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Abstract—Modern technologies have been greatly employed to support teachers and learners for facilitating teaching and learning processes. Recommender systems (RSs) for technology-enhanced learning (TEL) are among those new technologies that have been researched extensively within the past few years. This is because RSs for TEL are intelligent decision support systems that assist internet users in finding suitable learning objects that might match their preferences on the kinds of materials they could require to enhanced their learning activities. However, most of the existing RSs for learning used traditional techniques (2-dimensional user × item techniques) to recommend learning objects to users without considering the contexts in which the recommendation should be made. Those contexts could be the geographical locations, the level of education, the time of the day or week, their learning preferences, and so on. This paper proposed a conceptual framework of smart media-based context-aware RSs for learning that could consider the learning preferences of users as a context for making accurate and usable recommendations. The proposed system was designed to run on smart devices for learners to test and know their learning styles and receive learning object recommendations according to their learning preferences. The paper contains the conceptualization of the framework and the details of the design and implementation procedure.

Index Terms—Recommender systems, learning style index, smart media, learning object, contextualization, content-based filtering.

1. Introduction

Over the last few decades, RSs have been employed extensively in various domains of web-based applications that include the area of TEL, e-commerce, e-tourism, e-health, e-government, and other web-based service providers [1]. Their implementations involve choosing suitable recommendation techniques that would determine the process which the systems could follow to predict and recommend useful items to users. Several recommendation techniques exist such as a content-based filtering technique that uses items’ features and users’ profiles to predict unknown ratings, a collaborative filtering technique that works based on the opinions of similar users, a knowledge-based technique that requires knowledge about items and users’ specifications to build a knowledge model, and a hybrid-based technique that combines two or more techniques in different ways to estimate users’ preferences on items and provide more suitable recommendations [2], [3].

RSs for TEL try to predict and provide suggestions of relevant learning objects to users. However, finding appropriate learning materials can be a challenging issue especially when the requirements are not well known by the systems. To address this problem, designing RSs for TEL should include integrating contextual information into the systems for improving recommendation accuracy. The recommendation technique that require contextualization is called context-aware recommendation technique [4]. It is an extended technique that incorporates any additional information such as the time of recommendation, the geographical location of the user, the learning preferences of the learner, and so forth, as part the requirements for making recommendations.

Although much research has been carried out on RSs for learning, with few among them that followed context-awareness technique, no single study exist that used smart media such as smart-phones and tablets to integrate learning styles of learners for learning objects recommendations. This indicates the need to design and investigate the roles of combining learning styles as a contextual information for enhancing learning objects recommendation. This paper proposed a conceptual framework of smart media-based context-aware RSs for learning that could run iOS and Android devices. The paper is organized in the following ways: The current section gives the introduction of the work. Section 2 contains a brief background of context-aware recommendation and learning style index. Section 3 presents the proposed systems, and finally section 4 concludes the paper.
2. Background

2.1. Overview of Context-aware Recommender Systems

Traditionally, research in RSs for TEL focuses on designing, implementing, and testing systems that deals with only two different entities: the users of the systems and the items to be recommended to them [5], [6]. They predict ratings \( r \) of unseen items by the users using a utility function \( f \) (see Eq (1)) for each user and item in the sets of users and items respectively, where the value of \( r \) determines the degree of likeness of the item by the user. However, much uncertainty still exists about the accuracy of such RSs as they did not consider the context in which the recommendation should be done. Context-aware RSs (CARS) seek to overcome these limitations by extending the traditional systems to consider an additional entity (the context). Their utility functions extend that of the traditional techniques as shown in Eq (2) below:

\[
    f : \text{user} \times \text{item} \rightarrow r
\]

(1)

\[
    f : \text{user} \times \text{item} \times \text{context} \rightarrow r
\]

(2)

While variety of definitions of the term context have been suggested, among the most suitable definitions that related to RSs is the one given according to Dey et al [7] that saw it as “Any information that can be used to characterize the situation of an entity. An entity can be a place, object, or person that is considered relevant to the interaction between a user and an application, including the user and the application themselves”. In terms of recommending learning object to users, one of the most relevant information that might be required to provide accurate predictions is the learning preferences of the users [8].

Furthermore, it is interesting to mention some of the methods of incorporating context into the systems. Adomivicius and Tuzhilin [4] researched three different paradigms for incorporating contextual information in CARS.

1) Contextual pre-filtering: A paradigm where the system filters items that satisfied the given contexts before using the traditional user \( \times \) item technique.

2) Contextual post-filtering: The traditional user \( \times \) item technique is applied directly before filtering the context.

3) Contextual modeling: This paradigm uses user \( \times \) item \( \times \) context to filter and makes the prediction at the same time.

