

Interactive E-Learning Platform with Courses

Recommendation and Analysis of Learner

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Abstract

In this era, when every aspect of society is accelerating, people are always seeking improvement to stay competitive in their careers. E-learning systems fit into the ever-challenging situation and provide learners with remote learning opportunities and abundant learning resources. But there are plenty of resources available, and the learners get distracted very often, so, therefore, learners need support in deciding which course to take. Thus recommender systems are applied in E-learning to provide learners with personalized services by automatically identifying their preferences. An “E-learning task recommender” is a recommendation system that would recommend a learning task to a learner based on the tasks already done by the learner. The similarity matrix of the learners could be established using a user profile. And the profile usually contains the user’s Age, Gender, Occupation, Place of birth and soon. The user’s gender and profession are the most relevant. So, the user’s gender and profession will be used to construct the user similarity matrix. The E-learning services recommendation is essential in enabling precision instruction and personalized learning.

Index Terms—Keywords: E-learning services recommendation, Personalized E-Learning, User Similarity Matrix

I. INTRODUCTION

India is well known for Academics for ages. Conventional teaching-learning in ancient times in India was among the best in the world. People from everywhere around the globe preferred India for their respective Higher Education. The First University of the planet, which was established in 700 B.C. was Takshshila Nalanda University. This method of traditional classroom learning method was adopted by Indians. But this sort of learning was limited and didn’t have exposure everywhere around the globe. Multiple issues starting from the outdated syllabus, lack of practical knowledge, absence of qualified educators, and other issues formed the crux of the problem. However, we are able to observe that because the developments within the technology are happening, we can undoubtedly observe educational efficacy evolve with the support of technological means. Now almost every home has a computer and internet connection. e-Learning has played the role of a catalyst for bringing about an equitable approach to high-quality education. It has done so by providing unlimited teaching and learning opportunities to learners all over the world.

Learning has been over the years very essential to human life, as most of them view it as a means to acquire resources and a well-dignified life. The major challenge posed to learning in virtual environments is not just the

availability of learning content to users, but the ability to present knowledge in the right place, time, and form. The researchers are trying their best to improve the learner's experience by making changes in the traditional recommendation system. Personalized E-learning services based on educational data allow students to achieve desired learning goals within the shortest time. As the respective learner can watch the resources according to his/her choice (i.e. 1.5x,2x) and achieve the respective goal in the best possible time.

II. MOTIVATION

In today's world, where technology is continually expanding, education has embraced ICT and now provides handy solutions to assist people to improve their knowledge, education, and literacy level. An e-learning platform allows you to improve your knowledge and abilities from anywhere, at any time. It provides a self-guided platform via which an individual can create a customised bundle relating to key subject areas. The presence of a teacher is not needed, and students can choose their own study time and location. This gives the learner a lot of flexibility, allowing them to fit learning into their hectic schedules. In the absence of a physical instructor, it is critical for e-learning to be both powerful and engaging. This is accomplished by incorporating appealing images, audio, and other multimedia elements such as simulations and animations into e-learning courses. The motive of this research is to use such unique ways to pique learners' interest which leaves an indelible impact on the brain of students, allowing them to retain and apply more information.

III. LITERATURE SURVEY

A. Recommendation System in E-learning

Recommendation techniques are extensively studied and mainly classified into three categories: content-based, collaborative filtering (CF)-based, and knowledge-based. The three categories all have their characteristics and suitable application scenarios.[1] Content-based recommendation methods profile users with their past behaviours and recommend items like user profiles. It's suitable for recommending items with abundant content information, such as documents or web pages. CF-based recommendation methods assume that similar users will prefer similar items and generate recommendations with the collaboration of users.[3] It's widely employed in many scenarios and well-known through the Netflix competition. Knowledge-based recommendation uses explicit knowledge of users/items and business rules to profile user interest and supply recommendations. It's applied in some complex scenarios where items aren't rated or not frequently purchased, like cars, houses, and policies. The hybrid of the above three techniques is widely applied in many real-world recommender systems together technique draws on the merits of the others to offset its weaknesses.[2]

