

The new e-learning adaptation technique based on learner's learning style and motivation

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ABSTRACT

E-learning has increased in popularity, especially during the COVID-19, due to its numerous advantages that allow learners to study anywhere and anytime. Therefore, recommending a list of the most appropriate learning objects for learners according to their specific needs is a great challenge for adaptive e-learning systems. In an e-learning environment, the optimum adaptive e-learning system is one that can adapt dynamically to the profile of each learner. Within that particular context, various approaches were proposed. In this article, we propose a new adaptation technique based on learner's learning style and motivation score by using collaborative filtering technique, constrained Pearson correlation coefficient, adjusted cosine measure, and K-nearest neighbor algorithms. The proposed approach is focused on how to develop and construct an effective customized pedagogical learning scenario for learning resources, and improve the accuracy of the adaptation by choosing the most suitable learning objects for learners. Therefore, we used the dataset MovieLens100K containing 943 learners and 1,682 learning objects. Additionally, a few experiments have been conducted to validate the performance of our technique. The results indicate that taking into account the learner's learning style and motivation score can completely satisfy the customized needs of learners and improves the quality of learning.

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1. INTRODUCTION

The pandemic of COVID-19 reinforces the importance of online digital learning for higher education institutions, which is already a popular method of learning in the area of internet plus. However, to support customized e-learning, it is necessary to develop a customized system of learning materials that addresses to the different needs and features of various learners. According to Moraes *et al.* [1] and Vallejo-Correa *et al.* [2] providing students with coherent environments that consider their individual learning preferences and interests is one of the most crucial goals of customizing the learning process. When it comes to the adaptation of learning, learning styles (LS) and learning objects (LOs) are two highly intriguing concepts. The use of LOs can encourage students to learn and advance effective instruction [3]. Many studies on the customization of learning combine LS with LOs, meaning that learners are delivered content using learning objects that match their preferences as indicated by their learning styles. In this situation, intelligent tutoring systems provide adaptable learning environments that work from this perspective.

The main aim of adaptive systems in the e-learning environment is to predict learners' preferences for underused LOs based on their prior behavior. In this context, it is necessary to take into account that learners may have specific individual needs and features, such as learning style, knowledge levels, learning preferences. to achieve a specified competency within a given amount of time [4], [5]. It is critical to create a tailored learning scenario that can adjust to the learners' learning style and intelligently suggest learning objects, that will improve the learning process.

In this study, we provide our conceptualization of an adaptive and intelligent system that takes into account the pedagogical characteristics such as learning style and motivation score of the learner and the requirement to adjust learning activity sequences in an instructional effective manner. There are various learning paths for learners with various learning profiles and knowledge levels [6], [7]. Therefore, we attempt to estimate automatic adaptations to active learners based on their learning style and motivation score, as well as by capitalizing on similarities between other learners who have taken the same learning paths with the same motivation score.

In contrast to studies that only consider the learner's response, our approach in the modeling of adaptive systems considers other metrics that can reveal other indicators of performance, namely learner's learning style and motivation score, to dynamically adapt the pedagogical content to the specific needs of the learners. The aforementioned system employs collaborative filtering (CF), constrained Pearson correlation coefficient (CPCC), adjusted cosine measure similarity (ACOS) with K-nearest neighbor (KNN) algorithm for machine learning to identify learners based on their learning characteristics, especially learning style and motivation score. Then, based on each LOs prediction, a list of adaptations (learning path) is constructed. The given adaptation must be very precise to correspond to the needs of the learners to the learning path. Finally, depending on assessments, the system would try to decide if a particular learning technique is suitable for a particular learner.

This paper is structured as: Section 2 summarizes several earlier studies that are pertinent to our idea. The new recommended adaptation technique is described in section 3. The study findings to demonstrate the system validity are illustrated and described in section 4. Finally, the study conclusion and suggestions for further works are presented in the conclusion section as in section 5.

