Optimizing Student Achievement in Outcome-Based Education with Smart Recommendation Systems

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ABSTRACT

Every nation may benefit much from its students. Giving pupils the right advice or direction on matters pertaining to their education can eventually improve a nation's economy. Around the world, various educational methods are used, with Outcome Based Education (OBE) being one of them. Program Educational Objectives (PEOs), Program Learning Outcomes (PLOs), and Course Learning Outcomes (CLOs) are the three primary parts of the OBE education concept. The results that a student attains after completing a course are known as CLOs. One or more CLOs may be included in a single course. Personalized learning routes are crucial for improving student performance in the Outcome-Based Education (OBE) model, which places a strong emphasis on reaching particular learning outcomes. In order to maximize educational achievements, this study suggests a recommendation system based on reinforcement learning (RL) that offers dynamic, tailored learning recommendations. The system uses RL algorithms to continuously modify and suggest activities, study guides, and courses based on each student's performance and progress. Comparing this RL-based strategy to more conventional static suggestion techniques, experimental results demonstrate a considerable improvement in student engagement, comprehension, and overall academic performance. In addition to improving learning effectiveness, the suggested system facilitates OBE's scalability across many educational contexts, providing a route to more efficient and individualized instruction.

In order to help educators enhance their administrative planning and student services, educational data mining (EDM) has recently shown interest in the field of data mining. The application of data mining techniques to educational data is suggested in this research. To identify some information to support admission planning, the association rule was applied to admission data.

1. INTRODUCTION

The World Wide Web (www) is expanding rapidly. The search and identification of necessary educational resources on https://www is being hampered by the web's exponential expansion. Students spend a lot of time searching because there are so many educational resources available. This created the problem of identifying only those learning materials that meet the actual objectives, requirements, and preferences of a given student [1]. Recommender systems have been used to overcome this difficulty in a variety of domains, including smart cities, stock market trend prediction, optimization issues, intrusion detection systems, and especially in the field of education to provide students with educational materials that meet their needs and take into account their preferences and goals [2]. According to a student's demands, a recommender system functions as a software agent that produces pertinent recommendations on a certain subject or study situation [3], [4]. For recommender systems, Collaborative Filtering (CF) is a commonly used method. The CF technique relies heavily on similarity measurements to identify similarities between products or users. Numerous similarity metrics, such as cosine [5], PIP [6], NHSM [7], IPWR [8], ITR [9], and Jaccard-based metrics [10], have been proposed in the literature.

Higher education is becoming a need rather than a need in this technologically advanced society. Students' level of education is directly correlated with the nation's advancement in technologically sophisticated nations. The traditional educational systems of both industrialized and emerging nations are having difficulty resolving their problems. The explicit teacher-to-student teaching and learning process is the foundation of traditional educational institutions, which gives rise to arbitrary and inconsistent key performance indicators (KPIs). 11. One educational paradigm that tackles the problems with the conventional educational system is outcome-based education (OBE) [12]. The need for an outcome-based education system is growing daily, particularly in the engineering fields. Several nations, like Saudi Arabia, Bangladesh, and India, are eager to create and implement outcome-based education systems at engineering colleges. The set of procedures used to create the educational system outcome-based or result-oriented is included in the OBE paradigm. Consequently, the entire educational system's learning paradigm is changing from teaching-learning to teaching-outcome [13].

Aiming to accomplish specific goals, the OBE education model is an outcome-oriented approach [12]. Many educational institutions, particularly universities, around the world are changing and implementing the outcome-based education model in order to evaluate and generalize the responsibilities and procedures in an efficient manner. The OBE model is driven by the quantity of processes and workflows that are defined by the program learning outcomes (PLOs), course learning outcomes (CLOs), and program educational goals (PEOs). A CLO is a personal skill or competency that a student should possess after completing a course. Any of the three learning domains—cognitive, emotional, and psychomotor—may include this result. Similar to CLOs, every degree program is made to accomplish a certain set of Program Learning Outcomes (PLOs). PLOs provide a comprehensive list of the skills or competences a student has attained upon finishing a degree program, just like CLOs do. Program educational objectives (PEOs) are broad statements that outline the professional and career outcomes that the degree program hopes its students will attain [14]. After students complete their degree programs, PEOs are evaluated based on input from employers, alumni, business leaders, and entrepreneurs.

