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Recommendation method based on learner profile and demonstrated knowledge

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ABSTRACT

The COVID-19 pandemic is increasingly gaining popularity when discussing e-learning in the context of institutional and organizational learning because of its numerous benefits which make it possible for learners to learn regardless of the circumstances and/or the timing. Therefore, the expanding dominion of online learning has caused problem in terms of determining adequate learning activities for the learner in this context, and it relatively becomes a widely used learning technique for learners. Several studies in online learning focused mainly on increasing student achievements based on recommendation systems. An ideal recommender system in e-learning environment should be built with both accurate and pedagogical goals. To address this challenge, we propose a recommendation method based on learner preferences and knowledge level using machine learning technique. The learning approach is designed based on this technology to build a personalized e-learning scenario by selecting the most adequate learning activities for the learner. Moreover, several experiences were conducted in the real environment to evaluate our system. The results show the quality of learning and the learner's satisfaction.

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1. INTRODUCTION

E-learning has become increasingly popular in the last decade, where learners can learn new materials and skills in their own place and at their own pace. As a result of this change, learning management systems are commonly used as content delivery tools and repositories of learning objects [1]. The use of recommender systems (RSs) to help learners in locating their way through the options available in the e-learning area is obvious [2], [3]. The central function of RSs in e-learning is to make predictions about learners' preferences to unused learning objects (LOs) based on their past activities.

In the e-learning situation, We must keep in mind that different learners may have distinct demands and features, such as varied levels of skill, learning styles, prior knowledge, and that they desire to master a given skill in a specific amount of time [2], [4], [5]. It is of great thing to provide an adapted learning scenario which is capable of automatically adapting to learners' knowledge levels and recommend e-learning activities that will support and enhance the teaching and learning process. In this paper, we advance our tool of a recommender system for a personalized and intelligent method that considers the pedagogical goals of the learner and the necessity of recommending a series of teaching activities in an educationally order.

In personalized e-learning, learners having different learning profiles and different knowledge levels have different sets of learning paths [6]–[8]. ence, we aim to predict intelligent recommendations to a learner based on his profile and knowledge level, as well as by utilizing similarities among other students that share the same previous learning paths and knowledge levels. In the aforementioned system, learners are classified based on learning profiles using collaborative filtering (CF) technique. Next, a list of LOs (learning path) is created in accordance with the prediction of each LO. The provided recommended list is expected to be extremely accurate in matching learners' needs to learning paths. Finally, the system will attempt to verify whether a given teaching strategy is adequate depending on the assessments for a each student. The paper is structured as follows: section 2 describes some previous work related to our system. Section 3 presents the proposed recommendation technique. In section 4, we explain the results and studies of our experiences in real context. Finally, section 5 details the concluding remarks.

2. MATERIALS AND METHODS

Recently, in the e-learning environment, RSs have been introduced extensively and applied in order to identify suitable LOs as well as to provide learners with a variety of learning experiences [9]–[11]. Thus, in conformity with [12] LO is produced, structured, and distributed on a regular basis in many sorts of e-learning systems. Moreover, the large number of LOs presents sevral possibilities, but also poses issues for learners to find adequaqte e-learning activities [1]. In the e-learning environment, several RSs have been introduced over the last decade, especially in informal learning [13], [14]. By reviewing the previous works, it was observed that most researchers categorized recommender systems based on their underlying techniques into three main categories: (i) content filtering, (ii) collaborative based filtering, and (iii) hybrid based filtering [15]–[17]. Some of these RSs are discussed in the next paragraph.

Bourkoukou *et al.* [1], proposed a recommender system for online learning to obtain a personalized teaching strategies by selecting and sequencing the most adequate LOs. This system uses a hybrid recommendation technique using collaborative filtering and the algorithm of association rule mining. Rodríguez and colleagues [18] created a hybrid RS that uses learners' learning styles, knowledge level, language, and learners' opinions to discover relevant LOs from repositories. This system uses a two-phase process to generate the recommendations. It first clusters the learners using learning styles, and knowledge level. Next, it finds the LOs from repositories that match the learner's query and are also found interesting by similar learners. Another similar hybrid RS was built by Dwivedi and Bharadwaj [19]. This system categorizes learners based on their score similarity and recommends LOs for group of learners instead of individuals. This system uses learners' preview activities, learning styles, and their knowledge level to built learners' profiles. After that, it clusters the learners using the nearest neighbor algorithm, merges the profiles of the learners in each group and suggets recommendations based on the group's profile to learners belonging to the respective group.

