A Proposed Course Recommender Model based on Collaborative Filtering for Course Registration

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***Abstract*—Students face issues and challenges in making decisions for course registration. Traditionally, students rely on suggestions from academic advisers prior to course registration. Therefore, students spend a considerable amount of time waiting for advisers to help them register for the right subjects. However, the number of students rises yearly, thereby increasing the responsibilities of lecturers. Moreover, academic advisers experience constraints in analysing data during consultations for course registration. Therefore, this study proposes a course recommender model based on collaborative filtering. Collaborative filtering is adopted because it provides recommendations based on students' performance in previous subjects. A dataset from the Information & Communication Technology Centre (ICT) of the University Malaysia Pahang is used to evaluate the proposed model. The evaluation is conducted based on two experiments. The first experiment is performed by calculating the difference between actual and predicted scores to verify prediction accuracy. Results show that the average of the mean absolute error of the proposed model is 0.319, which is highly accurate. The second experiment is conducted by comparing the recommendations of the proposed model with those of experts to validate the course recommendation accuracy of the proposed model. Results of the second experiment show that the proposed model has a 91.06% accuracy rate with an error rate of 8.94%. In addition, average precision is 0.68 and recall is 0.724, which are considered accurate. Therefore, the proposed model can play a vital role in assisting students and academic advisers to recommend the right courses during registration, thereby overcoming the limitations of academic advising.**

***Keywords*—Course registration; recommender system; collaborative filtering; academic advisory**

I. Introduction

Numerous students have made wrong decisions in terms of course selection during registration, which can have a negative effect on their education [1]. Therefore, academic advisers play an important role in advising students regarding such matters. Academic advisers ensure that students will make correct decisions in course registration. An academic adviser must monitor a student's academic history to provide accurate and effective recommendations. Consequently, academic advising requires a considerable amount of patience, commitment and ingenuity. Given that academic advisers lack time sufficient knowledge about students, effective advising is rarely achieved. [2-5].

Moreover, knowledge on students' backgrounds, academic plans and goals is required to provide effective recommendations. Academic advisers likewise require certain skills to analyze students' academic history to make appropriate recommendations for students' course registration. Thus, academic advising has become an added responsibility for academic staff. Academic advisers face limitations in analyzing relevant data for student course registration, and academic advising requires psychological as well as people management skills [3, 4, 6].

Moreover, academic advisers are responsible for a large number of students. Owing to the increasing number of students, academic advisers handle a substantial number of redundant cases. Therefore, they experience a tedious process of solving redundant cases and answering repetitive questions. Consequently, the academic-advising process has become a time-consuming endeavor [3, 7]. Academic advisers need a tool that can facilitate their advising tasks and responsibilities. Thus, the functions of a recommender system are appropriate to overcome such issues for several reasons. a) A recommender system is a software that provides recommendations for users based on past preferences [8-11]. b) A recommender system helps users make decisions and select appropriate options. c) A recommender system eases users' tasks by filtering and identifying their preferred options [12, 13]. d) Finally, a recommender system assists users to process data, thereby saving time by filtering and finding suitable options [14, 15].

This research aims to provide a course recommender model to overcome traditional academic-advising issues. Hence, the essence of the course recommender model is not to replace academic advising but to support students and academic advisers during course registration by providing a set of recommendations that can facilitate the implementation of their tasks and responsibilities effectively.

The rest of this paper is divided as follows. Related works on academic advising are discussed in Section 2, and Section 3 describes the proposed course recommender model based on collaborative filtering. Section 4 explains the evaluation process and results, and Section 5 concludes the paper and discusses limitations and future work.

II. Related Works

Automating the traditional academic-advising process is necessary to help students enroll in the right subjects during registration. Similarly, smart academic advising can reduce the

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workload of academic advisers in terms of time and effort in providing guidance to a large number of students. Several advising systems have been proposed to personalize and thus facilitate the registration process.

Academic advising plays a crucial role in the development of education to achieve a university's vision and mission [16]. Academic advisers are lecturers who use knowledge and experience to advise students regarding academic requirements. Specifically, academic advisers assist students in determining their study plan. Hence, academic advising is initiated during the early stages of education [17].