B. Monitoring Students by their Performance

Learning Analytics (LA) focuses to facilitate the learning assessment in the context of e-learning involving large amounts of data.[4] LA allows an enhancement in the quality of student progress. In this paper, we present SapeS (Student Academic Performance Evaluation System), a model equipped from a review where a gap in the research was identified regarding the use of LA and Computational Ontology, to monitor students' performance in a coordinated way [5]. Using the student interactions for examining the learning experiences, SapeS allows the trainer to follow the students or the class development and readapt pedagogic plan according to the students'

performance and their achievement level by using software agents, we selected ontology as a formal representation of learning objectives to get the explicit assumption of the knowledge around abstract concepts related to the specific domain. SapeS proposes to gather data in real-time based on the process data using methods of the LA and the xAPI framework (Experience API), and it integrates the ontology, OntoLO (Ontology – Learning Objectives). In the end, they analyze and process students' results on the dashboard with the information on students' performance.

C. Personalization of E-Learning Environment Using the Kolb's Learning Style Model

In the E-Learning environment, different types of learners should take responsibility for their learning. Personalization of E-Learning, context is critical to a successful learning process since it espouses learning satisfaction, speed, quality, and efficiency. E-Learning personalization strives to achieve relevant education as well as a tailored learning environment for each learner based on their characteristics.[8] A customised learning environment can be created utilising a variety of characteristics; nevertheless, the selective learning style was the subject of this research. In this study, an E-Learning environment was used. Kolb's learning style was used to create tailored learning solutions for students. Finally, students' performance in an evaluation is evaluated in a well-designed learning environment.[9] An E-Learning course with 19 students was investigated. Personalisation in an E-Learning environment based on learning style has a significant impact on students' academic development and performance, according to the findings.[10]

D. Visualizing Analytics Through an Integrated Model for Learning Analytics in Adaptive Gamified

- The postulated model in this research provides the foundation for the new applicability of adaptive gamified educational systems in E-Learning.[4]
- The approach organises course content to focus on each learner, as well as each personalization and gamification is intended to enhance and navigate a unique, individualised, and inspiring learning pathway.[5]
- The paradigm presents gamification as the application of game design dimensions to a myriad of discourses, distinguishing it from other parallel notions such as serious games and other game-related contexts.
- This aids in identifying a student's learning weaknesses while also increasing his sense of engagement and mastery, resulting in improved encouragement.

IV. SYSTEM FLOW

A. Collaborative E-learning

An alternative approach to individualized learning can be called collaborative learning. Collaborative learning is e-learning where students can socially interact with many other students, as well as trainers/instructors. The notion is that students, working together, can grasp the knowledge more than by themselves, especially when they bring it competitively. (Cumming Self, 1989). In essence, learners work together to expand their erudition of a particular subject or skill. Collaboration is a process by which individuals discuss and share meanings relevant to the issue solving the task at hand. Research in this area examines methods to precisely capture and analyze student interactions in collaborative or distance learning environments. Research overwhelmingly supports that online peer assessments can support a student approach when assessments are implemented through collaborative peer-to-peer communication, active participation, total interaction, attention, and

interactivities. Trainers need to view assessments as a process for learning as well as an assessment of learning. The design planning of collaborative activities is critical in supporting effective interactions. One benefit of assessment activities is student motivation, which is encouraged within learners by engaging them in real-world assessment circumstances. Another advantage of collaborative activities is that they encourage learners to use external evaluations to provide internal self-assessments of their learning.

B. Recommendation Engine

- Interface: It is responsible for generating the requested webpages and handling the user interface logic and events for the learners.
- Server: The database stores all the data of the system, which include mainly the learner database and the item database. The learning database contains the information and behaviours of each user, which will be used for conducting a learning profile. The item database contains the information of each learning material/object/activity.
- Recommendation engine: The recommendation engine is the core part of the recommender system. It implements the proposed recommendation method and generates recommendations for learners. First, data from various sources need to be processed by data extract, transform, and load (ETL). After data are processed, the engine trains the recommendation methods. The recommendation engine component contains the learner profiling module and item profiling module and implements the recommendation methods. Recommendation results are usually generated as a ranked list of items and are presented to users to help them make decisions.

C. Kolb's Learning Styles

- In the e-learning environment, considering the differences between learners, one of the necessities is presenting personalized educational approaches for helping effective learning in the learner [11, 12].
- For Kolb, learning is a process through which the experience is converted to knowledge. In experiential learning theory, the experience is regarded as a source of learning, and learning is emphasized through personal experience and with emphasis on the present instead of focusing on teacher-centred learning [13]. 'Experiential learning' is a dynamic view of four stages, which stimulate brain function. These four stages include: concrete experience (CE) (feeling), abstract conceptualization (AC) (thinking), active experimentation (AE) (doing), reflective observation (RO) (observing).
- These four orientations, two perpendicular dimensions, create four spaces or contexts in the learning cycle that are filled with four orientations of Assimilating, Converging, Accommodating, and Diverging the knowledge that can be used to identify learning styles [13].

