Recommendation Strategies for Personalize Mobile Educational Systems

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ABSTRACT: Recent technological advancements shifted the trends of learning from e-learning to mobile learning, thus added new dimensions such as learning process can take place at anytime and anywhere. However, this shift faces some technological and design issues in m-learning and e-learning (i.e personalization). The factors that lead towards personalisation are the frequent growth of learning resources as well as differences in the characteristics of learners. Recently, recommender systems have been exploited as a new form of personalisation. This paper proposed a hybrid recommendation approach for mobile learning environment, based on identified users’ learning style for providing more personalized recommendations. The reported results indicate significant differences in the performance of learners having personalized recommendations.

Keywords: Hybrid Recommendation, Mobile Educational Systems, M-Learning, Personalisation

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1. Introduction

Internet has significantly changed the delivery of computer based education by creating greater opportunities for distance education (e-learning). Therefore, expanding and delivering the educational resources to diverse students and remote geographical locations. Recent technological advancements have shifted the trend of distance learning from e-learning to m-learning. This shift has added new dimensions to the learning process. For example, learning can take place at anytime and anyplace [8][11]. Moreover, learning services and educational content can be accessed easily which makes the learning process more efficient. However, Chang et. al[8] mentioned some challenges such as personalization, technological and design issues in m-learning.
Khibri et al.[23] and Kinshuk et al.[25] declared that the need for personalization on the one hand is due to the fact that current e-learning systems are providing the same educational contents to all of the learners without taking into consideration their preferences/characteristics. On the other hand, learning resources are growing very frequently. This considerable growth of information leads to the problem of information overload, where learner finds it difficult to locate right and personalized content [33].

The technological and design issues deals with the poor availability and visibility of learning contents. When the learning contents are poorly available and visible then ultimately it effects the performance of learners [43]. This is due to, limited memory, delaying response time, screen size, limited computation power, and poor, and ultimately results in displeasure and dissatisfaction of learners. This further strengthen a need to provide personalized information to the users. The personalization support (adaptivity) provided by the e-learning systems commonly deals with the course delivery, content presentation, collaborative support etc. Researchers recently introduced recommender systems as new form of personalization in e-learning environments to support and assist learners through the learning process [36].

Personalized recommendations initially gain attention in e-commerce sites by providing recommendation for products, and thus assisting customers in purchase of products or services. Recommender systems has the potential to store informations useful for making recommendations. For example, Amazon stores all the information about registered users, available books, and interaction history such as purchase or rating of books in its database. Later on, these informations are used for making recommendations. The successful implementation of recommendation systems in e-commerce domain has increased interest in the e-learning domain as well [29] [22]. Applications of recommender systems in domain of e-learning is different in a way that it recommends learning content within the learning context without affecting the learning progression [15].

Similarly, M. Salehi and I. N. Kmalabadi [39] declared that recommendation systems play a significant role in elearning by providing personalised as well as appropriate recommendation of learning materials. For providing personalization or personalized recommendations, initial step is to get informations about the user’s learning process. These information are reflected in the user model. Currently e-learning systems are providing personalized recommendations based on individual user model. This research study introduces community user model. This model takes into consideration the characteristics of learners. The learners having similar characteristics are grouped together. Afterwards, personalized recommendation of contents and activities are provided, keeping in view that what worked well for learners with similar characteristics, learning history, and performance. Rest of this paper is organized as follows: In Section 2, the previous related work on recommendation techniques for e-learning purpose are discussed. Section 3, discusses the recommendation techniques and their benefits as well as their limitations. Section 4 introduces the proposed system i.e. Mobile Learning Recommender, overall system framework and describes the proposed mechanism step by step. Section 4.4, presents the design and implementation of MLR. Moreover, experiments, result and evaluation of the system are also discussed in the sub sections of Section 4. Finally, Conclusion section provides the concluding remarks.