The role of academic advisers is to ensure that students make the right decisions during course registration. Advisers are responsible for advising students based on the students' abilities. Academic advisers must have knowledge of a student's academic history to provide accurate and effective recommendations. Hence, they require a considerable amount of patience, commitment and ingenuity. Given the limitations of academic advisers, effective advising is rarely achieved [3-5, 18]. Moreover, knowledge of students' backgrounds, academic plans and goals is required to provide effective recommendations. Academic advisers likewise need excellent decision-making skills to analyze students' academic records. Thus, they experience limitations in analyzing relevant data for course registration. In addition, academic-advising tasks are added responsibilities for academic advisers who should possess psychological and people management skills [3, 4, 19].

The number of students increases yearly; thus, academic advisers encounter issues and challenges regarding consultation time. Moreover, academic advisers cannot become fully committed to students given their other responsibilities as lecturers [3, 5, 7, 18-20]. Academic advisers are responsible for a large number of students, and the increasing number of students generates a substantial number of redundant cases for them to handle. Therefore, they face a tedious process of solving such cases and answering the same questions repeatedly. As a result, academic advising has become a time-consuming process [3, 7].

Table I presents common academic advising issues and challenges. These issues render the advising process extremely difficult and increase the responsibilities of academic advisers. Therefore, developing a tool that can facilitate academic advising tasks and responsibilities is of vital importance.

The works of [3, 5, 7, 18-20] identified academic advising as a time-consuming process. Meanwhile, [3-5, 18] stated commitment and patience as issues and challenges in academic advising. Knowledge and experience were highlighted by [3, 4, 19], and [5, 19, 20] reported the increasing number of students as the main issue and challenge related to the process. Furthermore, redundant cases were also emphasized by [3, 7].

Various techniques have been applied by researchers to overcome these issues and challenges. For example, Mostafa, Oately [19] utilized a case-based reasoning method for an academic advising system in Egyptian educational institutions and used the historical cases of students to provide recommendations. The authors utilized a survey to evaluate their proposed system. Daramola, Emebo [18] implemented case- and rule-based reasoning methods in an expert course advisory system and employed rule and historical information to generate recommendations for students. The authors likewise adopted a survey to evaluate their proposed system. Meanwhile, Rajput [7] proposed a multilayer neural network method for an intelligent advisory system and used rule and content features to provide recommendations. Henderson and Goodridge [3] proposed a rule-based reasoning method in an intelligent web-based application for academic advising and used the rule feature to generate recommendations. Shatnawi, Althebyan [5] adopted the association rule-mining method for a smart academic advising system and employed the historical feature to provide recommendations. Furthermore, Abdelhamid, Ayoub [20] implemented an agent-based method in an intelligent academic advisor system and used the rule feature to provide recommendations.

Table II shows that rule and historical features are the most common features used in research. However, most researchers did not employ evaluation methods for their proposed systems. Thus, the present research utilizes rule and historical features in the proposed system by employing collaborative filtering techniques. Mean absolute error (MAE), precision and recall methods are adopted to evaluate prediction accuracy and the accuracy of the proposed system.

TABLE. I. ACADEMIC ADVISING ISSUES AND CHALLENGES

Issues and Challenges	[19]	[18]	[7]	[3]	[5]	[20]	[4]
Time consuming	✓	✓	✓	✓	✓	✓	
Commitment and patience		✓		✓	✓		✓
Knowledge and experience	✓			✓			✓
Increasing number of students	✓				✓	✓	
Redundant cases			✓	✓			

TABLE. II. ACADEMIC ADVISING METHODS

	Techniques	**[19]**	**[18]**	**[7]**	**[3]**	**[5]**	**[20]**	**Current research**
Features	Rule		✓	✓	✓		✓	✓
	Content			✓				
	Historical	✓	✓			✓		✓
Method	Rule-based reasoning		✓		✓			
	Case-based reasoning	✓	✓					
	Multilayer neural network			✓				
	Association rule mining					✓		
	Agent based						✓	
	Collaborative filtering							✓
Evaluation	Survey	✓	✓					
	MAE							✓
	Precision							✓
	Recall							✓

III. Course Recommender Model based on Collaborative Filtering

In this research, the collaborative filtering technique is applied to the academic advising process to provide recommendations for students during course registration. A collaborative filtering engine will search for suitable courses for students based on a program structure and transcript file. The input of the proposed model is the case data of a specific student. The case data consist of a program structure containing a course code and a transcript file with student ID, course code, points and status. The output of the course recommender model is recommended courses for the subsequent semester's registration. The proposed model, which is based on the collaborative filtering method, involves six steps, as shown in Fig. 1.