Another group of RS generates recommendations based on similarities between learners and LOs rather than similarities between learners. For example, Salehi and colleagues [20] built a content-based RS that considers the learners' past activities extracted from server logs' files as well as different attributes of both the LOs and learners to provide a prediction model and predicts the learners' interests to unused LOs. Some other systems use different rules to match and recommend the best LOs to the learners while generating recommendations. For instance, Chen *et al.* [21] built a rule-based RS that uses LO response theory and applies some pre-defined rules to recommend LOs to learners based on learners' learning abilities. This system determines the learners' abilities by asking learners to complete a questionnaire. Additionally, this system categorizes the course materials based on their difficulty level. In this system, all materials are marked as moderate difficulty level at the beginning by default. Another rule-based system was proposed by Dorça and colleagues [22] which defines a set of rules that are used to classify LOs based on their teaching style. Next, it identifies the learners' learning style and recommends LOs with a teaching strategy that support a learners' learning style.

In the paper, Wan *et al.* [23] proposed a hybrid recommendation approach combining self-organization-based approach, and analysis pattern algorithm, for making recommendations to learners. Asadi *et al.* [24] designed a recommender system which takes learner attributes into consideration to recommend adequate LOs. The system used clustering to identify learners with similar preferences and competences. Vedavathi and Kumar [25] developed an e-learning RS for learners' interests based on hybrid algorithm. This algorithm use a deep recurrent neural network and enhanced with whale algorithm. This method can assist students in grasping their current level of knowledge and learning direction, as well as improving their learning efficiency. Trifa *et al.* [26] developped a RS based on an intelligent agent which can help in understanding learners interactions to trace the learner knowledge level. The agent's distinctive feature is that it analyzes the external and internal interactions of the learner using several algorithms to produce a complete learner model.

3. PROPOSED RECOMMENDER SYSTEM

The proposed system attempts to recommend learning activities to the learner by taking into account the preferences of the students and previous surfing information gathered from the log files. This approach is based on collaborative filtering algorithm to improve the quality of recommendation list.

3.1. Recommendation process

The recommender process for e-learning is depicted in Figure 1. The learner profile can be revisited dynamically using the learner's interactions with the system by extracting their interests and preferences from web log files that are generated, in order to recommend the most appropriate list of learning objects. In e-learning contexts, the instructional material is arranged into numerous courses, each with multiple chapters. A chapter can be thought of as a collection of learning units or concepts arranged in a tree. Figure 2 shows the structure of our suggested domain model.