2. Recommendation Techniques

Now a days recommender systems are the most popular and fruitful way to facilitate users to access the information over web that meets their needs and preferences[48]. Previous studies [31] [33] [7] have reported, recommendation techniques into content based filtering, collaborative filtering, demographic, knowledge based and hybrid recommendations. Content based filtering deals with the likes and dislikes of learner and it’s interaction with system. For example, NewsWeeder [28] automatically learns user profiles for Netnews filtering, where Netnews is software used to access Usenet discussion groups. On the other hand, collaborative filtering approach deals with recommending items to a current user on the basis of previous users having similar characteristics. For example, GroupLens [42] uses a collaborative filtering approach to recommend news article.

However in demographic filtering content/item is recommended using the demographic information of the user[6]. Demographic filtering and its combination with other filtering techniques are being used in restaurant recommendation systems [34]. While in knowledge based items recommended are based on specific domain of knowledge. In this filtering technique items features are used to meet the preference and needs of user[6]. In e-learning knowledge based recommender system use ontology to represent learning content and knowledge about learner[44]. Some noteworthy knowledge based recommender systems are cased based which are presented in [9][37]. The next approach deals with hybrid recommendation. In recommender systems combination of different filtering techniques has been suggested to increases the precision and performance accuracy [?]. This approach combines different techniques such as content based filtering, collaborative filtering, knowledge based techniques,
demographics information techniques [33] [7], and sequential pattern [12] to resolve the limitations of earlier techniques [1].

3. Related Work

In mid-90s recommender systems arises as an independent research field [2] [16] [30], and in recent years significance of recommender systems has manifestly increased. Most widely used techniques in the recommender systems are the content and collaborative filtering. Regarding recommendation in learning, Khribi et al. [23] proposed online automatic recommendation approach based on learner’s current navigation, while analyzing the differences between learners preferences and learning content at the same time.

Moreover, some recommender systems used hybrid approach by combining two or more approaches such as content with the demographic one or collaborative filtering with content based [10] [19]. Hybrid recommendation technique provide better performance than a technique used alone[5]. For example, collaborative filtering has new-item problem which can be resolved by content filtering [7][46]. Chen and Hue [10] proposed an algorithm based on demographic information of the user. They calculated the user similarity without their rating records. However, their results produced cold start problem in the system. Additionally, the accuracy of recommendation also depends on user profile or demographic information. The accurate information provided by users results in the generation of more accurate recommendations. Khrbi, Jemni, and Nasraoui [23] developed a personalization approach that provides recommendation of learning objects to current user automatically without explicit feedback. This approach consists of two modules i.e. offline and online module. The former generates user model based on information collected through implicit and explicit feedback. On the other hand, online module generates recommendations of learning objects. Regarding the recommendation phase hybrid approach are used by combining content based filtering and collaborative filtering.

Meihua Hsu [19] developed an online personalized English learning recommender system for ESL(English as a second language) students. This system utilizes the content, collaborative, and data mining techniques. The working of this system can be divided into three steps. Firstly, they used clustering algorithm to group the students on the basis of similarity in their study behavior. Similarity association rules were applied for the analysis of association between learning content/ lessons. After that, an initial score was set for each lesson using the content based filtering technique. Finally collaborative filtering was used to recommend relevant lesson to related student. Performance of the system have been tracked for one year by analyzing real reading data and generating recommender scores which helps student to select appropriate lesson. Experimental results shows that the personalized recommender system of English learning for ESL student has proved to be workable and effective.

4. Mobile Learning Recommender(MLR)

Personalized recommendation of most of the e-learning systems is usually based on likes and dislikes of a learner in the past.
However, these information are not enough to generate accurate recommendations. Therefore, this work presents community user model for modeling of the learners, and a hybrid technique for the recommendation process.

4.1 MLR Framework
This MLR framework shown in Figure 1 is twofold. The first one is to identify similar learners for building community user model. User model plays a fundamental role in providing personalization. Therefore potential characteristics of learner are exploited in order to categorize learners. The second one is to make recommendation strategy for current learner based on the information of already registered users having most similar characteristics to the current learner.