A. Gather Course Score

Course code and student ID, points and status are collected from the program structure and transcript file in the 'gather course score' step. This information is stored in the matrix, which is illustrated in Fig. 2, where the columns represent courses and the rows represent students. The values in the cells represent student scores for the courses. A cell contains no value if a student has not registered for a course in the columns.

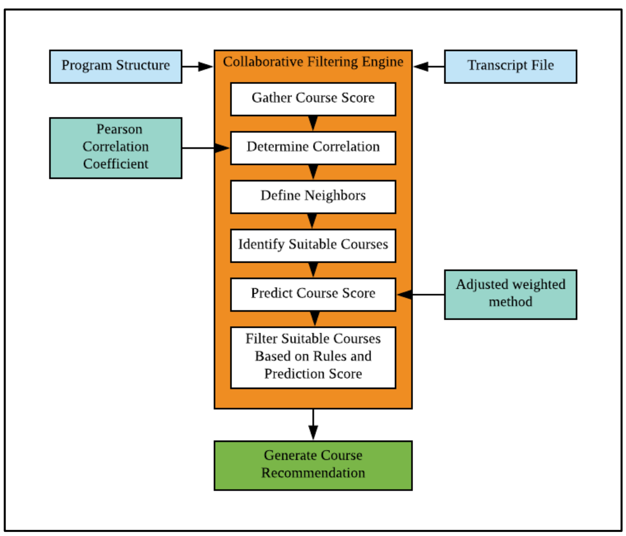
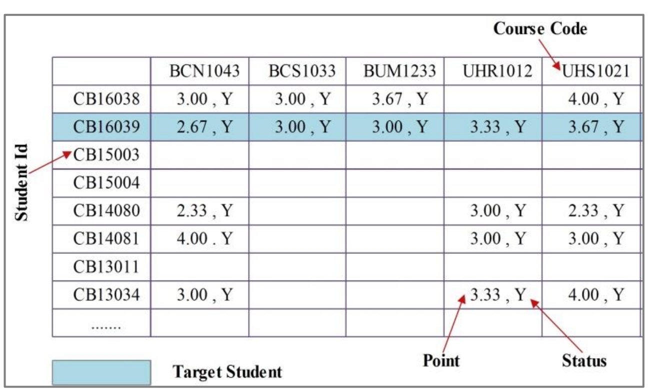


Fig. 1. Model Workflow.



	BCN1043	BCS1033	BUM1233	UHR1012	UHS1021
CB16038	3.00 , Y	3.00 , Y	3.67 , Y		4.00 , Y
CB16039	2.67 , Y	3.00 , Y	3.00 , Y	3.33 , Y	3.67 , Y
CB15003					
CB15004					
CB14080	2.33 , Y			3.00 , Y	2.33 , Y
CB14081	4.00 . Y			3.00 , Y	3.00 , Y
CB13011					
CB13034	3.00 , Y			3.33 , Y	4.00 , Y
....					

Fig. 2. Matrix for Gather Course Score Step.

B. Determine Correlation

The next step involves determining the correlation. The correlation for each student is determined by the Pearson correlation coefficient (PCC) formula [21], as shown in Equation (1). The PCC formula is described in Table III.

$$S(x,y)^{PCC} = \frac{\sum_{i\in I_{xy}}(r_{x,i}-\overline{r_x})(r_{y,i}-\overline{r_y})}{\sqrt{\sum_{i\in I_{xy}}(r_{x,i}-\overline{r_x})^2}\sqrt{\sum_{i\in I_{xy}}(r_{y,i}-\overline{r_y})^2}} \quad (1)$$

The correlation is determined to identify similarities between two students. If student *x* and *y* have similar scores for a course, then they have the same learning level for that course. However, if student *x* and *y* have different scores for a course, then they have different learning levels for that course. The correlation is stored in a similar matrix and illustrated in Fig. 3, where the columns and rows represent students. The values in the cells represent the correlation between two students.

C. Define Neighbours

In this step, students are sorted based on their correlation with target students, and only 30 students are defined as neighbours of a target student. This process is illustrated in Fig. 4. The neighbours are used to identify suitable courses for a target student and to predict the course scores of the target student.

