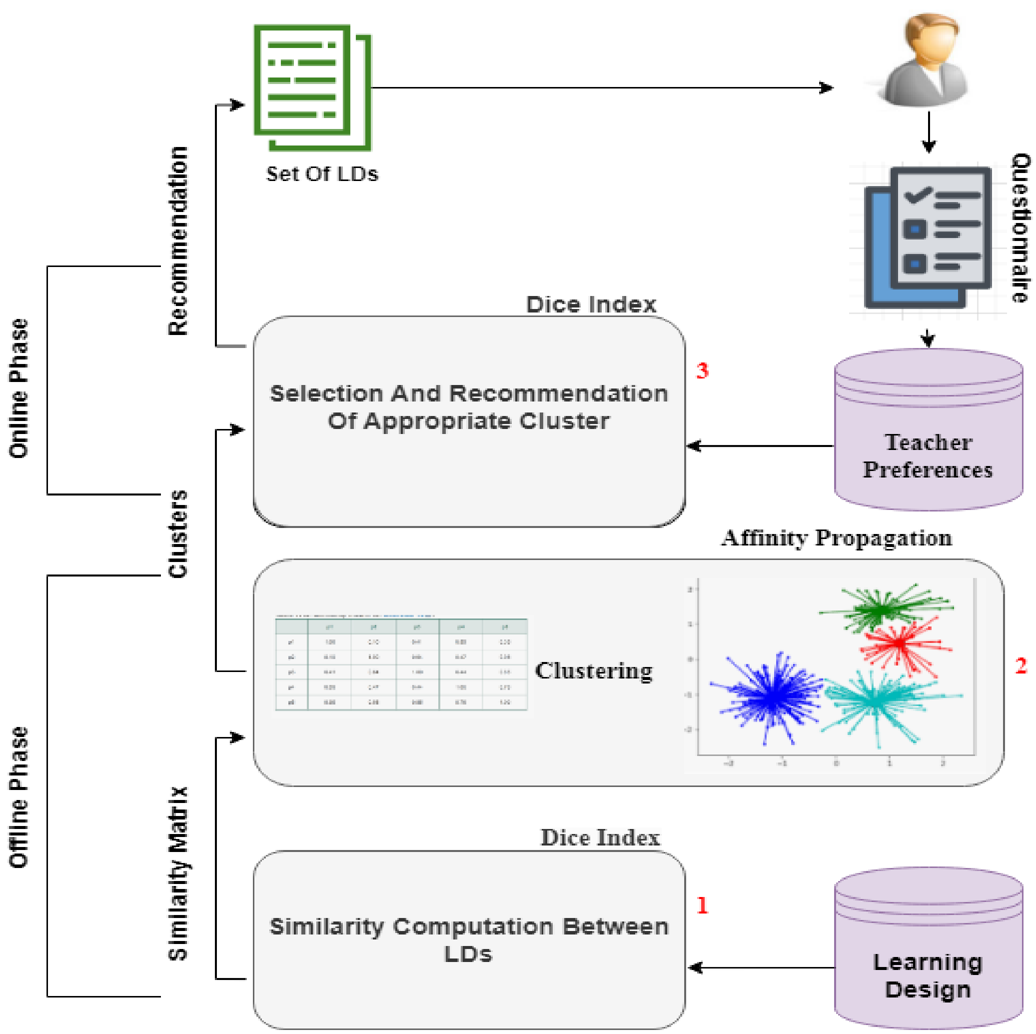

Figure 3: The process of selection and recommendation

Then, availability is updated by:

$$a(i,k) = 0,r(k,k)+. \qquad (5)$$

The aforementioned availability rule is employed to gather data in order to create a candidate exemplar that will be useful. The self-responsibility r(k, k) and the total of the positive responsibilities candidate exemplar k obtains from other points are used to determine the availability a(i, k).

3.3 Reuse and adaptation

This phase involves the use of retrieved LDs that provides possible solutions to teacher, where he/she gets the system's assistance to construct his/her LD, by reusing the recommended LDs and modifying them to meet specific learning needs and contexts. He may either reuse a LD completely as it is without changes, or he can modify it to suit his needs and/or reuse only specific activities or sequences of activities to create a new LD for improvement the recommended solution. Our system assists the teacher in adapting and reusing the source LD to solve his current problem. In our system, the LD is not fixed, it is adaptable according to the needs of the teachers by modifying LD taking into account learners preferences presented by the system as well as the text messages to direct him in tailoring the information to the learning styles of the learners, or he can move on to adding his own activity resources. Adaptation can also be done after the execution of the LD and adapts it according to the feedback obtained.