2. PREVIOUS RELATED WORK

In this section, on the one hand, we have briefly reviewed work related to the relationship between LOs and LS in recommendation of adaptive e-learning systems, on the other hand, the adaptive systems in e-learning environments and the machine-learning approaches that are used to identify and adapt learning objects to learners. In the literature, LOs and LS are being applied in different approaches [8], [1]. Raj and Renumol [9] affirm that customizing a learning environment by recommending learning objects based on learning styles could focus predominantly on the cartography between learning styles and learning objects. According to iterations with the system and the learner's LS, EL Aissaoui and Oughdir [10] offer an ontology-based recommender system to identify LOs that are appropriate for the learner. For the purpose of personalizing the information, this establishes a map between learning objects and learning styles.

Adaptive systems have recently been widely developed and used to find appropriate LOs, and offer a diversity of learning activities to learners [11]. In other terms, adaptive systems are filtering or sorting systems that which are used to identify the preferences of a given individual learner, or to predict the evaluation of a a particular item [12]. In order to provide a recommendation and adaptation, information must be obtained from learners, either explicitly or implicitly. Recommender systems can also use personal information stored in the learner's profile (learner data profile) such as age, nationality, and gender [13]. Numerous adaptation methods have been established in the e-learning environment over the past decade, particularly in informal learning [14]. Reviewing earlier research, it was found that the majority of researchers divided adaptive systems into four broad categories: i) Collaborative filtering (CF): This system generate recommendation based on learner ratings; ii) Content-based filtering (CBF): This system provides recommendation by using learner ratings and product features; iii) Demographic filtering (DF): This system recommends item by using learner's demographic profile; and iv) Knowledge filtering (KF): This system generate recommendations on the basis of area knowledge of product features that correspond to the learner's interest [13]. The following section discusses a few of these systems:

For the sake of creating tailored learning experiences, a model of adaptation was proposed for the e-learning environment by Bourkhoukou *et al.* [15]. This methodology involves choosing and ordering the most suitable LOs. Utilizing a mixed adaptation method system based on combining an association rule mining method with a collaborative filtering strategy. Zhong and Ding [16] had created a hybrid recommendation design of educational resources for learners' individual needs and how to construct a hybrid intelligent recommendation scheme of educational resources based on content and collaborative filtering in the internet environment. Previous study [17] had created a new personalized learning resource

recommendation system for K12 learning platform. Wei *et al.* [18] have proposed a new adaptation method by combining CF algorithm and deep learning. In the same way, da Silva *et al.* [19] have proposed an evolutionary approach to combining the results of recommendation techniques by using the genetic algorithm as a search algorithm. On the other hand Colombo-Mendoza *et al.* [20] have proposed a new hybrid recommender system based on semantic web technologies, context-awareness and ontology for recommending movies. Salehi *et al.* [21] developed a content-based system that builds a prediction model and predicts user interests for hidden learning objects using historical learner activities that were collected from server logs as well as other article and user variables. This algorithm analyzes previous rating data to identify which learning object features are most enticing to the user. Then, it employs a genetic algorithm and a KNN to determine the relationship between the learners' preferences and the accessible products, which after determines the items match the user.

Other systems generate recommendation by using CF and CBF. Their results demonstrate that the technique outperforms previous algorithms on precision and recall measures. Ean Heng *et al.* [22] research focus mostly on personalized learning, and they advocate adapting the educational process by providing learning resources that are tailored to individual student's learning preferences. The outcomes show how learners' learning can be improved by properly presenting learning objects. To create relevant and adaptive courses, Riad *et al.* [23] proposed an intelligent adaptive e-learning system, that takes into consideration the deep learner profile to recommend the most appropriate learning objects for learner. The proposed system uses machine learning and reinforcement learning algorithms to recommending a list of the most appropriate learning objects for learners according to their deep profile.

