ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1299

A Smart Academic Advisor Model for Undergraduate Students

Mohamed Saied El-Sayed Amer
Canadian International College, New Cairo, Egypt.
Orcid: 0000-0001-8499-461X

Abstract:- The undergraduate enrollment rate is rapidly increasing. Many students want advice on their journey to graduation. The students are unfamiliar with the major sheets and academic timetable of the university where they have enrolled. Thus, a model that handles the advising process for students who are unclear about how to choose their courses must be designed. This study provides a model for an academic adviser who may help students navigate their university experience. The model recommends a list of courses to the student depending on his current study level and categorizes the major sheet's courses by difficulty, which varies from easy to challenging based on previous exam results. Lastly, with so many students, the suggested model can assist in automating the advising process without requiring a lot of work.

***Keywords**:- Automated Academic Advising, Advising Online, Course Registration, Academic Advising, Course Selection.*

I. INTRODUCTION

When a student first enrolls in a college's undergraduate program, he may struggle to distinguish between the proper and bad paths. Thus, in order for the student to grasp what he intends to accomplish in terms of postgraduate studies for the scientific disciplines offered at his institution, an academic counselor must be supplied[1].

An academic adviser is one of the most important resources that colleges must have in order to assist students in finding the right path or subjects to study throughout their academic careers. One of the responsibilities of the academic advisor is to supervise the student throughout his academic career till graduation from the university[2].

As technology advances, it is imperative to develop a model that provides automated academic guidance for students. Since more and more students are applying to universities, having an automated system in place to support the academic advising process is one of the most important requirements. Additionally, the development of the current generation and the accessibility of the Internet of Things (IoT) make it simple to put in place an automated academic advising system that supports students throughout their academic careers[3].

Additionally, the rise of fog computing has made it easier to manage the university's cloud-based systems. As more students use the cloud-based educational system, pressure mounts on it regardless of the use of cloud computing; therefore, integrating fog computing, which is essentially an extension of cloud computing, will make it easier for the greatest number of students to access the educational system and receive academic advising in a timely and convenient manner.

This paper will propose a model for academic advising that chooses subjects based on the student's academic standing and areas of study qualification. In some universities, admission tests are administered, and the student is placed in a particular academic situation to study a particular set of subjects based on the test results. As the semesters go by, the student receives automatic academic guidance regarding his career path and subject-matter grades.

In order for the students to study these materials or books and earn excellent grades throughout their study tenure, the suggested model will conduct a recommendation process for the study materials. This process will assist in determining the recommendations for the materials based on the tendencies and abilities of the students.

II. RELATED WORKS

The most well-known recommender systems are found in any setting where there are plenty of possibilities. Users can easily choose content relating to their requirements or interests thanks to the suggestion process.

The academic adviser is thought of as a kind of recommender system that makes it easier to study all of a curriculum's courses. The practice of academic advising helps students study the subjects allocated to them in their university specialization more easily and progresses in terms of these subjects' complexity.

Universities and other educational institutions are increasingly using recommender systems, also known as academic advising systems, extensively. Every one of these fields has problems and works in the advisory process. The execution and efficacy of course recommendations based on student level and grade level are the main focus of the research. Recommendation systems are mostly categorized as:

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1299

A. Content Based Filtering (CB):

Content-based (CB) strategies leverage the item's features that have been gathered and compare them to other features of items that a targeted user has previously preferred. The user is recommended things that are comparable to each other.

Two steps are involved in the operation of content-based filtering: Based on the item features that the user prefers, it saves user information. By comparing similarities between two items, these traits are utilized to map how similar they are to one other. The features of each item are then compared to the user data, and the items with the highest degree of similarity are suggested [4].

B. Collaborative Filtering (CF):

The most often used and popular recommendation technique is CF. Users with similar interests are more likely to give new and future items the same intercept preference, laying the groundwork for collaborative filtering. This approach consists of two steps. It first serves as a criterion for picking a group of people with similar ideas to form the basis of a suggestion (nearest neighbors). Furthermore, it uses these viewpoints to extend the group and boost its effect on the recommendation [5].

Prior research has shown that less than 75% of new students at four-year educational institutions return for a second year, although the ratio is significantly lower for students at two-year educational institutions. Although the reasons for this type of attrition are complicated, poor counsel is unquestionably a problem. A few years ago, the original author created an expert advising system that neglected to account for accurate schedules, which are a crucial component of student advice. This effort updates an obsolete advising system and addresses the issue of course scheduling [6].