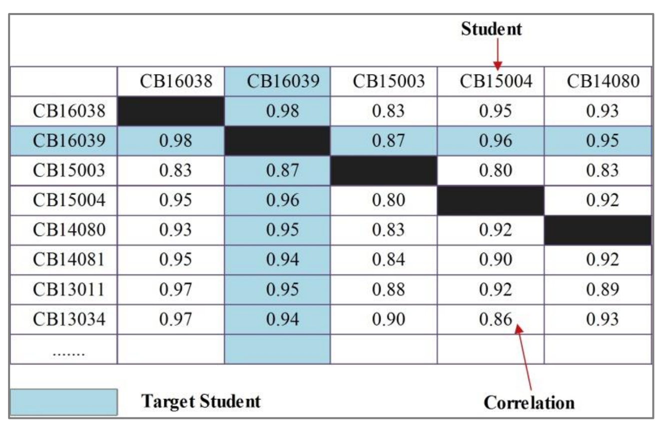
D. Identify Suitable Courses

Courses that have been taken by neighbours but have not been taken by a target student are listed as suitable courses. Fig. 5 shows a sample list of suitable courses.

$$P_{x,i} = \overline{r_x} + \frac{\sum_{y\in G_{x,i}} s(x,y)*(r_{y,i}-\overline{r_y})}{\sum_{y\in G_{x,i}} s(x,y)} \quad (2)$$

TABLE. III. PCC Formula Description

Formula	Description
$S(x,y)^{PCC}$	Correlation between student *x* and student *y*
I_{xy}	Set of subjects taken by student *x* and student *y*
$\overline{r_x}$	CGPA of student *x*
$\overline{r_y}$	CGPA of student *y*
$r_{x,i}$	Score of subject *i* taken by student x
$r_{y,i}$	Score of subject *i* taken by student y



	CB16038	CB16039	CB15003	CB15004	CB14080
CB16038		0.98	0.83	0.95	0.93
CB16039	0.98		0.87	0.96	0.95
CB15003	0.83	0.87		0.80	0.83
CB15004	0.95	0.96	0.80		0.92
CB14080	0.93	0.95	0.83	0.92	
CB14081	0.95	0.94	0.84	0.90	0.92
CB13011	0.97	0.95	0.88	0.92	0.89
CB13034	0.97	0.94	0.90	0.86	0.93
....					

Fig. 3. Matrix for Determine Correlation Step.

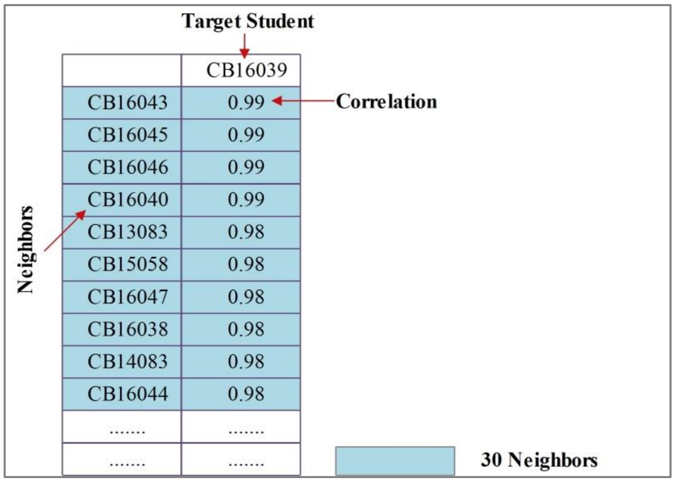


Fig. 4. Matrix for Define Neighbours Step.

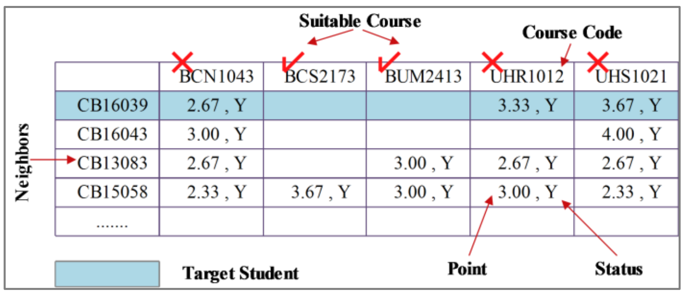


Fig. 5. Matrix for Identify Suitable Course Step.