Vedavathi *et al.* [24] created an effective e-learning system for learner preferences. The whale optimization approach is used to improve the deep recurrent neural network foundation of this algorithm. In order to offer a list of LOs appropriate for learners, Yan *et al.* [25] incorporated online learning style features into a collaborative filtering algorithm with association rules mining. This resulted in a new learning resource recommendation approach that is based on an online learning style. In a similar vein, Bourkoukou *et al.* [26] suggested a recommendation method in an e-learning environment based on machine learning techniques to identify each learner's level of knowledge and provide a list of learning objects to the learner in question. To enhance the quality of learning for learners in our study, we suggest, a new adaptation technique based on learner's learning style and motivation score, by using CF, CPCC, ACOS, and KNN algorithms. The proposed approach aims to construct a customized pedagogical learning scenario while picking and recommending the best and the most suitable learning objects for learners to use in a learning activity.

3. RESEARCH METHOD

The approach proposed in this paper, for the design of adaptive systems in the context of an e-learning environment, takes into account other metrics that can reveal other indicators of performance, namely the individual learning style and motivation score of the learner. This approach aims to generate dynamically an appropriate learning path during the learning activity in order to enhance learning and improve the quality of learning for learners. It uses the information stored in the learner data profile as log files and the domain model to provide the appropriate recommendation. At first, all learners are categorized based on their individual learning styles utilizing the collaborative filtering technique, as the most used technique for recommender systems [27], then we use CPCC and ACOS to establish a community of learners who share the same learning style and score of motivation. This technique enables us to find a learning path for every learner by calculating the similarity between learners or LOs. The basic approach takes into account a motivation score matrix attributed by the learner to the LOs and gives the learner the results of the assessment.

Then, a list of adaptations is generated based on the prediction of each LOs. The adaptation provided should have a high degree of precision in adapting the learners' requirements to the learning path. Finally, the system will try to evaluate whether a given learning approach is suitable for a particular learner based on assessments. The similarity examinations can be split into four categories, they are: i) Predefined similarities; ii) Learned similarities; iii) Preference-based similarities; and iv) Mixed similarities [28]. In this research, the focus was on predetermined similarities, cosine and Pearson are instances of this category.

3.1. Overall process for the proposed adaptation system

We can extract from the individual learner's log files, a significant volume of important information about the characteristics of the learner, e.g. preferences, learning style, knowledge level. The proposed approach aims at adapting learning objects to the learner, taking into account his individual learning style, motivation score, and his browsing history extracted from the log files. The general process of adaptation process of the proposed approach was presented in Figure 1.

