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Promotion of Personalized Learning Paths (PLPs) in India's K–12 Education System through Strategic Mechanisms

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The main focus of a personalised learning environment (PLP) is to understand and adapt to the learners' needs. Learners have different individual needs, goals, and preferences that affect their learning process. Similarly, different learners have different characteristics regarding the learner's background knowledge, learner's history, competency level, learning style, and learning activities. This work proposes an adaptive learning path system for the Indian K–12 education system, which suggests a learning path—an ordered set of cognitively connected learning materials according to the learning need. In this research, ontology is proposed to store knowledge about learners and learning resources due to its dynamic nature and knowledge-sharing capability across the domain.

Keywords: Personalized Learning Environment (PLPs),K-12 Education System,Cognitively.

1. Introduction

Personalization is becoming more critical in e-learning systems as complex e-learning environments arise, defined by large-scale information, high interactivity, and no space-time limitations. The users of these systems have various aims, backgrounds, abilities, and personalities. This is referred to as personalized learning, in which e-learning systems provide educational experiences tailored to users' needs, goals, and interests. Recommendation strategies can be used to personalise the experience [1].

To alleviate information overload, algorithms and methodologies are proposed that automatically collect data and proactively adjust it according to user preferences, such as which products to purchase (via Amazon), which music to listen to (via Last.fm), and which websites to visit (via Wikipedia) (Trip Advisor). To provide users with more relevant and personalised results, big search engines like Google and e-commerce sites like Amazon use recommendation algorithms [2]. The techniques and approaches utilised by conventional recommenders do not, alas, have any bearing on online education. Wanted learning activities could not be enough of an educational fit, but music recommenders depend on user interests and preferences. People who share interests should have access to supplementary learning materials and activities that take their skill levels and learning objectives into account. Users with greater expertise should have access to more complex information, while those with less experience should be directed to more basic learning materials. In order to aid users in selecting e-learning courses, resources, or learning materials, recommender systems must be developed [3–5]. Students in grades K–12 who are seeking to further their careers via skill development are the target audience for e-learning recommendation systems. Experts in the field have devised a number of algorithms and methodologies that may analyse a user's interests, expertise, and browsing history to determine the most effective learning materials or browsing paths. Online learning recommendation systems should ideally guide students to courses and resources that are a good fit for their individual profiles. To keep users engaged and ensure they finish their learning activities, these suggestions need to be delivered in the correct context at the right time [4]. In order to achieve flexibility and adaptability in tailoring content suggestions, the paper lays out several approaches to proposing learning materials. A sequential study of the system is formed through experimentation using an incremental development approach that moves from less complicated to more sophisticated operations. In the first stage of the project, a basic static recommender based on rules is established [5]. The next step involves developing an ontology framework to hold the characteristics of the learning object and student model using these principles. Similar learner groups are retrieved from the ontology using their history data [6]. An ontology-based method is combined with a sequential pattern mining technique [7] to test how well learning sequence recommendations work. The last step is including learning path recommenders.

2. Rationale

The goal of a MOOC, or massive open online course, is to make online education accessible to everyone. The "one-size-fits-all" method could not work anymore when pupils are given uniform learning materials. Information overload occurs as a result of the abundance of online learning materials [8]. In order to improve students' learning outcomes and happiness, the classroom setting should be customisable. Prioritising the alignment of learner learning preferences with learning object features should be the primary goal when PLPs propose learning items. The immediate needs of customers are given more weight by traditional recommenders, who seldom take their long-term objectives into account [9]. Current recommenders put consumers' immediate needs first and seldom think about their future goals. In order to provide educational resources, modern recommender systems evaluate students' existing knowledge. In this case, the student would be completely unable to grasp the material given his or her existing level of education and experience. The recommender's primary responsibility, therefore, is to promote the learner's own knowledge in a manner that allows them to acquire the target idea via a sequential process of learning from the recommended learning resources. As a result, the recommender's principal role is to facilitate the user's acquisition of the content target notion (the end objective) by providing a sequence of relevant and useful learning resources. These goals and requirements are out of reach for the majority of existing recommenders since they do not have a qualifying strategy. Regarding this, we suggest that, along with attending to urgent demands, you should also try to foresee those that may arise in the future. By sequentially producing a collection of relevant content suggestions, learners should be guided towards a defined long-term goal. A course or subject of study is defined as a long-term goal in this thesis. In light of this finding, the primary objective of this thesis is to develop a recommendation system capable of helping students achieve their long-term objectives. The goal, therefore, is to devise an adaptive approach that, in response to user input, alters a learning trajectory.