E. Predict Course Score

In this step, the scores for each suitable course are predicted (see Fig. 6) by using a prediction formula (i.e. adjusted weighted method), as shown in Equation (2). The description of the prediction formula is provided in Table IV.

TABLE. IV. PREDICTION FORMULA DESCRIPTION

Formula	Description
$P_{x,i}$	Prediction score of course *x*
$\overline{r_x}$	CGPA of student *x*
$\overline{r_y}$	CGPA of student *y*
$r_{y,i}$	Score of the subject taken by student *y*
$G_{x,i}$	Set of students who are neighbours of student *x* and have taken subject *i*
$s(x,y)$	Correlation between student *x* and student *y*

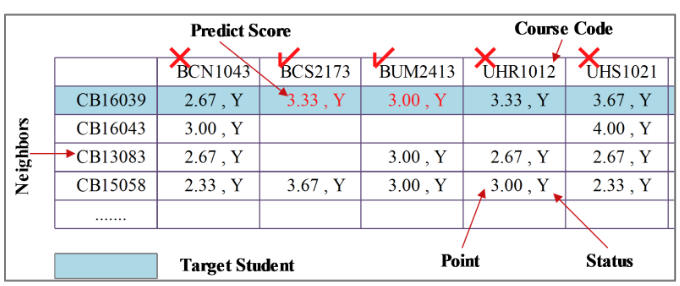


Fig. 6. Matrix for Predict Course Score Step.

F. Filter Suitable Courses based on Rules and Prediction Score

Fig. 7 illustrates the process of filtering suitable courses. Several weights have been added based on the prediction score and priority rules. The priority rules are shown in Table V. Subsequently, the courses are sorted to identify the most relevant ones for a student. Suitable courses are compared with a list of available courses based on faculty rules, as shown in Table VI. Course recommendations are generated after the filtering process.

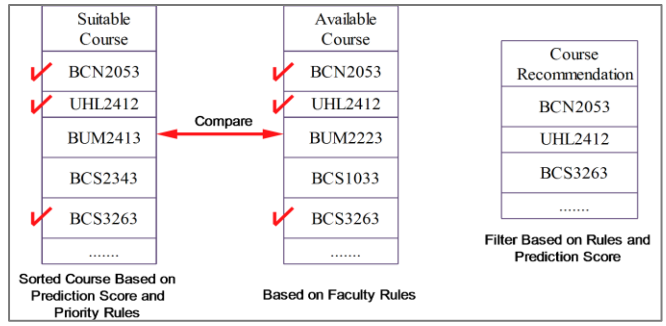


Fig. 7. Matrix for Filter Suitable Courses based on Rules and Prediction Score Step.

TABLE. V. PRIORITY RULES

Rule	Description
Rule 1	Failed courses have high priorities
Rule 2	Courses that are prerequisite to a large number of courses are given higher priority than those that are prerequisite to a small number of courses.
Rule 3	Courses in the high-level category in the curriculum are given higher priority than those in the low-level category.

TABLE. VI. FACULTY RULE

Rule	Description
Rule 1	A student must pass the prerequisites of a course before registering for that particular course.

IV. RESULTS AND DISCUSSIONS

This research used a dataset gathered from the Information & Communication Technology (ICT) Centre of the Universiti Malaysia Pahang (UMP) in Pekan, Malaysia, namely, the dbCSR database, to evaluate the proposed model. The dbCSR database consists of information of 500 students as well as the program structures and transcript files covered in the tertiary education of the Faculty of Computer Systems & Software Engineering. Moreover, the database includes 14,286 records of the scores of 500 students for 43 courses.

An evaluation of the proposed model was conducted based on two experiments to verify prediction accuracy and to validate course recommendation accuracy. Fig. 8 shows the experimental design for the model evaluation.

The prediction score generated by the proposed recommender model via collaborative filtering was compared with an actual score from a transcript file to verify prediction accuracy. Moreover, the recommendation generated by the proposed model was compared with an expert recommendation to validate the course recommendation accuracy of the proposed model.