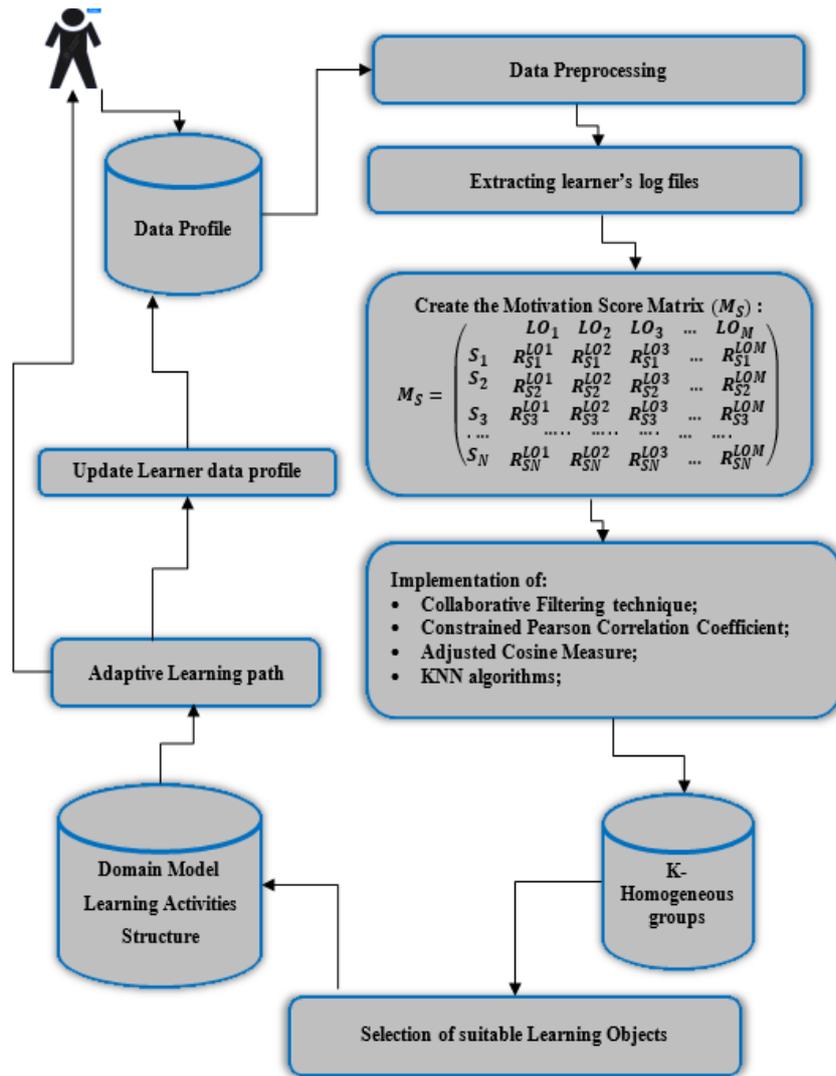


Figure 1. The general process for the adaptation system of the proposed approach

Figure 1 presents the general adaptation process of the proposed system. As a result of the data pre-processing and extracting log files stage, we were able to create the learner motivation score matrix of "i" rows and "j" columns. Where the rows "i" of the matrix MS_{ij} represents the number of students $\{S_1, S_2, \dots, S_N\}$ while the columns "j" represents the number of learning objects $\{LO_1, LO_2, \dots, LO_M\}$. This matrix (learner motivation score matrix) MS_{ij} is written as (1):

$$MS_{ij} = \begin{pmatrix} S_1 & LO_1 & LO_2 & LO_3 & \dots & LO_M \\ R_{S_1}^{LO_1} & R_{S_1}^{LO_2} & R_{S_1}^{LO_3} & \dots & R_{S_1}^{LO_M} \\ S_2 & R_{S_2}^{LO_1} & R_{S_2}^{LO_2} & R_{S_2}^{LO_3} & \dots & R_{S_2}^{LO_M} \\ S_3 & R_{S_3}^{LO_1} & R_{S_3}^{LO_2} & R_{S_3}^{LO_3} & \dots & R_{S_3}^{LO_M} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ S_N & R_{S_N}^{LO_1} & R_{S_N}^{LO_2} & R_{S_N}^{LO_3} & \dots & R_{S_N}^{LO_M} \end{pmatrix} \tag{1}$$

3.2. Domain model of our approach

The domain model in our approach for the adaptive e-learning system includes the learning resources that are structured to simplify the adaptation process when using intelligent e-learning systems. The model that has been adopted is composed of four distinct layers represented as a hierarchical network: i) Learning activity (course); ii) Chapters (concepts); iii) Learning unit; and iv) Learning objects (LOs). Figure 2 describes the overall domain model structure of our system.