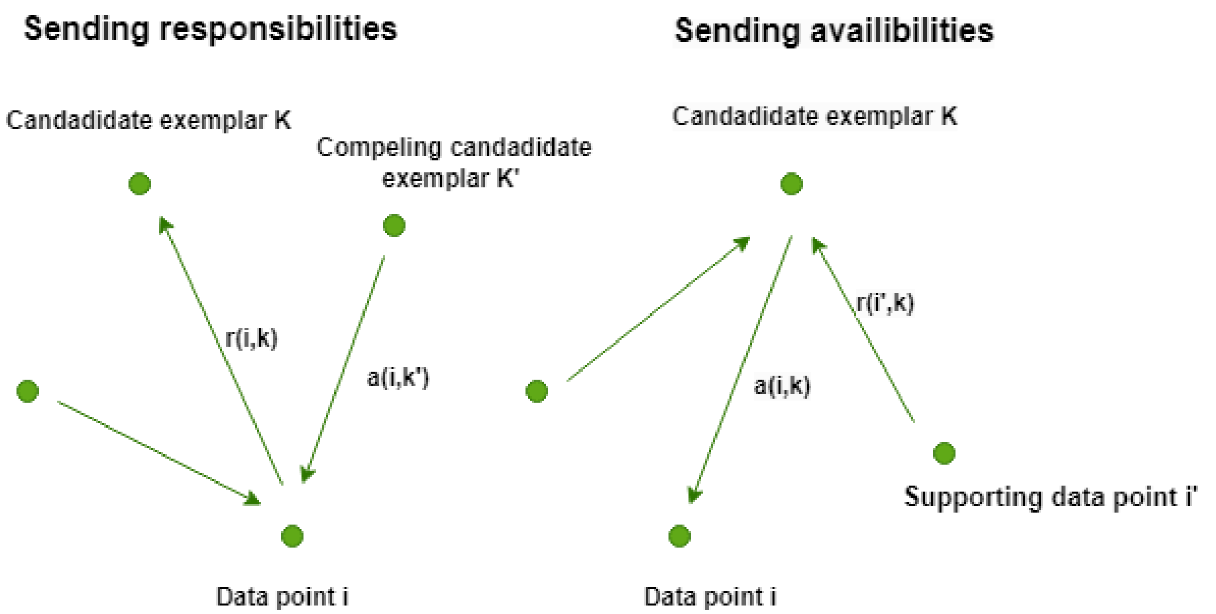

Figure 4: Message-exchange process of affinity propagation

3.4 Execution and Evaluation

This section covers "Execution and Evaluation," step 4 and 5 of the process shown in Fig. 1. Once the LD has been created, it is implemented 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 LDs' 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 indicators, 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):

$$SR(x)i = \frac{Numberofgoodresponses}{Totalnumberofquestions} \qquad (6)$$

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

$$SR(x) = \frac{\sum_{i}^{n} SR(x)}{N} \quad (7)$$

Where N is the total number of evaluation.

4 Evaluation

4.1 Live user experiment

To be able to validate the proposed approach, an experiment is conducted with the collaboration of Computer Science teachers and students from the University of Chadli Ben Djdid-El-taref (Algeria) and University of Badji Mokhtar Annaba (Algeria).Our goal is to test the teacher perceived 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 department 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 123LDs and 120 learning resources throughout 6 learning units. Learners were asked to complete exams, download resources, answer questions about their learning preferences, and consult the platform's resources. Fig. 4 presents some screenshots from 'CBRS' system that show: "Teacher space", in which he can:

- Re-design his/her 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.