1. Diverging (Concrete Experience/Reflective Observation)

This style of learning adds a different and inventive approach to learning. Individuals tend to evaluate concrete experiences from diverse perspectives rather than examining them through their behaviours.

2. Assimilating (Abstract Conceptualization/Reflective Observation)

The significance of this learning technique is in reasoning. Individuals that exhibit this learning style are able to analyze facts and evaluate the entire experience.

3. Converging (Abstract Conceptualization/Active Experimentation)

This learning style reinforces problem-solving as a method of instruction. Individuals who choose this method of learning are capable of making judgments and applying their ideas to new situations.

4. Accommodating (Concrete Experience/Active Experimentation)

This method of learning is adaptive and straightforward. These folks prefer to learn through trial and error, preferring to figure out the answers for themselves.



Fig. 1. Kolb's Experiential Learning Cycle

D. Customized Adaptive Gamified E-learning

The Customized Adaptive Gamified E-learning approach is said to give a supplement to standard learning environments by allowing for organised learning analytics. In addition to the game mechanics extension, the model addresses methods that provide learners with a more tailored educational experience as well as an accurately assessed and analysed performance. As a result, a comprehensive paradigm for adaptive gamified education is created. There are five primary modules in the model.[5]

– The Main Interactive Roles

The proposed model interacts with three roles: The Course Designer, representing the expert responsible for building the course. The Learner, representing the person who learns through the course's OERs presented in a gamified context, in which the learner's behaviour is monitored and stored for analysis and evaluation. The Supervisor, who can be a teacher, consultant, academic advisor, social advisor, parent, or Course Designer.

– The Repositories

The model has four repositories, in which the data are constantly updated: The Course repository stores the course information, with flags to the associated OERs for each course element. The actual built OERs are stored as individual objects in the OER repository to allow their reusability in any other course. The Learner Portfolio repository stores the Learner's data. The duty of the Learning Behavior History repository comes when the learner has started the learning process. It acts as a Learner's log, recording his/her learning behaviour through an OER, together with his/her feedback on it, which in turn, is used to collect feedback about the learning process.

– The Course Design Module

The contribution of the course designer is required for detailed planning and designing of the course before the learner can enroll into the gamified course. It consists of two submodules:

The Course Structure Builder

The course designer sets out the general aims of the course and builds its initial structure. It communicates first with the (a) Elements Specifications Associate to define the topics/subtopics of the courses for both explanatory and exercising materials. The course designer defines the elements, associated with their specifications, learning objectives, and prerequisites. After having a well-defined course structure, (b) Achievements Locator defines the set of course elements that can be treated as an accomplished milestone. This submodule compels the course designer to follow the game mechanics, as having achievements located after a set of course elements allows the learner to feel accomplishment victory on a regular basis, keeping him/her motivated enough to continue with the process [14].

The OER Builder

As OERs are interchangeable, the course designer can either utilize a preexisting with about the comparable learning objective(s) or build a new one. In this submodule, the course designer develops the OERs, which include: (a) OER Assets Combiner, where the course designer builds the OER by associating all applicable assets for it, like video, and audio, etc. [15]. The (b) Rewarding and Evaluation Mechanism Designer allows the course designer to define what action would offer points to the learner.