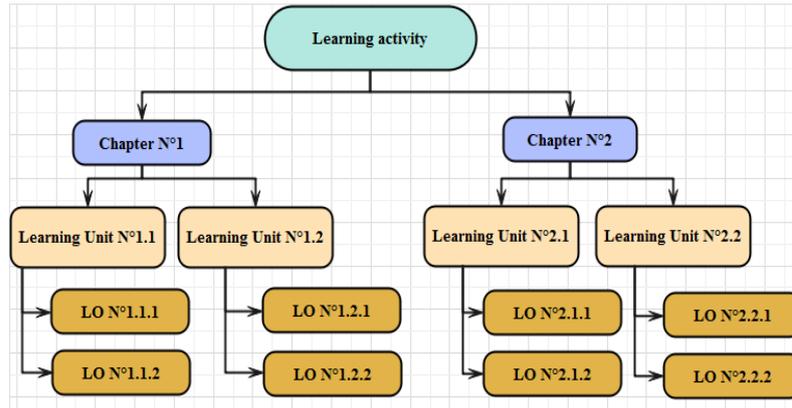


Figure 2. Learning activity organization

The learning activity (course) organization presented in Figure 2 is mapped into four hierarchical layers. The 1st layer represents the root of the domain model structure, which presents the “learning activity” to be taught. The 2nd layer represents “chapters”, which particularly address a learning activity element to be taught. The 3rd layer represents the “learning unit” of each chapter and is generally identified by a level (advanced, intermediate, or beginner), and the 4th layer represents the different types of “learning objects” (LOs), that represent external representations, such as images, pedagogical activities, small examples, comprehension exercises, and glossaries [7]. Each LOs are characterized by many properties such as autonomy, adaptation, indexing, accessibility, durability, and reusability as the most important property.

Based on our proposed approach presented in Figure 1, we can determine a learning scenario for each learner. For instance, Figure 3 and 4 show how this learning scenario could be arranged and presented for four students $\{S_1, S_2, S_3, S_4\}$ as an individualized learning path. Thus, we find that in traditional learning e-learning, all students utilize a linear learning path $\{LO_1, LO_2, \dots, LO_n\}$ to learn without considering their characteristics and specific needs as seen in Figure 3. However, the organization and structure of LOs for students in a personalized adaptive learning system can be mapped in a non-linear path, to construct the optimal LOs sequence for each learner as seen in Figure 4.

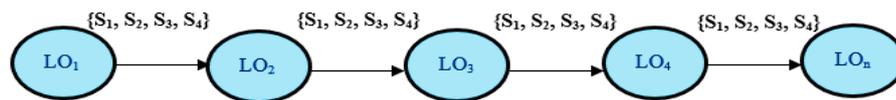


Figure 3. Structure of learning path in a traditional adaptive system

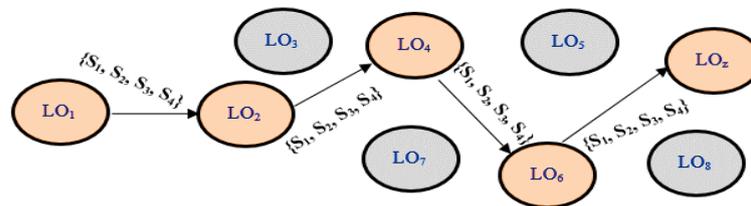


Figure 4. Structure of learning path in the modern adaptive system

The optimum learning scenario can be suggested for a certain student based on the optimal sequence, that we have identified. In this customized scenario, for example, some learning objects like LO₃, LO₅, LO₇, and LO₈ can be ignored by the system because it does not match the profile of the students $\{S_1, S_2, S_3, S_4\}$. We provide an instrument for determining motivation score to improve our adaption process. This module enables users to assess the suitability of a certain pedagogical learning scenario for a given learning profile. In fact, the learner’s motivation will be measured and evaluated at the end of each chapter of

each learning activity (course). The new and the next chapter is triggered and the process of learning is initiated if the learner passes the current chapter’s examination. In case of failure during the initial phase, the learning scenario is revised according to the learner’s score of motivation, and the system proposes and recommends other learning activities.

3.3. Predefined similarity measures: Collaborative filtering technique

In general, determining the similarities and dissimilarities between students or LOs is the most critical phase in classification. Several methods and approaches for calculating similarities and differences have been established in this area; the most generally used are the Pearson correlation coefficient (PCC), the cosine similarity (COS), and Spearman’s rank correlation coefficient [16]. In our approach we employ the following formulas to calculate the similarity measure between two learners, "S₁" and "S₂" (they might also be used for items). Equation (2) shows the formula for calculating similarity using PCC, while (3) shows the formula for calculating similarity using COS:

$$sim_{S_1,S_2}^{PCC} = \frac{\sum_{i \in I} (r_{S_1 i} - \bar{r}_{S_1}) \cdot (r_{S_2 i} - \bar{r}_{S_2})}{\sqrt{\sum_{i \in I} (r_{S_1 i} - \bar{r}_{S_1})^2} \cdot \sqrt{\sum_{i \in I} (r_{S_2 i} - \bar{r}_{S_2})^2}} \tag{2}$$

$$sim_{u,v}^{COS} = \frac{\vec{r}_{S_1} \cdot \vec{r}_{S_2}}{\|\vec{r}_{S_1}\| \cdot \|\vec{r}_{S_2}\|} \tag{3}$$