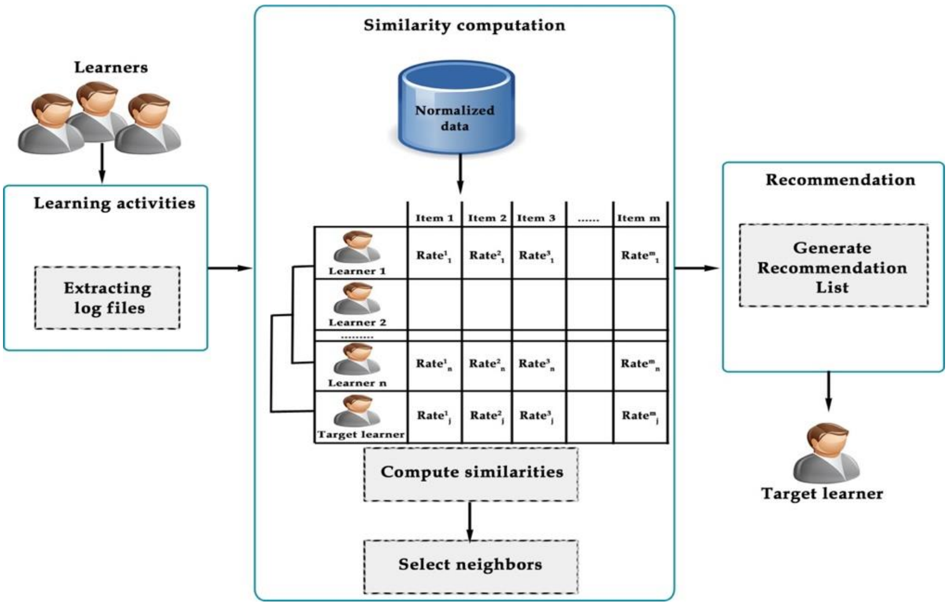

Figure 1. Recommender system process

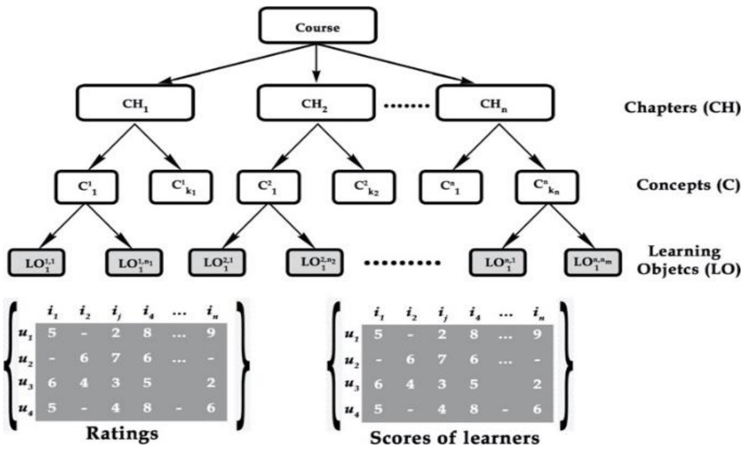

Figure 2. Domain model

A learning concept holds one unit of pedagogical knowledge and display different components of it using various sorts of LO, such as QCM, collaborative activities, examples, exercises, tests [8]. After the pre-processing phase, we obtained two matrix of learner-item-ratings with where *rows* presents learners $L = \{l_1,$

$l_2, \ldots, l_n\}$, and columns presents LOs $I = \{ i_1, i_2, \ldots, i_m\}$. We applied a novel technique using CF in order to create a virtual learning community with similar profiles and knowledge levels. This technique allows finding learning scenario for each learner by computing the similarities between learners.

In Figure 3, an example illustrates how this learning experience could be designed and sequenced for three participants as a customised learning scenario $\{l_1,l_2,l_3\}$. Indeed, learners follow a straight path to learn in a traditional e-learning session $\{ j_1, j_2, \ldots, j_{12}\}$ without taking into account their own preferences or degree of learning. However, a teaching strategy could be developed and delivered in a nonlinear way in order to create the best list of Los for a specific learner. An optimal learning path represents; the best teaching situation can be offered for a specific learner. In this learning situation, for example, in the first chapter the learning objects j_9 is dismissed or excluded because he is not meet the learner need.

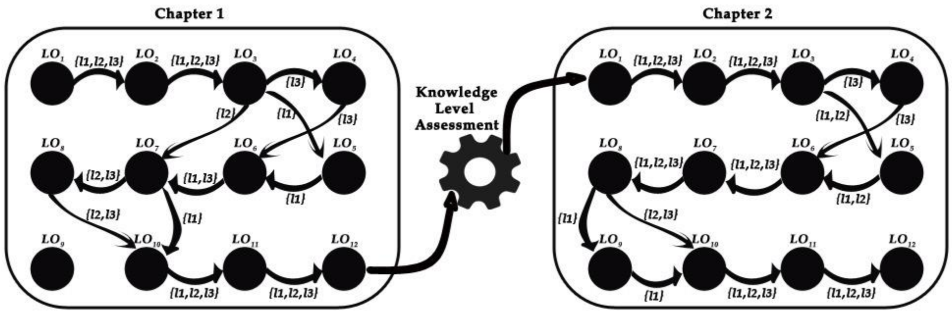

Figure 3. Example of knowledge level assessment process

In order improve our recommendation process, we propose a knowledge level assessment tool. This module helps to verify whether a recommended learning scenario is adequate for a specific learning profile or not. Indeed, at the end of each chapter, the learner achievement and learning acquisition will be measured and evaluated. If the learner is successfully examined in the actual chapter, the next chapter is then activated and thus, the learning process is initiated. In case of malfunction at the first phase, the learning scenario is revisited based on the learner's degree of knowledge and the system suggests more learning activities.