4.2 Community User Model
User model is the illustration of learner’s information which is used to acclimatize the system according to learner’s needs and preference. Unlike typical individual user model, the community user model is generated by grouping similar learners. For generation of the community user model, system requires information about each learner. The community user model helps student in getting more personalized content as compared to individual student model. As the two individual having the same interest may have the same choices in many other aspects. The benefit of community user model is that groups are made for learners possessing similar characteristics, by this separate model for individual learner is not required.

Regarding community user modeling shown in Figure 2, the similarity between users is initially identified on the basis of similarity between their profiles. For example, if user 'A' and user 'B' are from the same institute and having similar/same educational background, then they are treated in one group. The characteristics of learners included in the profiles in order to find similarity between users are demographic information, educational history, work experience, interest and activities. The demographic information includes name, city, country, gender, and age. On the other hand educational history consists of previously attained highest degree, courses studied during that degree program, and affiliation with the institute. Moreover, work experience means the duration of relevant experience. At start the interests of user’s are captured through profile information and afterwards user interaction with the system is used to capture their interest. However, interest and activities includes user’s interest and their interaction with the system respectively. The rate of similar attributes decides the similarity ratio between users. On the basis of these initial characteristics the model is made. Later on the interaction history, learning tasks record, captured learning styles dimension are added to make the model more mature.

Here, when user logged into the system, his interaction with the system is recorded such as how much time the user stay logged in. Moreover, the result of the assigned learning tasks such as quiz is recorded as well to check the learning performance of the users. However, to capture the learning style dimension of the user, his/her way of accessing learning material in the system is observed. On the other hand if user access the content randomly in three consecutive log-in sessions then his/her learning style is captured as global learner, if user access the content in the organized or given way then his learning style is captured as sequential learner. Each user profile shown in Figure 2 is considered as a vector. To measure the similarity between users so cosine similarity measure is used, where the shortest vector represent the higher similarity. By doing so the recommendation
process becomes easy by community user model, as less comparison and computation is required.

4.3 Recommendation Process
In recommendation process, hybrid recommendation strategy is used by combining content and collaborative filtering. The Figure 3 demonstrates the recommendation process.

![Figure 3. Personalized Recommendation of Learning Content](image)

The main advantage of hybrid technique is to overcome the limitations of collaborative and content-based filtering techniques. For organization of similar learners we have used collaborative filtering while for organization of learning material content-based filtering is used.

Content-based Filtering faces overspecialization and limited content analysis i.e. user for privacy issues could not provide contents and poor description of item contents. To overcome this limitation vector space model is used for personalize contents. However, the main function of content based recommender system is to organize content of the items to make recommendations based on user profile, and Vector Space Model [40] is the best way of representing content.

![Figure 4. Vector Space Model](image)
This model is used to represent text such as document, sentence, word, query or entire encyclopedia as term weighted vectors to retrieve most similar documents to the query. In VSM model a V-dimensional vector space is created where each document is represented as a vector of term weight, and each weight show the level of association between document and term (Figure: 4). Common term weighting depiction are term frequency and inverse document frequency.

Term frequency counts the number of times a specific term appears in a document, while inverse document frequency frequency counts how many times a term appears in whole set of documents [47]. The general representation of TF-IDF is mathematically demonstrated as:

$$w(t, i) = tf_i \times idf_t$$  \hspace{1cm} (1)

Here $t$ is a particular term or attribute value, $i$ represents an item or document, $tf_i$ is the frequency of $t$ in $i$, and $idf_t$ is the inverse document frequency of term $t$. Recommender system uses this technique for representation of documents, users and their preferences as a vector and then similarities between them are compared by interpreting vectors.

On the other hand, collaborative filtering is used to organize the users. When a new user logged into the system, he/she has very limited interaction history, so in order to given recommendation to the new user he/she is matched with the users in the group to make recommendation of unseen items. For this, profile of a current user is compared with other user in order to find the top similar users according to their needs and interests. To overcome limitations of CF many method were proposed in research like k-nearest neighbors and other clustering algorithms. The K-mean clustering techniques reduce the search space and performs sound on numeric data in general [20] [38].