Where the parameter "I" is the collection of items that learners "S₁" and "S₂" both co-rated, "r_{S₁i}" and "r_{S₂i}" stand for the rate values assigned by learners "S₁" and "S₂" to learning object "i". Respectively, "̄r_{S₁}" and "̄r_{S₂}" represent the average ratings that learners gave, and "→_{r_{S₁}}" and "→_{r_{S₂}}" are the rating vectors of learners "S₁" and "S₂".

The formula (1) makes it obvious that the PCC only takes absolute values into account and ignores any negative rating values. As a result, a fresh alternative known as the (CPCC) has been suggested [29], as defined by (4):

$$sim_{u,v}^{CPCC} = \frac{\sum_{i \in I} (r_{S_1 i} - r_{med}) \cdot (r_{S_2 i} - r_{med})}{\sqrt{\sum_{i \in I} (r_{S_1 i} - r_{med})^2} \cdot \sqrt{\sum_{i \in I} (r_{S_2 i} - r_{med})^2}} \tag{4}$$

Where the parameter "r_{med}" is the median value of the rating range. The COS similarity, however, does not take into account the user’s rating preferences. In this context, it was noticed that certain students tended to give an item a low rating even though they liked it. The ACOS has been suggested with the following formula [30] to account for learner preference, as expressed in (5):

$$sim_{u,v}^{ACOS} = \frac{\sum_{p \in P} (r_{S_1 p} - \bar{r}_{S_1}) \cdot (r_{S_2 p} - \bar{r}_{S_2})}{\sqrt{\sum_{s \in S} (r_{S_1 s} - \bar{r}_{S_1})^2} \cdot \sqrt{\sum_{s \in S} (r_{S_2 s} - \bar{r}_{S_2})^2}} \tag{5}$$

Where the parameter "S" represents the collection of all LOs. When learner s does not provide Learning Objetc "s" a rate, "r_{S₁s}" is set to 0.

3.4. Proposed similarity measure

To address the shortcomings of conventional approaches, we suggest in this paper a new technique for calculating learners’ similarity that is based on the learning experiences including learner’s learning style of Felder-Silverman model [31]. The core idea we intend to formulate is the grading of adaptations that come from learner details, given the fact that the adaptations of the learners with the highest scores are given a higher weight, than the adaptations of the learners with the lowest scores, as well as the customary closeness between their prior learning route and the other learners. Many metrics can be used to assess a student’s "A" motivation (MS_A) about the adaptation that will be obtained from (him) a student "B" with a score of motivation ML_B, will provide. Initially, we use the (6) to compute motivation score (MS) for each learner’s "A" and "B":

$$MS_A = \theta(\text{Exp}(LO_i) + \text{Imp}(LO_i))_{1 < LO_i < n} \tag{6}$$

Where the parameter "Exp(LO_i)" indicates the explicit feedback of learner "A" on learning object "i", "Imp(LO_i)" significates the implicit feedback of learner "A" on learning object "i", and the parameter " θ " is the rating on a scale of 0 to 10 received by the individual learner at the termination of each chapter of the learning activity.

In our contribution, the choice has been done to use a straightforward, asymmetric formula that may be determined using the (7). The formula chosen relies on how one wants to balance the link between the score of motivation shown by each pair of learners and the specifics of the adaptive systems themselves.

$$\text{dif_ML} = \begin{cases} MS_B - MS_A, MS_B > MS_A \\ 0, MS_B \leq MS_A \end{cases} \quad (7)$$

Based on this formula, it is also feasible to use different metrics, such as those described in (8).

$$New_{SM}(A, B) = \frac{1}{T} \sum_{t=1}^T f(MS_A, MS_B) * sim_{I(A,B)} \quad (8)$$

The new similarity measure " New_{SM} " between learners "A" and "B" can be calculated by the (8), where the first expression in the equation is the motivation score and the second expression is the similitude of the students based on their personal learning style by implementing of CPCC and ACOS algorithm illustrated in (4) and (5). The parameter "T" stands for the overall sum of learner motivation ratings with the learning objects.