3.2. Improved collaborative filtering

The definition of similarity and dissimilarity between learners or learning objects is a crucial stage in memory-based CF techniques. Indeed, several ways to computing similarities and differences have been offered, the most popular of which are as follows: Cosine similarity, Pearson's correlation [9], [27], [28]. We develop a new learner similarity metric using learning experience of learners to tackle the deficiencies in traditional methods. The basic principle we'd like to define is the weighing of recommendations based on learner information, not only do they appreciate the typical resemblance between their previous learning path and that of the other students, But it's also important to keep in mind that the recommendations of students with higher grades/scores have more weight than those of students with lower grades. In order to determine for a learner u a learner's knowledge level (KL_u), depending to the recommendations of LOs that will be received from an other learner v with knowledge level (KLv), it is essential to define a set of metrics for our purpose. Firstly, we compute KL using as (1).

$$KL = \beta\,(d_i)_{1<i<n} \tag{1}$$

In the metric (1), KL was therefore established as the weighted average of all scores obtained by the learner u, for β represents the score on a 0–10 number scale obtained by the learner at the end of each chapter. In this study, it was chosen to utilize a basic metric that can be established using the function f (2), However, different factors, such as those presented in (3), could be used as well. The choice of formule over the other is based on how the relationship of knowledge indicated by each pair of learners is to be weighted, as well as the nature of the RS information.

$$f = \begin{cases} KLv - KLu, & KLv > KLu \\ 0, & KLv \le KLu \end{cases} \tag{2}$$

In this way, in the formule (2), if the knowledge level calculated for learner v is 7 on graduated system (0–10) and that the learner u is 2, The weighting of learner u's knowledge score to learner v would be 5, whereas learner v's knowledge level to learner u would be 0. As defined in (3), a new measure of similarity between the learners' u and v can be established. The first element in the formule presents the knowledge level degree, while the second part presents the learners' similarity based on their profiles based on some standard measures (Pearson, Cosine, MSD). The sum serves to find the numeric mean of the T notes that evaluate the knowledge degree of the learner; a note that is not gived must be initialized with the minimum note (0 on the graduated system of 0–10). $KL_{u,t}$ refers to the knowledge degree of the learner u on the t LO, test, exercice, and exam.

$$S(u,v) = \frac{1}{T}\sum_{t=1}^{T} f(KLu, KLv) * sim_{I(u,v)}) \qquad (3)$$

The similarity values obtained between pairs of learners are used to obtain the necessary k-neighborhoods for each learner, similar to how classical CF measures are used, and recommendations list can be made based on the evaluations given to the k learners who are most similar to each other. We'll assume that target learner u's choice for studying object j is p_{uj}. These principles are quantitatively expressed by (4)-(6).

$$\overline{KL}_u = \sum_{t=1}^{T} KL_{u,t}, KL_{u,t} \in [0,1] \qquad (4)$$

$$w_{u,j} = \frac{1}{\mu}\sum_{u=1}^{\breve{U}} \overline{KL}_u r_{u,j} \ \forall j \mid \exists\, r_{u,j} \neq \emptyset, \breve{U} \in U \big| \exists\, r_{u,j} \neq \emptyset, \mu = \sum_{u=1}^{\breve{U}} \overline{KL}_u \qquad (5)$$

$$pu, j = \frac{1}{|\breve{K}|}\sum_{k=1, k\# u}^{|\breve{K}|} S_{u,l} * \beta w_{k,j} \qquad (6)$$

In (6) $w_{u,j}$ denotes the rating estimation for learner u and ratings of all learners that have rated learning object j.

4. RESULTS AND DISCUSSION

An experiment to compare the proposed approach to a classic recommendation method has been carried out. One that does not use a knowledge level metric, but instead measures students' understanding after the learning process. Also, a study on the effectiveness of the proposed system in learning "Java programming" is set up. The main research question was: "Does learner profile and level of knowledge based on personalized learning scenarios affect learning outcomes?"

In four months of 2016, participants were chosen from a pool of 163 Computer Information Systems Bachelor's degree students at ENS, Cadi Ayyad University in Marrakesh, Morocco. Students were required to study the four learning chapters. The chapters concerned are: Chapter 1: Java introduction, Chapter 2: Java language fundamentals, Chapter 3: Java Classes and methods and Chapter 4: Framework Collection. In order to create individualized learning environments for students with various profiles, we incorporated four versions of topic content in the proposed system. The sessions were scheduled at the beginning of the course, over a period of eight weeks. Under the same conditions, students followed the learning materials using one of these approaches. Student performance was measured at the end of each course and at the end of each chapter using multiple choice questions (MCQ). The MCQ is made up of questions divided into three levels of difficulty (easy, medium and difficult). The scores for this experiment were calculated on a scale of 0 to 20. Figure 4 depicts a typical tailored course scenario for students. The 'while loop' expression is the concept in this case. The system simulates the principle of the notion and links an electronic medium with a picture.