K-means algorithm classify or group the $n$ objects on the basis of attribute and features into $K$ number of group, where $K$ is positive integer number selected and $K < n$ by assuming that object attributes forms a vector space. K-mean method takes number of clusters($K$) and a data set($D$) containing $n$ elements as input and return a set of clusters ($K$) as output. In this method $k$ is randomly selected as initial center point, then each user is allocated to the cluster such that the distance between user and central point is minimum. Diagrammatic representation of K-mean process is given in the Figure: 5. K-mean algorithm consists of four steps as follows:

![K-Mean Process Diagram](image_url)
1. Randomly select initial cluster
2. Assign every object to cluster to which the selected object is the more similar
3. Compute the mean of the assigned objects for each initial cluster
4. Repeat 2,3 until no change

In this research, currently logged in learner is taken as centroid. The size of cluster K was kept 20 users per cluster. In the second step, similar users are combined in a cluster and similarity between them was calculated on the basis of user profiles and interaction with the system. In parallel, content studied by similar users in the cluster are extracted to make recommendation list to current/centroid user. Lastly, the proposed system is evaluated in term of recommendation accuracy and learner performance and satisfaction.

4.3.1 Learning Style
Learners have diversity in needs and preferences. Similarly, every individual has the different learning style. Hence, to provide more personalized recommendation to the learner, the learning style dimension is also considered. According to theorists defined mode of learning are divided which is linear vs. holistic, reasoning vs. insight, impulsive vs. reflective, and visual vs. verbal [24]. Learning styles don’t delineate other learning styles, i.e. a learner can have more then one style and not restricted to only one style. Moreover, learners can use the combination of learning styles to get most appropriate learning. In this study, the work focus on FSLSM (Felder-Silverman learning style model). Various researchers have documented the FSLSM as a reliable and applicable learning style model [14]. FLSM has four dimensions as shown in Figure 6. The dimension of FLSM are sensory/intuitive, visual/verbal, active/reflective and sequential/global. This defined the scope of our work and it follows the sequential and global dimension of FSLSM in recommendation phase, in which the learning styles of current learner with other members of the group is matched to make most efficient and suitable recommendation list. If the learner is clicking in given order and not pass over any topic then he/she is considered as sequential learner. However if the learner is passing over the topics and not accessing the learning contents in given order then he/she will be taken as global learner. The threshold value of identifying the learning style is 3, i.e., if the learner possess the same behavior of accessing contents continuously in three session, then the followed behavior is taken as his/her learning style dimension.

4.4 Design and Implementation
This section presents the implementation of mobile education system along with the personalized learning resources recommendations. The framework of PHP chosen for implementation of this research study is web application framework CodeIgniter. For this purpose, front-end framework Bootstrap was selected, which is written in HTML, SASS, LESS, CSS, and JavaScript and compatible with all web browser. Bootstrap is made for device of all shapes form cellphones, tablets, and

![Felder-Silverman Learning Style Model](image-url)
desktops. While, Apache HTTP and Open source database MYSQL is used as a server, which adds protection and reliability to implemented system. It also provides easiness in setting to view and test the code being developed for the proposed system.

4.4.1 MLR Interface
Mobile Learning Recommender(MLR) has two interface. One is on the server side (back-end interface) which is controlled by the admin of the system while other is client side (front-end) which is run time interface for the learner. The back-end interface is used for managing learning contents, where the admin can add the course and their related contents, which is finally saved in database. Moreover courses can be edited and deleted as well. While on the front end, user can select course and topics from the chapter at their own choice. Interface of the back-end and front end of MLR is shown in Figure 7. Recommendation section presents recommendations to the active learner based on the activities of similar learners. Recommendation are provided with every chapter of any course. When user open the chapter of the selected course, content in different file formats will be shown

![Figure 7. MLR courses interface](image)

![Figure 8. MLR recommendation list](image)
and also the related topic which were studied by similar users and had improved their performance. All the learning content is download-able i.e. the chapters files can be downloaded and saved in memory for later use. In this way, learners can access the learning content offline as well. On the same interface Quiz is given with every chapter, the quiz contains ten question which are generated randomly form the chapter content. Quiz is also conducted after every chapter. Questions arrangement in the quiz are randomized in order to make different for every learner. The result of the quiz the was saved in the database to know performance of learner in relevant chapter. Every correct answer contain one marks. Moreover, the Chapter’s interface of the selected course has also some recommended topics related to that chapter, under the heading of “You May Also Interested In”. At the first session of the registered user these topics are retrieved using VSM from the database where learning contents is kept, according to there similarities with chapter topics. Later on, recommended topics form group members of the concerned user are also added in the list as shown in Figure 9.