3. Methodology

The generation of learning routes based on features that characterise learning materials and the characteristics of users is accomplished via the introduction of a variety of methodologies. A number of these methods, which are used to produce a learning path for a user, are discussed in the chapter that came before this one. The learner is led through the process of learning a subject or acquiring a set of skills methodically by using a learning path, which is a succession of learning items. The aim of this work is to address various issues related to recommending personalised learning paths for students [7]. This work creates a platform for further discussions by introducing the nature of PLPs, subsequently discussing the research method applied in the thesis to recommend personalised learning paths for e-learning environments, the datasets used in the experiments, and the evaluation metrics used to measure the effectiveness of the recommendation models. In the modern world, personalisation is required to make any service or product more appealing to the target audience. This is particularly true in the case of eLearning. As a result, the concept of personal learning environments (PLEs) has become increasingly significant in today's academic world. The PLEs customise the interface, learning content, learner assessment, and interaction between instructor and learner according to the learner's preferences [8]. The different stages of offering learning content to new learners include creating learner and learning object models, data pre-processing, similar grouping learners, and providing top-N learning resources for the target learner [11]. The learner feedback in the form of ‘ratings and engagement quotients is fed back to the modelling phase and rebuilt the models accordingly. Figure 1 shows the control flow between the different phases in PLPs.

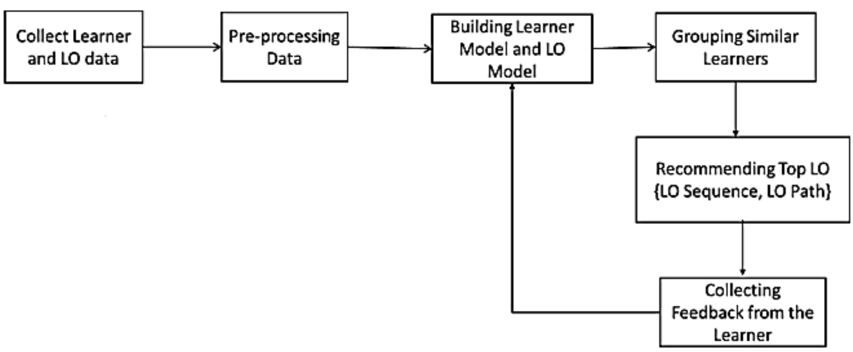

Figure 1. Development phases of the recommender system

The notion of adaptation is defined as the concept of making adjustments in the educational environment to accommodate diversity in the learner's needs and abilities in order to maintain the appropriate context for interaction. Adaptive sequencing is defined as the process of selecting learning objects (LO) from a digital repository and sequencing them in an appropriate way that is appropriate for the targeted learning community or individuals. In this perspective, many works have been done in the last decade about personalisation and adaptation of learning using e-learning systems [9], [10], and [11]. In fact, several adaptive systems were introduced; most are based on learner preferences [9], [10], and [12]. The main goal of our work is to propose a personalised e-learning system based on collaborative filtering methods according to the cognitive style and learners learning preferences. Our proposal consists of adapting the learning path to a learner's preferences by implementing an orchestrated web component in a service-oriented architecture. These components are responsible for extracting and collecting learners' traces and adapting and regulating learning paths to learners preferences.

4. Rule-Based System for Mapping Learner–Lo Characteristics

Flexibility and responsiveness are key in today's online classrooms. The "one size fits all" mentality is not welcome in an enthusiastic learning community, as mentioned earlier in the book. Information excess is another consequence of the vast quantity of e-learning products. Because there is such a vast amount of information to cover, instructors may get overwhelmed and forget to recommend some topics to their students. In order to boost students' motivation, performance, and happiness, the learning environment should be customised to their specific requirements. Learners have been shown to benefit from individualised learning methods in several recent studies. Consequently, PLEs should be able to understand and identify the unique learning requirements of their users. Systems that understand and can accommodate their users' demands will be increasingly important as the number of students using digital resources to supplement their education grows.

With our method, you may choose the best route of study based on factors like your own learning style and level of comprehension, the complexity of the subject, and the pace of the class. Here, we settled on a service-oriented architecture (SOA) framework. Breaking down our web service model's functionality is the main objective. Our proposed SOA architecture consists of three interdependent parts.

To create an individualised learning plan, these services are in charge of gathering, analysing, adapting, predicting, and regulating learning objects (LO). Figure 1 illustrates the different steps of the suggested method.

According to our method, the pedagogical responsibilities of the instructor are best handled by the teacher themselves or by an engineer. He sets up the course in chapters, and inside each chapter are learning objects (LO), which are knowledge items that need to be acquired. He then associates each LO with instructional hypermedia. The Global database stores this information, which constitutes the domain model. In addition to developing the first Cognitive State Test (CST) to assess the learner's beginning knowledge—their prior understanding about the subject matter—the instructor is also responsible for defining tests linked to each Learning Outcome (LO) for future assessment. The global database stores this information, which is used to initialize the learner model LM. Along with these dynamic data points representing the learner's learning style (LS), the learner model also includes additional static information about the learner, including their name, age, and so on.

5. Conclusion

The end objective of any educator is to provide their students with the knowledge and skills necessary to become competent in a certain area under controlled and guided circumstances. One obstacle to this learning process is the diversity of learners. That being the case, the best way to educate one student may not work as well for another. One of the primary objectives of online learning spaces is to provide a personalised learning environment that is both engaging and conducive to the learner's requirements. Offering a customised course to help each student achieve the desired proficiency is at the heart of our proposition. The principles of collaborative filtering and the implementation of a service-based system tailored to each individual student's profile and interests form the basis of our methodology. To personalise the learning process, this article suggests an adaptive exam that, based on the learner's profile and their progress, selects the best questions to ask in a predetermined order.

Conflicts of Interest

The authors declare that they have no competing interests.

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