A. Verify Prediction Accuracy

The first experiment was performed by calculating the difference between an actual score and a prediction score. MAE was used to verify prediction accuracy based on the number of neighbours by calculating the difference between an actual score and a prediction score. A low MAE value represents high predictive accuracy. The lowest MAE value was 0.0, which meant that the prediction and actual scores had the same values. The purpose of this experiment was to determine the number of neighbours that should be selected. Prediction accuracy was improved by determining the suitable number of neighbours. Seven different numbers of neighbours were assigned, and the neighbours with the lowest MAEs were selected.

This experiment was carried out for each of the following number of neighbours: 1, 10, 20, 30, 40, 50 and 60. Fig. 9 presents the results of the experiment. The selection of few neighbours causes similarities with the original meaning to be lost, as students have similarities with more than one student [22]. Thus, the highest MAE value, that is, 0.415, was generated by selecting only one student as a neighbours. Unfortunately, accuracy decreased when a large number of neighbours was selected owing to the differences and similarities among the students [22]. Hence, the MAE value continuously increased as the number of neighbours increased. Therefore, 30 neighbours were a suitable number to select, because it generated the lowest MAE value, which was 0.319. From the first experiment, it can be concluded that prediction accuracy was high when 30 neighbours were selected. Thus, the prediction score generated by the proposed model was close to an actual score when 30 neighbours were selected.

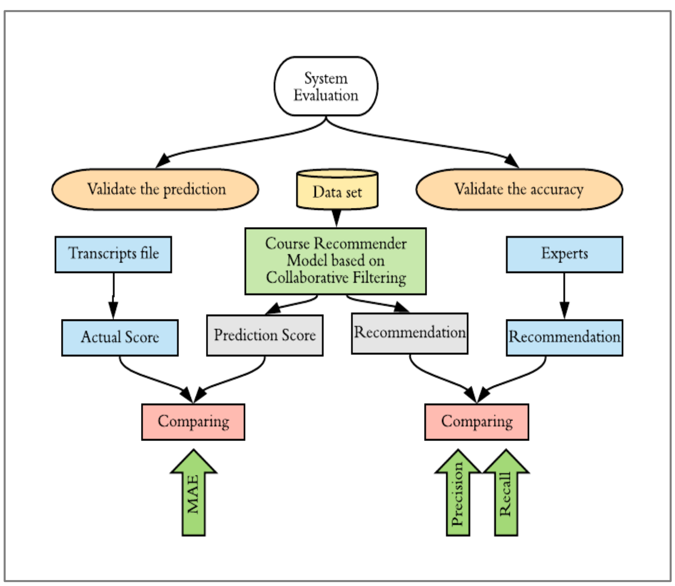


Fig. 8. Experimental Design.

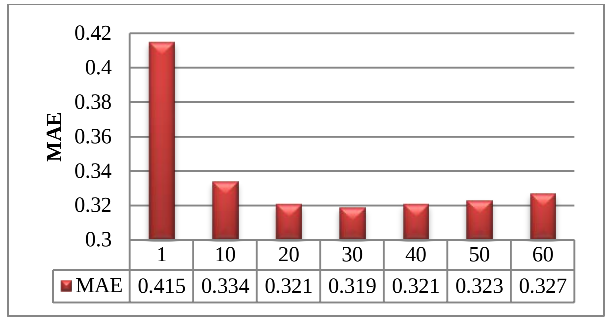


Fig. 9. MAE Results.

B. Validate the Accuracy of the Course Recommendation by the Proposed Model

The second experiment was conducted by comparing the recommendations of the proposed model with those of an expert. This experiment was time consuming and required substantial effort; thus, five different cases based on a discussion with expert lecturers were selected to represent student performance, as shown in Table VII. The purpose of this experiment was to validate the course recommendation accuracy of the proposed model.

Experiment contingency and confusion matrices were generated, as shown in Table IX, by comparing the recommendations of the proposed model with those of experts. The courses were classified as either relevant or not relevant and recommended or not recommended. Contingency and confusion matrices were adopted in this experiment owing to their capabilities to validate accuracy [23]. The proposed model made 214 correct predictions and 21 incorrect predictions in the confusion matrix. Thus, the proposed model exhibited a 91.06% accuracy rate with an error rate of 8.94%.