OBE provides many advantages over traditional educational systems, including greater flexibility, improved subject delivery, and enhanced student learning [15]. The university must constantly be on guard and keep a close eye on the caliber of its graduates when OBE is being implemented [16]. The creation of a suitable mechanism for student evaluation based on the student's CLO achievement level is the primary obstacle in OBE. To do this, a clear CLO assessment procedure must be followed in order to accomplish ongoing learning quality improvement. Any educational institution's program of study is developed and evaluated based on the assessment of students in CLOs [17]. We were guided to investigate the perspective of RL on student performance by a review paper by Juan L. et al. [18] on several approaches that were used to predict students' success in various learning environments. This review paper examined 70 research publications and categorized the methodologies and methods employed in these 70 research papers into three main categories: supervised learning, CF, and neural networks. However, there was no work on reinforcement learning.

CLO is the base entity in the CLO-PLO-PEO cycle [13]. Students who do better on CLOs also perform better on PLOs, which helps them fulfill PEOs more effectively. Improving a student's CLOs is our primary goal in this work. The data analysis of the student-to-CLO matrix created from the CLO attainments of previous and current students serves as the foundation for the suggested task. In the form of performance percentages attained in various assessment questions, the student-to-CLO matrix indicates the strengths and weaknesses of students in any field of study. Under the current manual-based OBE system, a course instructor will help students who are lacking in CLOs by verbally recommending books, research papers, and other topics to help them make up for their shortfalls. But in this sense, a student is ignorant of how his current CLO deficit may impact his dependent's future CLOs. Therefore, rather than having the teacher recommend resources or letting him find them on his own, our sole goal is to identify online resources that can help him improve his present CLOs. Our second goal is to forecast which CLOs, based on their performance in previous CLOs, may also become weak in the future. in order for him to be more watchful of such CLOs in the upcoming semester. We used the biclustering algorithm Bibit on the student-to-CLO matrix to mimic an RL environment [19]. This allowed us to group students with similar deficits and efficiency in CLOs. Depending on the student's efficiency and deficiencies in each CLO, Bibit may place them in one or more biclusters. After that, these biclusters are mapped onto a fixed-size 2D grid. Our suggested reinforcement learning agent will operate in this 2D grid. Learning a policy that can forecast future CLOs of students who may become inadequate based on their present performance is the agent's goal. With order to assist him with enhancing his present inadequate CLOs, we are also recommending online resources that fall into the four major areas of webpages, YouTube videos, research publications, and online tutorials. Then, using each student's unique login credentials, the suggested reinforcement learning agent is coupled with a mobile app that is loaded on their phone.

Our rest of work is divided in few sections. Section II contains a literature study, Section III gives complete working methodology of our work including dataset acquisition and preparation, Section IV discusses results and evaluation parameters and Section V concludes our work and gives some future insights.

2. RELATED WORK

According to the research [20], the main issue that needs to be addressed is the complexity of data calculation, as current OBE systems rely on human computation. The University of Tun Hussein Onn Malaysia (UTHM) Faculty of Electrical and Electronic Engineering (FKEE) held a critical discussion on a manual system-based approach and how to progress with the online form of outcome-based education systems. PLO and CLO results have been personally measured and analyzed using two implementation strategies for evaluating PLOs and the CLOs. The results showed that these processes require a better system to handle diverse restrictions, including changing student batches and courses. It goes without saying that an AI-based OBE system should be able to eliminate manual computation and address these issues.

The study [21] demonstrates how the continuous quality improvement (CQI) process is applied to a particular engineering course that employs a constructive alignment [22]. The accomplishment of the CLO and the overall course requirements, which include the grades earned from the assignments, examinations, and final exam, are the performance metrics. The activities reflect the evaluation of general skills as determined by the rubrics, whilst the tests and final exam constitute cognitive assessment. CLO accomplishment data from tests, assignments, and final exams are analyzed using the Pareto chart [23]. The Ishikawa diagram quality control technique is used to investigate the potential reasons for the CLO's poor performance. Constructive alignment-based CQI exercises are developed and used throughout the course based on in-depth research on the Pareto and Ishikawa diagrams. Results from CLOs demonstrate notable benefits when CQI is used.