4.5 Experiments
Since testing of implemented system(MLR) is essential to know that how useful is the information of previous learner for making recommendation to the current learner. Other experimental setup which are set to evaluate the MLR includes selection of users, learning history, browsing sessions, learning styles, learning content similarity, performance, and related learning contents. Regarding, the selection of the learners to perform experiments for the evaluation of the MLR, 20 students of the five groups were selected. After selection of the user’s their learning history is recorded, and time limit of one session for browsing the system was set for one hour, i.e. in one hour of the browsing whatever course, chapter and topic user accessed is saved.

As stated before, that learning style of the user was also identified in order to make recommendation more personalized. To identify the learner style, their way of accessing the content was recorded continuously in three sessions of browsing the system. For example, if a learner access the learning content in a given sequence by the system in three session, the in the 4th session the content was provided to the learner with the same indexing of the learning contents. Moreover, in the recommendation list related content of the chapter is presented, which is retrieved through VSM and also most relevant to the topics of the selected chapter. Regarding, performance measurement of the learner is done through quiz which is attach with every chapter. After analyzing the performance of the learners, the learner who got high score in the quiz is ranked higher and his accessed related topics are strongly recommended to the other group members who scored less.

4.6 Evaluation Metrics
Implemented system is evaluated in order to know how accurate recommendation are generated by the system to current learner by using previous and similar learner data. Evaluating recommendation system and determining recommendation accuracy as predictive accuracy measure can be done by Mean Absolute Error (MAE), which measure the quality of result [26] [27]. Mean Absolute Error can be defined as the divergence between predicted and learner ratings [13][21]. Smaller value of MAE means higher the accuracy of recommendation system. Consequently Mean Absolute Error is used as evaluation metric in this research.
study. MAE is widely used statistical metric for evaluation of recommender systems [41], it finds divergence between system predicted rating and learner given ratings. MAE is basically the average value of the absolute deviation of real rating from the predicated ratings [3]. The formula of MAE is:

$$MAE = \frac{\sum_{i=1}^{N} |P_i - r_i|}{N}$$  (2)

Where “$P_i$” represents the predicted ratings for item $i$, “$r_i$” is for ratings given by the learner to item $i$ and “$N$” is the total number of ratings.

4.7 Results and Evaluation

As the MLR is based on community user model, so this research takes four groups of learners form the community user and three courses to evaluate the recommendation system. Every group contains five members and the subjects on which the evaluation is performed are Data Communication, Assembly Language and Programming, and Introduction to Programming Language. The evaluation is done on the performance of learner before and after recommendation. The difference in the quiz score shows the improvement in performance of the learner after recommendation from group members.

Initially, the quiz is given to them without the recommendation from their group members, and their score in the quiz was saved. Later, the topics studied by the high scorer learners are recommended to other group members and quiz is conducted again. Then the score difference is calculated to know how accurate is the recommendation and how it effects the performance of the students. To classify students on the basis of their performance we refer to the criterion reference model [35]. We assume the criterion into three levels such as poor, good and very good. Moreover, to classify student on the basis of performance, below 40% are considered as “poor”, 40% - 60% was treated as “good” learners while learner performing 60% - 80% was considered as “very good” learners. Figure 10 show the performance of MLR learner’s.

![Learners Performance](image1)

Figure 10. Learners Performance in MLR

![MAE for MLR Courses](image2)

Figure 11. MAE for MLR Courses
As mentioned earlier that MAE was used as evaluation metric to check the recommenadation accuracy of the MLR system. First MAE was calculated for each subject based on the results of learners performance. The MAE value show the significant difference in the performance of students getting recommendation as compared to the students without recommendations.