In the first phase of the experiment, a questionnaire is given to evaluate that the recommender proposed by our approach is effective and acceptable from the teacher's point of view. We have decided to employ a ResQue (Recommender systems' Quality of user experience)[26], a unified evaluation framework for recommender systems. 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 intentions The first component of this questionnaire was created to evaluate how users perceived the recommendations objective features, it contained four dimensions: the quality of recommendations that relies on the level to which users believe the recommendations match with their tastes and preferences, the interface adequacy focus on the users' satisfaction. The interaction in the other hand, examines how well the system facilitates user feedback, the information sufficiency and explicability, the capacity of a system to show price, quantity, the image, user reviews, or any other information of any item to assist users in making a selection. The second component was designed to assess users' concerns and focus on how well the system assists them carrying out activities. The third section of the questionnaire was made to measure users' perceptions of a recommender generally. The fourth part of the questionnaire was created to evaluate whether or not the system is capable to influence users' decision to utilize the system. In order to verify the suggested approach, we have selected 18 questions from ResQue questionnaire and added two additional questions that are consistent with the hypotheses we wish to validate. 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). To validate our proposal, we use the ResQue questionnaire to verify the hypotheses that we proposed:

- H1: the use of CBRS helps teachers to satisfy their needs.
- H2: CBRS offers reliable LDs.
- H3: CBRS helps teachers and makes easier the LD process.
- H4: CBRS provides Useful LDs and resources.

Using ResQue as a framework for evaluating recommender systems provide several benefits compared to other evaluation methods:

1. User-centered focus: ResQue focuses on evaluating the quality of the user experience with the recommender system, rather than the accuracy or relevance of the recommendations. This ensures that the evaluation is centered on the needs and expectations of the users.
2. Easy to use: ResQue questionnaire is easy to administer and can be completed by users quickly.
3. Comprehensive evaluation: ResQue offers a set of metrics for assessing the usability, usefulness, and satisfaction of the user experience. This makes it possible to assess the recommender system in greater detail.
4. Standardized methodology: ResQue provides a standardized methodology for evaluating the quality of user experience in recommender systems. This allows for consistent and comparable evaluations across different systems.

In comparison, other evaluation frameworks for recommender systems 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 how successful the recommender system. This might not give a full picture of how well the recommender system works from the viewpoint of the user[27].

Overall, utilizing ResQue as a framework for assessing recommender systems places a strong emphasis on the needs of the user and offers a thorough, standardized method for assessing the level of user experience.

4.1.1 Results of questionnaire

The results of the questionnaire are shown bellow. Fig. 6 displays the average values for the questionnaire's 20 items. These mean values vary from 3 to 4.88, this indicates that the questions' responses are favorable.

The overall findings' standard deviation ranges from 0.4 to 1.11, as illustrated in Fig. 7.

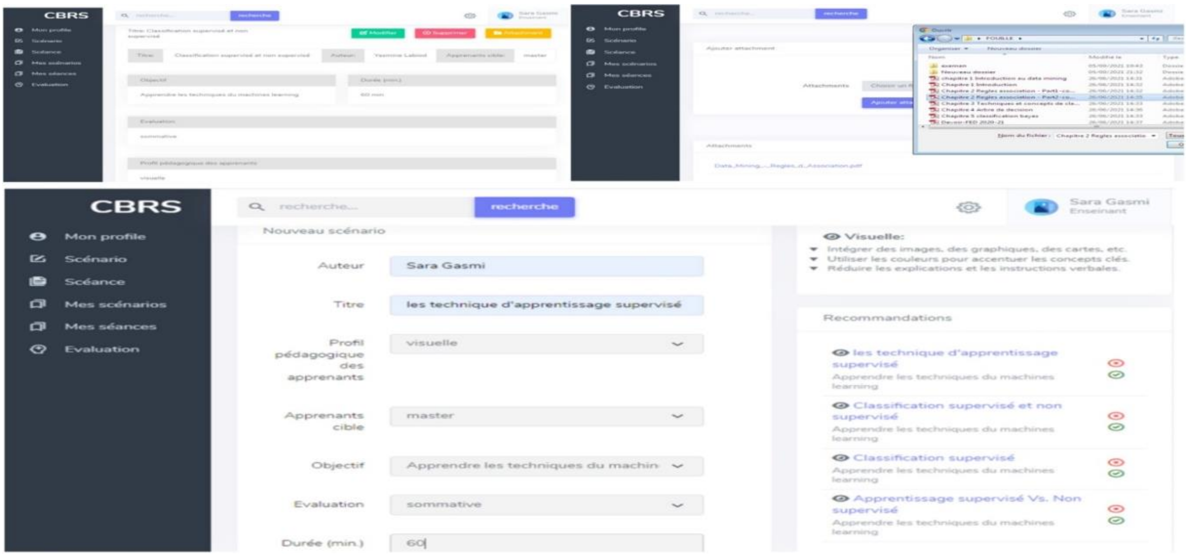

Figure 5: Screenshots of 'CBRS' system

Table 2:Questionnaire questions

Hypothesis	Construct	Question
H1	Attitudes 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?*
H2	Quality of recommended items	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?
H3	Interface adequacy Perceived ease of use	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?
H4	Perceived usefulness	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?