According to research [24], engineering schools have had to continuously monitor and implement curriculum modifications in order to consistently generate students who are ready for the workforce. A system of education that places more emphasis on measuring outcomes than curriculum input is known as results-based education. Results may include a variety of data, skills, and methods. This project aims to demonstrate a novel assessment approach based on the outcomes of engineering education training for the IT department. To present a novel strategy, a study of the RIT Engineering Education Institute [25] was examined. The aforementioned institute's information technology department was exposed to OBE and evaluated for each subject's program outcomes. The evaluation of the in-semester exam (ISE), the mid-semester exam (MSE), and the end-semester exam (ESE) were the main components of the course assessment at the aforementioned institute. For evaluation purposes, the Course-CLO-Program's learning outcomes were plotted. For the course outline and CLO-Program with the highest educational achievements and a better consideration of OBE-based courses, feedback from students, businesses, and other stakeholders was taken into account. According to this research study, OBE has a beneficial impact on engineering training in the firm under review.

Presenting a framework for an education system that is result-based for ongoing quality improvement is the goal of the work in [26]. The program's training objectives, well defined program-based outcomes, and evaluation procedures were put in place to guarantee graduates' performance. The evaluation approach was implemented both directly and indirectly. Surveys of students, companies, and course assessments were used to evaluate the results indirectly. Exams, contests, assignments, and educational projects, on the other hand, were utilized to evaluate the results directly. Framework boards and educational process groups have been merged into a set agenda to continuously evaluate and track educational practices. Additionally, it has been anticipated that the program objectives board and the course improvement board will independently review and continuously evaluate program outcomes and CLOs. Various metrics and forms have been developed to assess the pupils' performance.

According to the research [27], the OBE approach has been created and implemented in Malaysia's educational system, especially in higher education. The accreditation body requires it as a condition for certification. The Institute of Information Technology of Malaysia (MIIT) adopted the OBE approach in all of its courses in order to meet requirements To encourage continuous quality improvement (CQI), MIIT has created an automated system that connects the assessment of CLOs and PLOs and expedites the evaluation process.

The goal of the research in [28] was to categorize the level of expertise and practice of COE professors in the University of Philippines' adoption of outcome-based education. The research conducted for this study was primarily descriptive in nature. The findings demonstrated that faculty fellows in the Engineering Faculty have a broad range of knowledge and experience when it comes to applying OBE. Through preparation, teachers who possess a high degree of knowledge and comprehension of the OBE application are more likely to help achieve the OBE objectives. As long as research on the issues faculty fellows encounter when presenting the OBE requirements is continued, the planned action can be implemented and evaluated to ensure its efficacy and use [29].

Research paper [30] analyzes the implementation of OBE at Alfarabi College of Medicine in Riyadh, Saudi Arabia for medical MBBS program. It identifies a practical approach to using the SPICES model in the MBBS study plan. The curriculum review procedure is explained by the SPICES model. Using Harden's Outcome-based Education implementation inventory, the curriculum is assessed in this paper [31]. The study determines the extent to which OBE is applied in the undergraduate MBBS curriculum at the program level, analyzes gaps, and makes pertinent recommendations to improve the representation of OBE. Additionally, by suggesting a model in the form of the mnemonic "ADAPTATION Species" to be used for faculty development in order to promote OBE, it can aid in faculty development techniques. To facilitate OBE deployment in comparable contexts, these recommendations can be applied to comparable OBE programs and educational cultures.

In 2016, a thorough review of the impact of OBE on nursing students' experiences was conducted by Work in [32]. Eight electronic databases were searched for publications published between 2006 and 2016 for this review: PROQUEST, PUBMED, WEB OF SCIENCE, EMBASE, CINAHL, SCIENCE DIRECT, EBSCO HOST, and SCOPUS. Six research projects were deemed appropriate after 646 publications were identified from these databases and vetted at various points. According to a review of these six relevant research, OBE techniques in nursing education can improve nursing students' learning experiences in terms of attitude, knowledge acquisition, and skill performance. Additionally, OBE lowers cognitive strain, improves thinking skills, and increases learner pleasure.

3. METHODOLOGIES

➢ User Interface Design

To connect with server user must give their username and password then only they can able to connect the server. If the user already exits directly can login into the server else user must register their details such as username, password, Email id, City and Country into the server. Database will create the account for the entire user to maintain upload and download rate. Name will be set as user id. Logging in is usually used to enter a specific page. It will search the query and display the query.

➢ Admin Uploads Topics for Discussion:

In this module the admin will uploads the topic for discussion. After he uploading each teacher will give their views on topic. If discussion is completed between the teachers, teachers will give their report to the admin. Admin will pass this result to the researchers. Researchers will give their ratings according to the answers which is given by the teachers.