As with typical collaborative filtering procedures, to establish each learner's necessary K-neighbors, similarity values gained among pairs of learners are used. In this approach, adjustments can be made depending on the ratings provided to the K learners who are almost identical to one another. In this context, we will suppose that target learner "A" prefers " $P_{A,LOj}$ " for " LOj ". These ideals are mathematically calculated by the following set of equations, as expressed in (9) and (10).

$$w_{A,LOj} = \frac{1}{A} \sum_{u=1}^{\bar{u}} \overline{MS}_A r_{A,LOj} \quad (9)$$

Where " \overline{MS}_A " represents the learner's "A" motivation for topic " LOj ", the test, and " $w_{u,j}$ " refers to the assessment estimate for learner "A" and the evaluations of every learner who has assessed " LOj ".

$$PS_{A, LOj} = \frac{1}{|\bar{K}|} \sum_{k=1, k \neq A}^{|\bar{K}|} S_{S_{A,l}} * \beta w_{k,LOj} \quad (10)$$

Where the parameter "K" indicates the number of learners most similar to each other.

4. RESULTS AND DISCUSSION

4.1. Datasets specifications

Many datasets are produced every day on the Internet. For our experimental study, we used the dataset MovieLens100K, which was taken from the internet [32]. The datasets specifications in terms of number of learners, number of learning objects, and density are summarized in Table 1. To assess the level of efficiency and performance of our technique. The datasets must be divided into 80% for the training and 20% for the testing.

Table 1. Datasets MovieLens100K specifications

Number of learners	Number of learning objects	Density	Ratings
943	1,682	6.3%	100 000

4.2. Assessment measure: Mean absolute error (MAE)

Some studies have evaluated their algorithms in terms of prediction accuracy based on mean absolute error (MAE) [30], [33], [34], and the roote mean squared error (RMSE) [33], [35]. We evaluated the performance of our technique using the MAE approach as expressed in (11).

$$MAE = \frac{\sum_{A,LOj} |P_{A,LOj} - R_{A,LOj}|}{m} \quad (11)$$

Where the parameter "P_{A,LOj}" is the projected assessment for student "A" on "LOj", the parameter "R_{A,LOj}" is the real assessment for student "A" on "LOj", and the parameter "m" is the total number of evaluations for all learners. The better algorithm performs, the lower the MAE value is. To measure the performances of our approach, there is several formulas the most popular formula is F-measure as expressed in (12). F-measure is the weighted harmonic mean of precision and recall [36].

$$F = \frac{(\beta^2+1)*(precesion*recall)}{(\beta^2*(precesion*recall)} \tag{12}$$

4.3. Experiment results and discussion

Several machine-learning algorithms as a kind of artificial intelligence or AI technique have been utilized to study data classification [37]. For instance K-means algorithm [38], KNN algorithm [39], [40], and support vector machines (SVM) algorithm [41]. We adopt in our contribution the KNN algorithm with multiple similarity measures by applying the (7), in order to identify the optimal number of K-neighbors in both the static datasets and the incremental datasets during the experiments. In the first experiment, we try to determine the impact of the number of neighbors K, similarity metric, and datasets size on the generation of results. The results obtained are presented and demonstrated in Figures 5-7.