2.2. Learning Style Index (LSI)

There are various ways that learners might prefer to learn, for instance, some people may prefer visual presentations of concepts using diagrams, pictures, flowcharts, movies, etc., while others may prefer only verbal instructions as their efficient ways of learning. The learning styles of a learner are different ways identified by the learner as the most preferable ways of learning. LSI is a tool designed to measure and analyze the learning preferences of a learner [8]. Building LSI follows several theories of learning styles that categorized learning styles using different modes of learning. The five commonly used categories of learning styles are 1. Active vs Reflective 2. Sensing vs Intuitive 3. Sequential vs Global 4. Visual vs Verbal and 5. Social vs Emotional preferences.

Generally, determining learning styles of a learner requires building a computational system containing multiple choice questions assigned to evaluate users’ learning preferences based on each category for users to answer. Following this manner, Felder-Silverman ILS [9] was designed based on the first four categories of learning styles mentioned above. It contains 44 different questions within which 11 questions are assigned to each of the four categories. Similarly, the extended LSI of Hassan and Hamada [8], [10] have used all the five categories of learning styles and they contained 55 questions by increasing the previous 44 questions with additional 11 questions related to social/emotional preferences.

3. Proposed Systems

The proposed system incorporates a learning style index that measures the learning preferences of a learner with CARSs so that recommended learning objects must satisfy the learning preferences of a learner. The system was designed to be accessible using smart devices, such as smartphones and tablets as presented in Figure 1. The smart media-based system will measure the learning preferences of users and use it to make more accurate recommendations. The figure shows how preferences of a learner can be measured using a smart media and store the resulting learning of a learner on the cloud. It also shows our plan to implement the system based on two platforms (iOS and Android). The learning style would be measured only ones and the resulting learning preferences could be used whenever recommendations of learning objects are to be made. Furthermore, users have the opportunity to update
their preferences at any instance if required. The system will first analyze and categorize learners into five basic categories of learning styles: Active/Reflective, Visual/Verbal, Global/Sequential, Sensing/Intuitive, and Social/Emotional preferences. The resulting learning preferences of users will be stored in a cloud database for future reuse.

In order to understand the design and implementation of the system, series of necessary implementations need to be clearly explained:

1) Designing and implementation of LSI for evaluating the learning preferences ($L_p$) of users. Here, an approach of building LSI similar to [8] and [10] was proposed.

2) Designing smart media-based applications to easily access the learning objects from the internet.

3) Designing the preferred recommendation technique for predicting the new learning objects. We proposed to use content-based filtering technique.

4) Designing a cloud-based server for maintaining the database of learners. The database is to store the preferences $L_p$ of the learners on each category of the learning styles and the overall preferences on the five categories of learning styles.

5) Designing the filtering technique based on contextual post-filtering technique explained in section 2.1, for recommending only the learning objects that matched with users’ preferences (see Figure 2, where $L_p$ is the learning preference of a user [4]). The first component in the figure contains learning objects (or just items) that the system will predict their ratings $r$ based on users and their respective $L_p$. The learning object can be obtained from institutional databases and search engines from the internet. Then the recommended learning objects $o_1, o_2, ..., o_m$ will be recommended to users after filtering and contextualization.

However, since our plan is to consider both iOS and Android, the above implementation in 2) would be carried in Java and XML for the Android and Objective-C for the iOS. Moreover, to evaluate the systems, two separate experiments are proposed to be organized, using user studies and offline experimental techniques [11]. The offline experiment could be performed by using a data set containing ratings of users on items and samples of learning preferences of the users. This could be achieved by simulating the behavior of users and their interactions with the systems. At this point, we intend to measure the prediction accuracy of the systems using some of the popular evaluation metrics like root mean square error, mean average error, correlation measure, etc. Similarly, the recommendation accuracy will be evaluated using metrics like precision, recall, $F_1$-measure, area under the curve of receiver operating characteristics (ROC), and others. Furthermore, a user study will be conducted to properly evaluate the effectiveness and the acceptability of the systems when real users interacted with them for a given period of time and report back their opinions about the systems.

4. Conclusion

The current study has proposed a smart media-based context-aware RSs for learning that can intelligently recommend useful learning objects to learners by incorporating their learning styles as the contextual information to the system. The proposed system will contribute significantly to the area of TEL as almost every student has access to smart devices and the availability of various learning materials on the Internet. This is the first study reporting the use of smart devices and integrating the learning style index with RSs for learning object recommendations. The study will also serve as a base for future research on smart-based CARSs for learning. As explained from the beginning, the study was not specifically designed to evaluate the effectiveness of learning preferences in improving the prediction accuracy, but to give a conceptual framework that could enhance our understanding of how to integrate and use learning preferences of users during the process of recommendation. Therefore, future work is recommended to implement and evaluate the proposed framework using the outlined approach. Finally, future research that could also focus on adding location as a context such as home, classroom, or outdoors to the current
proposed work is also needed.

References