TABLE. VII. LIST OF CASES

Case	**Student CGPA**
Case 1	1.83
Case 2	2.56
Case 3	3.05
Case 4	3.55
Case 5	3.91

TABLE. VIII. EXPERIMENTAL CONTINGENCY MATRIX

	Case 1	**Case 2**	**Case 3**	**Case 4**	**Case 5**
Relevant and recommended	3	5	5	5	6
Relevant but not recommended	3	0	3	3	1
Not relevant and not recommended	39	40	37	36	38
Not relevant but recommended	2	2	2	3	2

TABLE. IX. CONFUSION MATRIX

	Recommended	Not Recommended
Relevant	24	10
Not relevant	11	190

The results of each case in Table VIII are illustrated in Fig. 10. For example, in Case 1, the proposed model recommended three relevant courses. However, compared with the recommendations of experts, the proposed model did not recommend three courses that the experts considered relevant to students. In addition, the proposed model recommended two courses that were considered not relevant by experts. Nevertheless, the prediction score and priority rules (based on the collected data) stated that the recommended courses were highly relevant compared with other courses. Thus, the proposed model recommended those courses to students. However, validity is threated, as experts have different backgrounds and the experiments generated a variety of opinions in terms of decisions for the best plans for students.

The corresponding precision and recall values were obtained from the contingency matrix in Table VIII, which is shown in Table X. High precision and recall values represent high accuracy, and 1 is the highest precision and recall value. Table X shows that average precision was 0.68 and recall was 0.724. Thus, from the second experiment, it can be concluded that the accuracy of the proposed model was high.

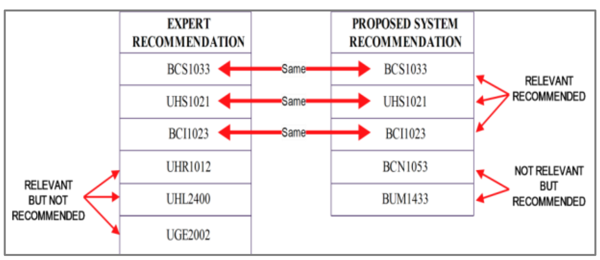


Fig. 10. Case 1 Evaluation.

TABLE. X. PRECISION AND RECALL VALUES FOR ALL CASES

	Case 1	Case 2	Case 3	Case 4	Case 5
Precision	0.6	0.71	0.71	0.63	0.75
Recall	0.5	1	0.63	0.63	0.86

V. CONCLUSION

The issues and challenges in academic advising have motivated the researchers of this study to carry out a preliminary investigation to develop a course recommender model to assist students and academic advisers during course registration. This research has achieved its second objective by developing a course recommender model using collaborative filtering for the UMP open registration process. Moreover, the developed model is capable of providing course recommendations for the subsequent semester.

The evaluation of the proposed model is conducted based on two experiments. The first experiment is performed by calculating the difference between actual and prediction scores to verify prediction accuracy. The results show that the average of the MAE of the proposed model is 0.319, which is highly accurate. Meanwhile, the second experiment is conducted by comparing the recommendations of the proposed model with those of experts to validate the course recommendation accuracy of the proposed model. The results demonstrate that the proposed model has a 91.06% accuracy rate with an error rate of 8.94%. Moreover, average precision is 0.68 and recall is 0.724, which are considered highly accurate. Therefore, the proposed model can play a vital role in assisting UMP students and academic advisers to recommend the right courses during registration. Furthermore, this research has achieved its third objective by evaluating the accuracy of the proposed course recommender model.

The proposed model offers recommendations based on students' scores. Generally, UMP accepts a new student every semester. Thus, the limitation of the proposed model involves new user cold-start problems. New user cold-start problems mean that the proposed model does not have adequate information on the historical record of a new student. Hence, it cannot identify which students have similarities with the new student. As a result, it cannot provide recommendations for the new student. Moreover, the program's structure is frequently revised, thereby adding to the proposed model's new item cold-start problem. This problem means that the proposed model cannot predict the scores for new courses until several similar students have registered in those courses. Moreover, the increasing number of students causes an increase in student scores. Thus, computation slows, thereby affecting the scalability of the proposed model.

Numerous improvements can be implemented to overcome the limitations of the proposed model. In this research, the proposed model only employs the traditional collaborative filtering approach. Thus, future studies can utilise a hybrid approach to solve the limitations of the collaborative filtering approach.

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