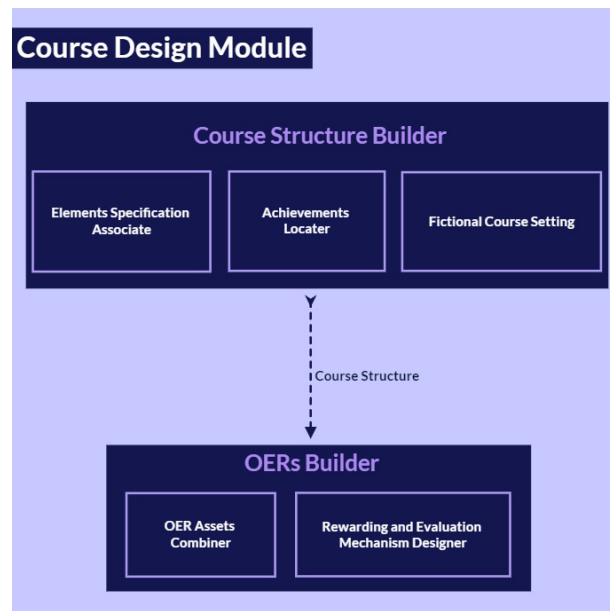


Fig. 2. Course Design Module Framework

– The Personalised Gamified Learning Flow Module

This module interacts with the learner and/or supervisor in order to explicitly and implicitly gather data that include the learner's preferences and status, resulting in a learning experience that best suits the learner.

– The Learner Portfolio Builder

This submodule collects the learner's deterministic and adaptive data in order to create his or her portfolio. The data collected is the learner's primary general knowledge, such as name, gender, age, and so on. The dynamic data is the learner's learning preferences and the learner's level of achievement in each course. This submodule is responsible for regularly updating the learner's portfolio with any alteration done, to be then organized into the Learner Portfolio repository.

– The Learning Preferences Initiator

It interacts with the learner to deduce his/her learning preferences through an initial activity, i.e. questionnaire, game, etc. with their evaluation mechanism. Through the learner's answers, his/her initial suggested learning preferences are implicitly deduced and initially considered to build the personalized learning settings.

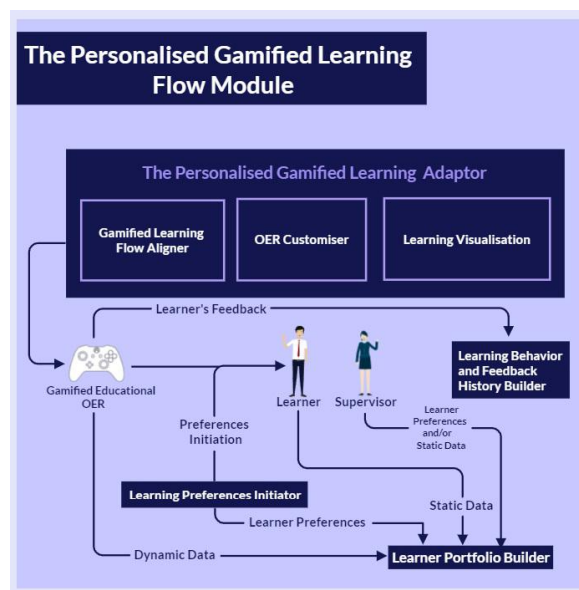


Fig. 3. The Personalised Gamified Learning Flow Module Framework

– The Learning Behaviour and Feedback History Builder

This submodule creates the learner's tailored customizable gamified studying conditions. It starts by first passing through the Gamified Learning Flow Aligner to arrange the appearance sequence of the OERs to create the gamified learning game with respect to their prerequisites and the learner's portfolio. The OERs Customizer also uses the course alignment to choose the best-matching OER among all those tagged with the same learning aim. All completed encounters are then submitted to the Learning Analytics and Personalized Adaptation module, where they are analysed and visualised for the student in the Learning Visualization module.

– The Learning Behaviour and Feedback History Builder

This submodule tracks the learner's learning behaviour during his/her interaction with each OER and receives his/her feedback on each one, as well as his/her feedback on the course as a whole. It accumulates the learning behaviour after each trial of solving an OER until its accomplishment while storing its parameters in the Learning Behavior History repository. The learning behaviour parameters are the number of failed attempts, the number of wrong actions made before the successful one and the time taken to have the successful attempt. On the other hand, it receives the learner's opinion about the OER.

– The Learning Analytics and Personalized Adaptation Module

This module utilizes the retrieved data from the repositories to evaluate both the learner's performance and the presented course quality to identify whether any necessary adaptations or recommendations are needed, as well as to visualize the learner's performance for the learner to track his progress.

– Learning Process Analyzer

Detecting any abnormality in the learner's learning behaviour after finishing an OER acts as a trigger to start analysis to avoid any upcoming dropout. Similarly, the trigger for analyzing the course or any of its OERs is typically negative feedback or when no learners are currently active. The output from this submodule includes various numerical scores or Boolean indicators about the learner and the course, which are sent to the Learning Adaptor and Learning Recommender respectively for further processing. Furthermore, the learner's activity results are communicated to the Learning Behavior and Recommendations Visualizer, which allows the learner to clearly grasp his development.