The system analyzes the learner's acquired skills for each chapter and course once the student completes the sequence of learning materials. In this study, the learner is regarded to have passed the final test for each subject if he receives a control score of more than 10/20. In Figure 5, the learners' outcomes might be interpreted as follows: (excellent) (18–20), (very good), (16–18), (good), (14–16), (average) (10–14), and (marginal) (10) based on the proportion of right responses. Several Several studies suggest that student happiness is a key factor in determining the effectiveness of an online learning process. Yet, satisfaction statistics are required to understand how students feel about the learning process, including content, methodology, and adaptability. To get a subjective evaluation of the proposed system, an obligatory surgery at the end of the course was prepared, participants' comments on the system's main features were collected in order to respond to the following questions: Did the organization of the material into different media presentations aid your comprehension? Did you find the adaptable framework to be simple to use? Did you enjoyed learning using our adaptive system 145 out of 163 participants completed the survey. The student's level of satisfaction with various adaptive educational systems is represented in Figure 6. These results were obtained by explicitly asking for their opinions. The notation score for our adaptive system ranges from 1 to 5, with 1 being the lowest and 5 being the highest.

Figure 4. An example for 'while loop' concept fitting to the learner profile

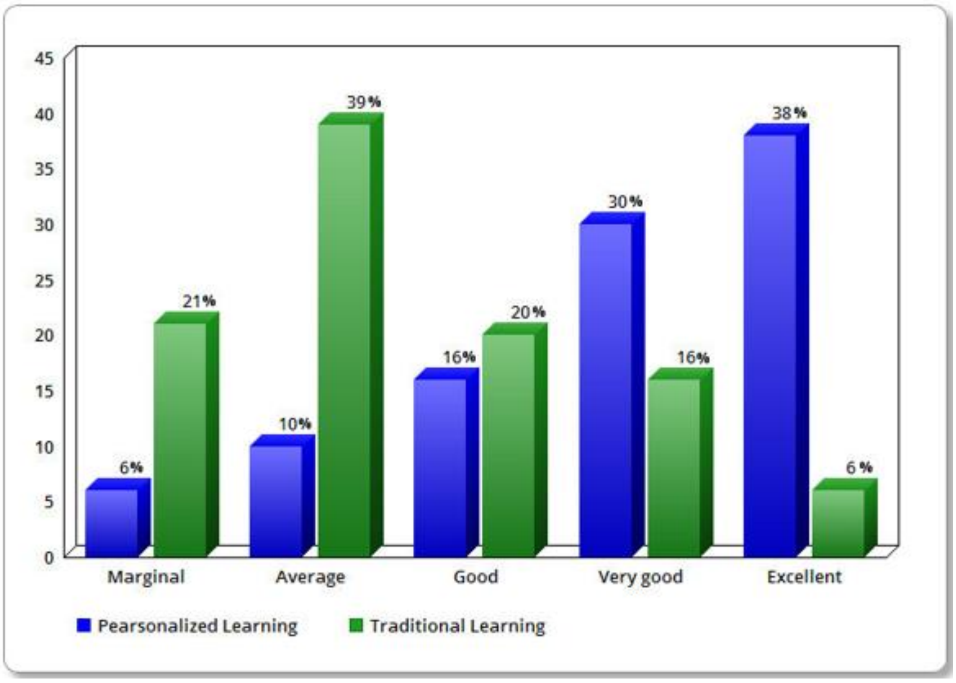

Figure 5. Comparison between traditional and personalized learning strategy

Results the findings reveal that the majority of students believe the educational recommender system is beneficial to their learning and that their needs are met. The majority of them deemed the system to be user-friendly. They were eager to study using the selected learner's profile and were willing to utilize the system again. The findings appear to back with previous research that found that matching learner profiles to learners' knowledge levels can assist students improve both learning efficacy and efficiency [2], [6], [22], [29], [30].