These questions' responses indicated that teachers agree that CBRS can simplify the LD process, additionally it provides useful and reliable resources as illustrated in Fig. 8 (mean value for H1=4.41, H2=4.06, H3=4.59 and H4= 4.36). This indicates that the hypothesis posed in our paper get an affirmative response. Finally we determined the Cronbach´s alpha to assess the questionnaire's reliability[28], 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, this indicates that the questionnaire was highly reliable and had a high level of internal consistency.

4.1.2 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

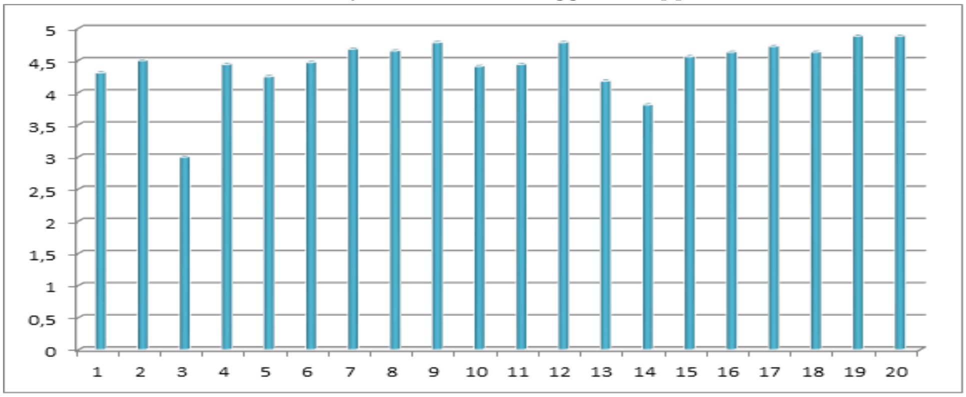

Figure 6: Mean Likert scale teachers ratings

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 were appropriate. We may come to the conclusion that the suggested approach's recommendations for LDs are relevant

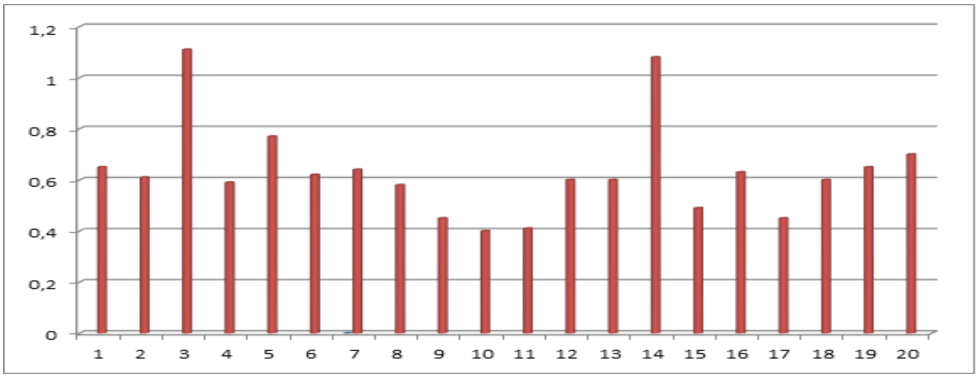

Figure 7: Standard deviation of teachers Likert ratings

and satisfy our initial expectations. Another benefit of CBRS, is that it incorporate both the preferences of learners and teachers to enhance the LD process since it take into account users need when opposed to the aforementioned similar studies[16][17][18] 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.