– The Learning Adaptor

Upon receiving the analytics results related to the learner, this submodule makes the necessary adaptations needed so that the learner continues the learning process more smoothly. Accommodations are made in accordance with the conclusions obtained. When one or more of the learner's LB parameters, as measured by OER, exceed the allowed range, abnormality occurs. Provide tips to aid the learner, attach a timer to keep him or her focused, adjust his or her learning preferences, or recommend a required alteration to that OER as the equivalent required adaption. This reported action is forwarded to the Learning Recommender, who will deal with it.

– The Learning Recommender

This submodule acts as a decision supporter to the course designer, reporting back to the Course Design module some modification suggestions that are expected to enhance the course's overall quality. The analysis results correspond to the learner's feedback given on an OER or the course itself, mapping it to the suggested modification needed to be made. It is then the course designer's responsibility to apply these suggestions if he confirms them as per his expertise. These changes reflect on one or more of the eight adaptation types proposed in [15]. At the OER level, the changes take place in the OER Builder, to be reflected on both newly enrolled and current learners. The usability adaptation refers to the user experience in the game, i.e. the controllers, sound quality, game performance, etc. The rewarding mechanism adaptation is also applied to increase, add, remove, or modify the point offered for each action.

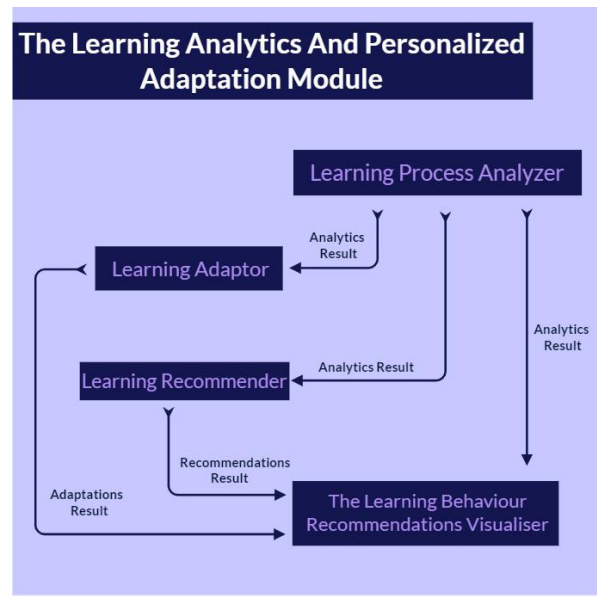


Fig. 4. The Learning Analytics and Personalized Adaptation Module

– The Learning Behaviour Recommendations Visualised

The resultant learning analytics and recommendations are interpreted in this submodule in a way that helps the learner and the course designer to visualize and understand the current situation. Regarding the learner, there exists a visualized representation of his/her performance and status after each OER. Moreover, it shows the learner his overall status in the course, total time consumption, the number of losses, accomplished achievements, etc., in addition to a unique leaderboard that is unlike the traditional ones ranking learners according to some rewarded points.[5] This leaderboard ranks the learners with respect to three different aspects of the learning behaviour which means that there can be three different learners ranked first at the same OER, but each is in a different aspect. For instance, one learner may be the fastest to accomplish OER1, another may achieve it with the least number of mistakes (i.e. wrong actions), while a third learner may be ranked the first since he/she has the least number of losses (failed attempts).[5] Thus, increasing the potential for everyone to taste victory and success in some aspect. In addition, this helps the learners to discover their skills and what they really can master best. This submodule serves as the learner's centre console, allowing them to keep track of their progress.

V. CONCLUSION

In this paper, Kolb's learning style paradigm is used to personalize the e-learning environment. After that, customized programs and contents are offered, depending on each individual's learning inclinations. The development of a recommendation system algorithm for an E-learning platform has been established that would improve the platform's usability and adaptability, along with the user's experience. Additionally, a gamification model is proposed to lessen the lack of motivation and other challenges the learners face and to enrich learning analytics by uniquely integrating the E-learning and traditional educational processes. Our research focuses on approach and adaptation based on the recommended learning preferences, additional gamification factors,

Kolb's learning style, learner feedback and evaluation are expected, and addressing collaborative learning and fictional story handling.

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