➢ Teacher's Views about Topics

In this firstly, admin will give the topics to the each and every teacher. Then teachers will share their knowledge, views, thoughts that will be stored in the database. The admin will collect the all the views of teachers and send it to the researchers. Researchers will verify the all the views which is given by the teachers and give ratings according to the answers. For good answers they will give the high ratings.

➢ Summerization

In this project, firstly admin will give topics to the teachers. Teachers will give their views, thought according to the teachers answers. And then researchers will give their ratings according to the answers. Whenever users searches for the same topic the high ratings answers will be shown to first. Then low ratings answers will be shown to the next. The focus of reflection could be technical and personalistic. Technical reflection was concerned with in structional, managerial, or contextual aspects of classroom teaching. Personalistic reflection dealt with teaching beliefs(the assumptions or claims of in-service teachers about ideal way of education)or professional development aspects of teachers . The level of reflection could be represented by description, analysis, and critique. Description provided descriptive information of an action. Analysis provided rationale and logic of an action.

➢ Researcher's Ratings

In Researcher's ratings module, the researchers will give the ratings according to the answers which is given by the teachers. There is a group of researchers for every topic discussion . Before going to give the ratings the researchers must register and then he has to login and then he will give to ratings.

4. OUR PROPOSED MODEL

Algorithm Working (Step-by-Step)

1. **Problem Formulation as an RL Task**
   - **Agent**: Recommendation system
   - **Environment**: Student and learning platform
   - **State (S)**: Student's current performance level, learning style, engagement metrics, previous history, etc.
   - **Action (A)**: Recommending a resource – video, quiz, assignment, peer discussion, remedial session, etc.
   - **Reward (R)**: Improvement in student's outcome (quiz score, CO attainment, engagement, etc.)
2. **Initialization**
   - Define a set of possible states and actions.
   - Initialize a Q-table (if using Q-learning) or a policy network (if using Deep RL).
3. **Data Collection**
   - Gather student data: performance on COs, participation, time spent, assessment results.
   - Track outcomes for every learning resource interaction.
4. **RL Training Loop**

   For each episode (student interaction):
   1. **Observe the current state** StS_tSt — e.g., student is weak in CO2 and has high engagement with videos.
   2. **Select an action** AtA_tAt using exploration strategy (e.g., ε-greedy):
      - E.g., recommend a short interactive quiz on CO2.
   3. **Student interacts** with the recommended material.
   4. **Observe reward** Rt+1R_{t+1}Rt+1:
      - E.g., test score improved by 10%, engagement time increased.
   5. **Update Q-values or policy** using reward feedback.
   6. **Move to next state** St+1S_{t+1}St+1 and repeat.

5. Policy Optimization

- Over time, the agent learns:

- Which types of resources work best for which types of students.
- What sequence of recommendations maximizes CO attainment

6. Personalization Layer

- Model can be extended with clustering or context-aware embeddings to tailor recommendations for:
  - Slow learners
  - Fast learners
  - Students weak in specific COs
  - Learning preferences (text vs. video)

7. **Deployment & Continuous Learning**

- The trained agent runs in real-time, continuously adapting to student behavior.
- Periodic retraining with new data ensures up-to-date policies.

5. RESULT

This section presents the results obtained after implementing the proposed RL-based recommendation system for students in the OBE model. The evaluation focuses on user interface, recommendation accuracy, CLO attainment improvement, and resource effectiveness.

1. System Interface

Figure 3 shows the Home Page of the system. Additional interfaces include the recommendation dashboard, where students receive personalized suggestions for improving their deficient CLOs.

2. Recommendation Accuracy

The proposed RL-based recommendation model was compared with a static recommendation system. The comparison metrics include accuracy, engagement score, and improvement in CLO attainment. The RL-based model significantly outperformed the static model, as shown in Table 1 and Figure 4.

Model	Accuracy (%)	Engagement Score	Avg CLO Improvement (%)
Static	62	0.58	5.2
RL-based	85	0.76	12.8

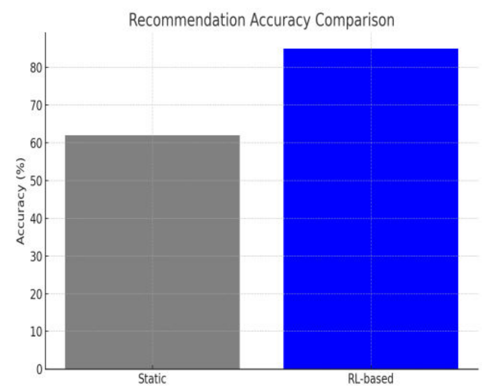

Figure 4: Accuracy comparison between static and RL-based recommendation methods.