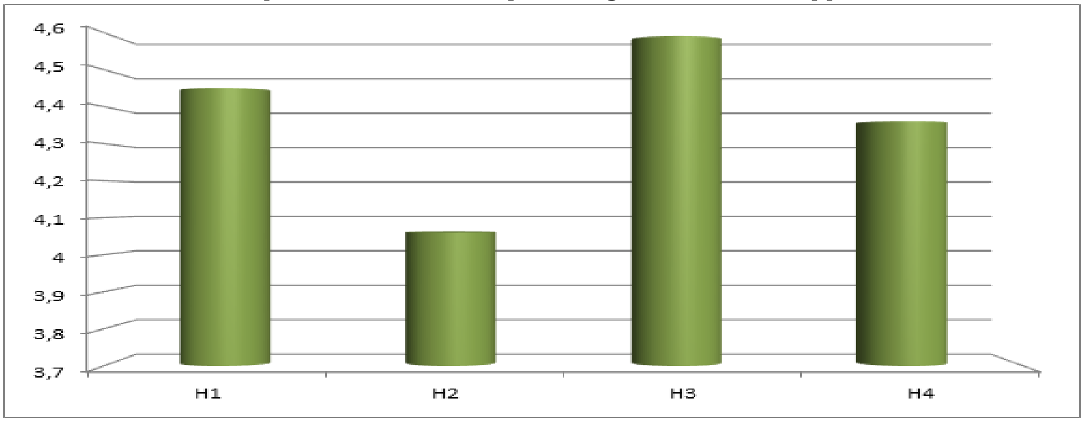

Figure 8: Average Likert scale teacher ratings

4.2 Offline study

4.2.1 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 recommender system is evaluated on a dataset that has been collected from CBRS for almost 6 month. This study provides a useful way to identify the strengths and weaknesses of the recommender system and determine how well it performs relative to other systems, it helps to identify weak points for improvement and inform future development and refinement. The following question may be answered by comparing a recommender system to others: How accurate is the proposed recommender system in comparison to other systems? The accuracy of the proposed approach will be compared only with three baseline algorithms; namely contentbased filtering, random and popularity-based recommendation, as it is challenging to compare a recommender system 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 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 [29].The F1 score is the harmonic mean of precision and recall, which are two important evaluation metrics for recommender systems. 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.

4.2.2 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 fig. 8. 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 to make recommendations. In contrast, baseline methods may struggle to provide recommendations in the absence of historical data.
4. 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

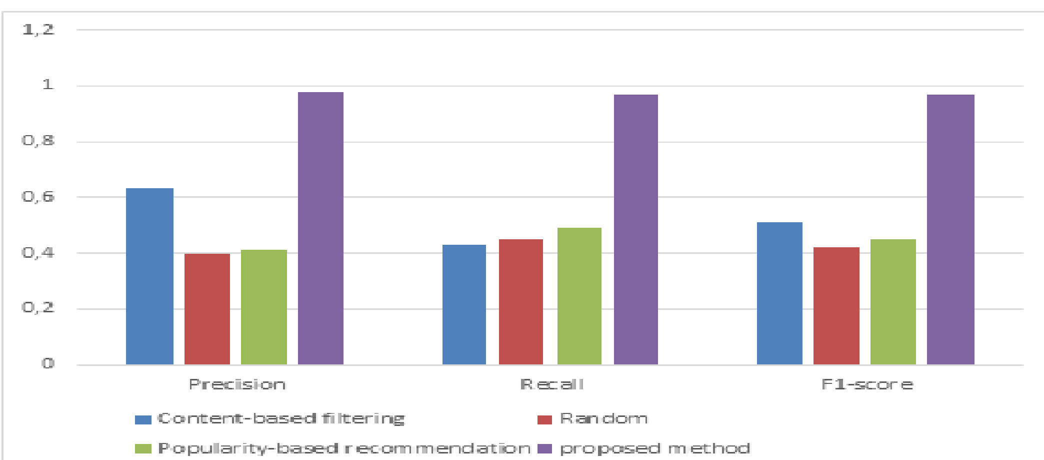

Figure 9: Average Likert scale teacher ratings categorized by hypotheses

5 Conclusions

This paper has presented CBRS, which is a case- based recommender system that 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 style presented by the system. We test 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 questions provided at the beginning of this paper were obtained. Generally, the experiment produces fruitful outcomes and showed that the responses of research questions are positive due to teachers' affirmation that the CBRS simplify 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, it 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 elearning 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, the evaluation of LDs by peer teachers to favor the most relevant LDs or to 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.

Declarations

Competing of interest

The authors declare that they have no conflicts of interest.

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Author Contributions

All authors contributed equally to this work.

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