Figure. 11 shows the MAE for the course “Data Communication”, “Assembly Language” and “Programming Language” respectively. The bar with lined pattern shows the result of with recommendation and dotted pattern bar shows the MAE result without recommendation. The graph in Figure. 11 shows the significant difference between performance of the learners. As the less MAE value mean the higher recommendation accuracy[45] [32] [17],which is clear from the represented graph.

Advantages of personalization in any system has the strong relationship with the quantity of the rated data which includes specific attributes of data [4]. Hence exact comparison of our results can not be done with other studies. Subsequently, the result of this research study is also compared with existing studies (Figure: 12) We did this comparison on the basis of techniques and student model used earlier.

![MAE for Different Approaches](image)

Figure 12. MAE comparison of our approach with previous

Chen and He [10] proposed an NCT/TF i.e. number of common terms divided by term frequency. They used demographic filtering and there result shows that quality of recommendation was improved. While Baltrunas et al. [4] proposed an approach (personalized MF + Context) to access and model the relationship between context of the user and item ratings. They implemented it for mobile recommender systems and compare their result with previous approaches liker personalized KNN [18], other includes item average and personalized matrix factorization. This graph in Figure. 12 clearly depicts that our result are far better then previous.

Here in the comparison graph the NCT/TF approach shows the higher MAE as compared to this study results. In NCT/TF approach, only three demographic attributes such as occupation, gender, and age were considered for collecting information about users. This was the major shortcoming of this work as the algorithm required more information for giving better recommendations. Another limitation of this work was as there was no recommendation for new user. While in this approach, more information is collected to make learner model for the students community, which give better recommendation results later. Moreover new user problem is also handled.

5. Conclusion and Future Work

This paper analyzes that how recommender system can be implemented in m-learning for mobile devices. The aim of the study is to provide personalized learning content to the learner in mobile education environment, by using the information of similar learner’s. Our problem definition leads us to the investigate that “How data of other learners with similar attributes such as characteristics, performance, and their learning history can be used for current learners to provide personalized recommendations using suitable recommendation technique."
The main purpose of this research work is to propose a solution to the problem of personalization and to implement it for mobile environment. Hence, hybrid recommendation technique was used by combination of content-based and collaborative base filtering. It reduces the search space, overspecialization problem and new learner are added in the system. The CB limitation of overspecialization and limited content analysis is resolved by vector space model. While CF limitation of search space is overcomes by K-mean method. The proposed framework is built in two steps, first is the grouping of learner based on their profile and similarities in attributes such as learning style and learning history, and next is the recommendation phase. Experiments have been carried out with learners. The results from the experiment showed that our system can provide accurate personalized recommendation to the learner.

For the evaluation of the proposed system popular metric is selected, such as, MAE to evaluate the recommendation accuracy and quality. Evaluation of results describes that system performance is satisfactory in order to give personalized recommendation to learner.

5.1 Contribution
The objective of this research study was to identify similar users for developing learner model and then make personalized recommendation. We focused on the users having similar profile attributes and characteristics in order to facilitate the active learners. To make the learner model we have grouped the similar learner in the form of community, and develop a learner model for respective community of the students. Before the modeling in e-learning or recommender system was done by using individual user model. By use of community user model the data of previous users was used for new user to make recommendation for him. Hence the main contribution of this research study is to bring personalization in mobile educational system on the basis of community user model.

Another contribution of this research work is the learning style based recommendation. Community user model was used to generate recommendation for the learner which are based on the learning style as well. The evaluation of results showed that using community user model the recommendation accuracy is better.

5.2 FutureWork
The future work can be continued along the following directions:

• Recommendation generation of personalized contents could be done using all available groups of learners.
• Other Learning style dimensions of FSLSM can be included to provide more personalized content.
• Lerner among the group can make recommendation to the other learners directly.
• Contextual information such as time, location , current activity of learner can be included to get more personalized recommendation.

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