3. CLO Attainment Improvement

The system's effectiveness was measured in terms of improvement in CLO attainment before and after applying RL-based recommendations. Figure 5 illustrates the comparative improvement for 10 sample students.

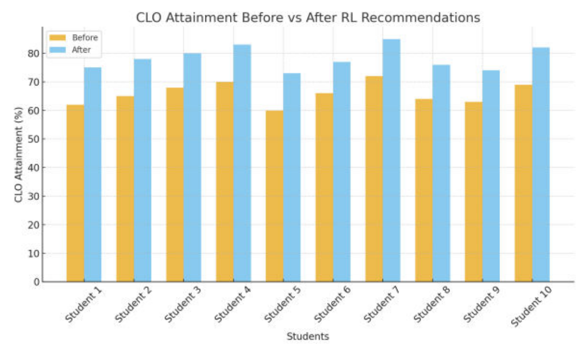

Figure 5: CLO attainment comparison before and after RL-based recommendations.

5. **Resource Type Effectiveness**

The system suggests resources across multiple categories including YouTube videos, online tutorials, research papers, and web pages. Figure 6 shows the distribution of effectiveness across these resource types.

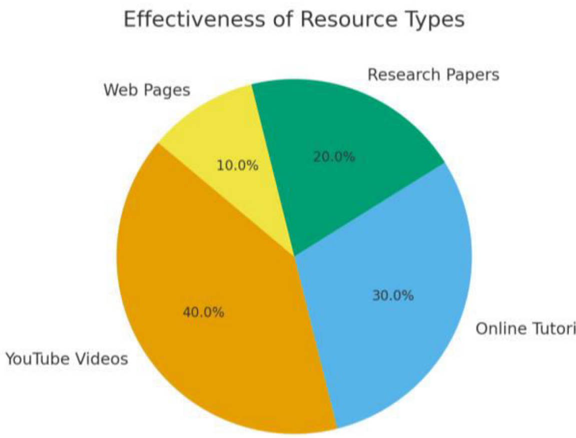

Figure 6: Effectiveness distribution of different resource types.

6. CONCLUSION AND FUTURE ENHANCEMENT

We created a recommendation system for students learning under the OBE educational paradigm in this work. Because students are a nation's greatest asset and may make significant economic contributions if given the right advice and direction. Therefore, the purpose of this study paper is to advise students on how to strengthen their weak or inadequate CLOs of the OBE educational paradigm. to simulate an RL scenario using the suggested student recommendation method. First, we created a student-CLO matrix with the students' CLO attainment scores for each CLO under study. After converting this student-CLO matrix to a binary matrix, the biclustering algorithm Bibit was used to identify comparable patterns within the binary matrix. Several biclusters were formed from these related patterns. Our suggested RL agent then operates in a deterministic environment created by mapping these biclusters onto a 2D grid. The suggested RL agent can do four defined actions on the 2D grid. The RL agent must use cosine similarity to establish the start state for movement in the 2D grid before a learner may receive any recommendations. Following start state determination, the RL agent determines the best course of action to help a student improve his CLO deficiencies or understand how his present CLO deficiencies may affect his future CLOs.

Students can significantly improve their existing CLOs by forecasting future CLO deficiencies.

The suggested RL based recommendation system is also coupled with a mobile app that suggests web resources that can aid students with their inadequate CLOs.

These online materials are divided into book chapters, research papers, YouTube videos, and online guides.

We only employed Q learning to solve the RL problem in the current work; in the future, we can also apply SA RSA to solve the same problem and observe performan ce differences.

This issue can also be resolved with more complex tech niques like value panelized Q learning and DQN. We now employ the Bibit biclustering technique, however we may test alternative biclustering algorithms as well as partitional and hierarchical clustering algorithms.

Furthermore, the current study only considers the viewpoints of students; in the future, it might be expanded to include the perspectives of teachers by assisting them in improving course materials and CLOs and suggesting the essential steps that each teacher should do for a student who lacks a CLO. The current study primarily focuses on improving a deficient CLO from a previous semester in order to reach a certain PLO; it does not model how CLOs from upcoming semesters may be used to accomplish that specific PLO without correcting a deficient CLO from a previous semester. For teacher-student interaction, which is now unavailable in the mobile app, a more coordinated communication method can also be offered.

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