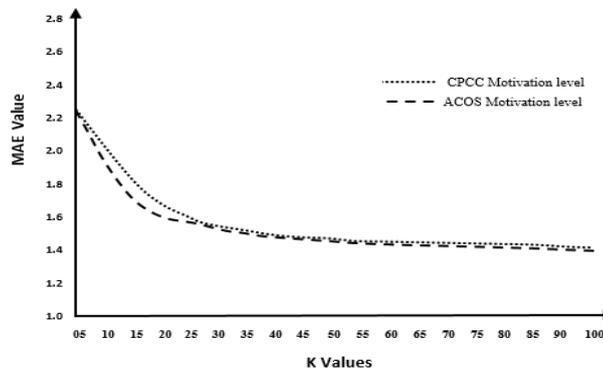


Figure 5. The 1st comparison between conventional and customized learning approaches

In Figure 5, we calculate the motivation score of learners by using CPCC and ACOS algorithms, we can observe that from K=45 the value of MAE is stable for both algorithms in the value 0.7. In order to identify the best K value of neighbors using KNN algorithm on our datasets, the number of neighbors K is located between 5 and 90 neighbors. The performance of KNN algorithm utilizing various similarity metrics can produce improved prediction accuracy by augmenting the number of neighbors. The consideration of learner motivation score surpasses the other KNN measures without, as can be observed in Figure 6 by altering the value of K. That is, when the value of K is approximately equal to 85 for the datasets, the best performance is attained.

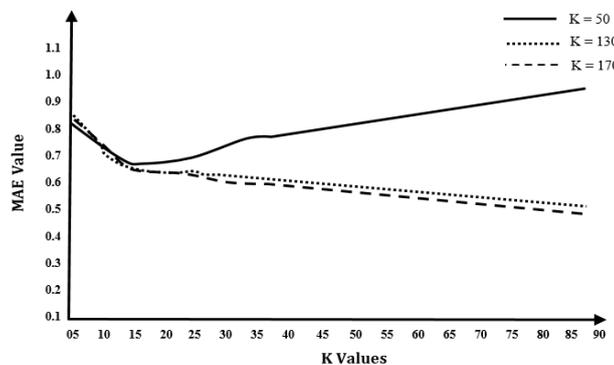


Figure 6. The 2nd comparison between conventional and customized learning approaches

In Figure 7, we can show the results of the experiment for the following values: 50, 130, and 170. We can get the best forecast by increasing the number of learners base while varying the K value, except for when K=50 for the majority of similarity measures. Because the matching MAE value is the minimum, K=130 is the best value for the KNN algorithm when employing multiple similarity measures.

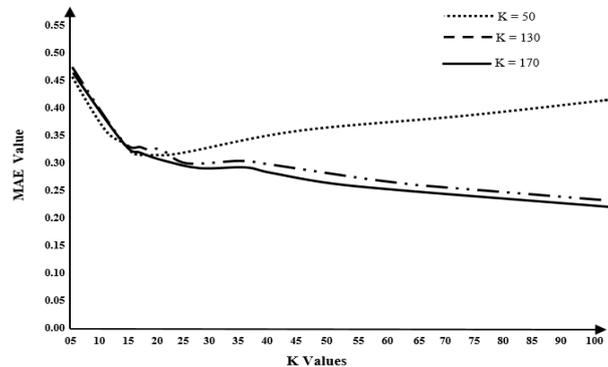


Figure 7. The 3th comparison between conventional and customized learning approaches

5. CONCLUSION

Today learning adaptive systems are being considered to encourage individual learning. Adaptive learning takes place when e-learning environments make deliberate attempts to design, develop, and provide educational experiences that match their learners' requirements, goals, knowledge levels, motivation score, learning style, and interests. Furthermore, concerns about adaptability in the learning process have been widely explored over the last decade and continue to be a focus for many academics today. However, the implementation of existing adaptation algorithms has several limitations. To overcome these constraints, in this paper, we suggest an automatic recommendation and adaptation system based on learner's learning style, and motivation score, by using the collaborative filtering techniques.

The fundamental goal of online distance learning is to offer customized adaptations for each learner by choosing the best and appropriate learning objects in a targeted order. Our results indicate that a mix of learner's learning style and motivation score in the adaptation process can improve the quality of a learning system in the e-learning environment while still maintaining the adaptation up-to-date. We intend to ameliorate the adaptation model in the future to handle several contemporary issues, including data correlation and sparsity. To capture learners' motivation in a smart classroom, we will take into account more sophisticated adaptation methodologies by integrating more aspects and utilizing other artificial intelligence tools, such as the internet of things or IoT.

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