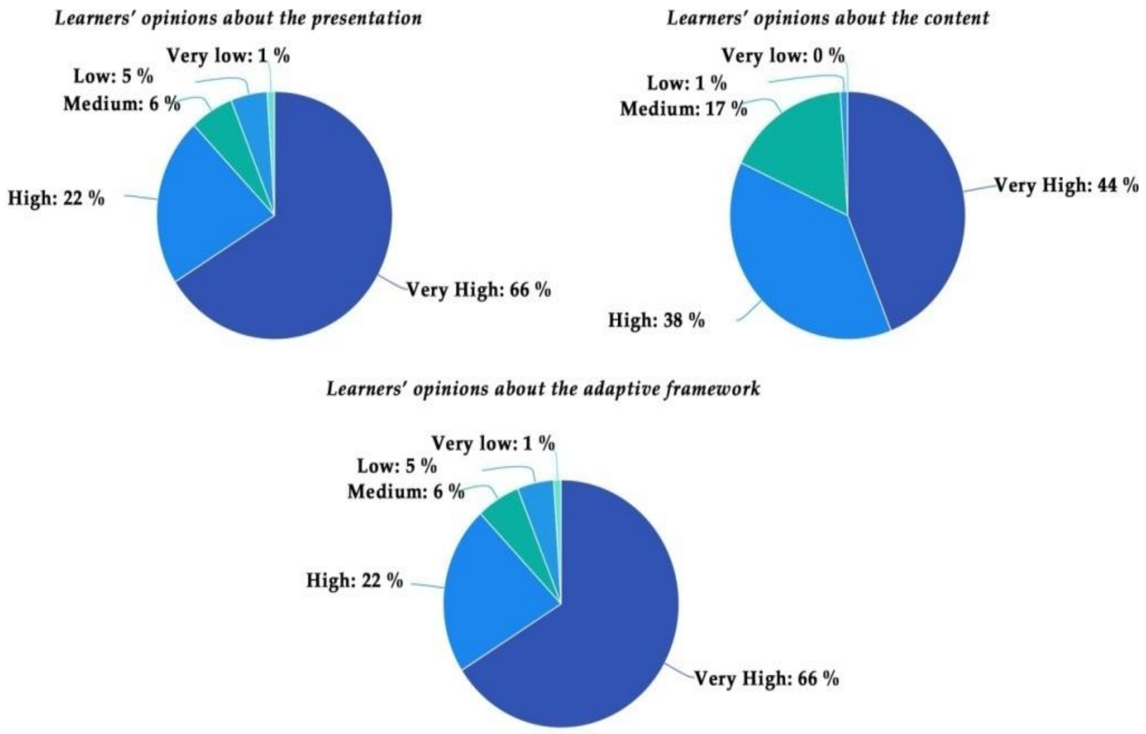

Figure 6. Learners' opinions about the main features of RS

5. CONCLUSIONS

Currently, individual learning is now supported by recommender systems in the context of e-learning. When online learning environments strive to develop, build, and implement educational experiences that are tailored to the needs, goals, levels of knowledge, and interests of its students, this is referred to as personalized learning. Furthermore, the concerns surrounding suggestion in the learning process have been extensively researched in recent years and continue to be a source of concern for many researchers today. However, there are a number of drawbacks to using existing recommendation systems. In this paper, an autonomous recommender system based on learning identification and collaborative filtering strategies to solve these constraints has been proposed. In online distance education, the basic goal is to provide individualized suggestions for each student by organizing the most relevant learning items into a cohesive, focused structure. Our experimental results show that a combination of the learners' learning profiles and knowledge levels in recommendation process has the potential to improve the quality of an intelligent e-learning system, as well as keep the recommendation up-to-date. We intend to improve the recommender model in the future to address various fundamental difficulties such as data sparsity and data correlation. Due to the fact that CF approaches are acknowledged to be susceptible to these issues in suggestion. Furthermore, we will investigate more complicated recommendation algorithms that incorporate additional elements such as learner motivation, as well as other clever artificial strategies. The findings suggest that using a mixture of learners' learning profiles and knowledge levels in the recommendation process can increase the quality of an intelligent e-learning system while also keeping the advice up-to-date. We intend to improve the recommender model in the future to address various fundamental issues such as data sparsity and data correlation. Due to the fact that FC approaches are known to be sensitive to the problems under consideration. Furthermore, we will investigate more complicated recommendation algorithms that incorporate additional elements such as learner motivation, as well as other clever artificial strategies.

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