According to a recent study, registering for classes as a student is an important and difficult step that might cause unwarranted delays in graduation. The United Arab Emirates University (UAEU) Department of Electrical Engineering is one site where students confront challenges such as incorrect course selection, advisers' inexperience and lack of information, students' ability to obtain competent assistance, and inadequate advising schedules, among other things. An Automated Course Advising System (ACAS) was created to assist students in registering online with the Banner System[7].

III. METHODOLOGY

The courses that a student must take have a significant impact on his or her academic career. At this point, the student adheres to an Academic Plan (AP) and begins studying the primary major sheet, which their faculty distributes in portions. As the student's studies progress, a variety of courses are available to assist him learn and apply what he has learned in the actual world after graduation[8].

The proposed model is considered as a tool that help the student to study subjects in specific order, first the courses are classified according to the difficulty level as the first level can study between 4 to 6 courses and may be more this could be assessed according to a placement exam for the student.

The advisor recommendation is based on the student's academic record, where the student academic record is divided into two types: (1) New-comer students. (2) return student. So, the architecture of the proposed system could be shown as in the following figure:

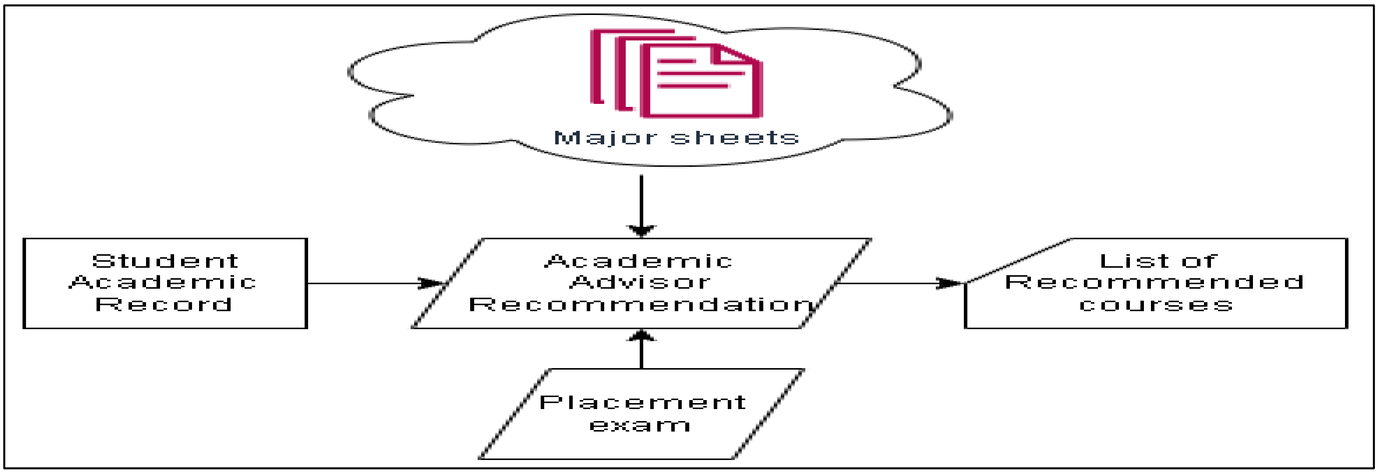

Fig 1: System Architecture

Figure 1 shows that there is a placement exam done for the new-comer students in order to define their situation from the study and how much courses could be taken by the student during his first term in the academic life. While on the other side, the major sheet is applied on the return students according to a previous academic record.

The proposed model is working on both new-comer students and return students, according to some conditions must be satisfied to apply a number of courses (mentioned in the major sheet) in the running term. Also, it takes in consideration the difficulty level of courses and the status of the student in the running academic term.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1299

Also, the student academic level taken in consideration when recommending a list of courses for them to be studied during the term, this will help him to avoid bad grades and allows them to concentrate more on the courses assigned to him.

The proposed model makes a classification and filtering for the courses according to conditions set on the used major sheet. The rating of courses difficulty is collected from old students who studied the selected major sheet and this data are classified according to those students (cumulative GPA) CGPA and saved as Course Rate Dataset (RD).

The recommendation or advising process takes places according to the student entrance type if new-comer or return student and then check on the student academic level and his cumulative GPA (CGPA). The return students already pass some semesters inside the campus while the newcomer did not take any semesters yet, so they enter a placement exam to check if accepted or not. Figure 2 shows the data flow diagram inside the proposed model.

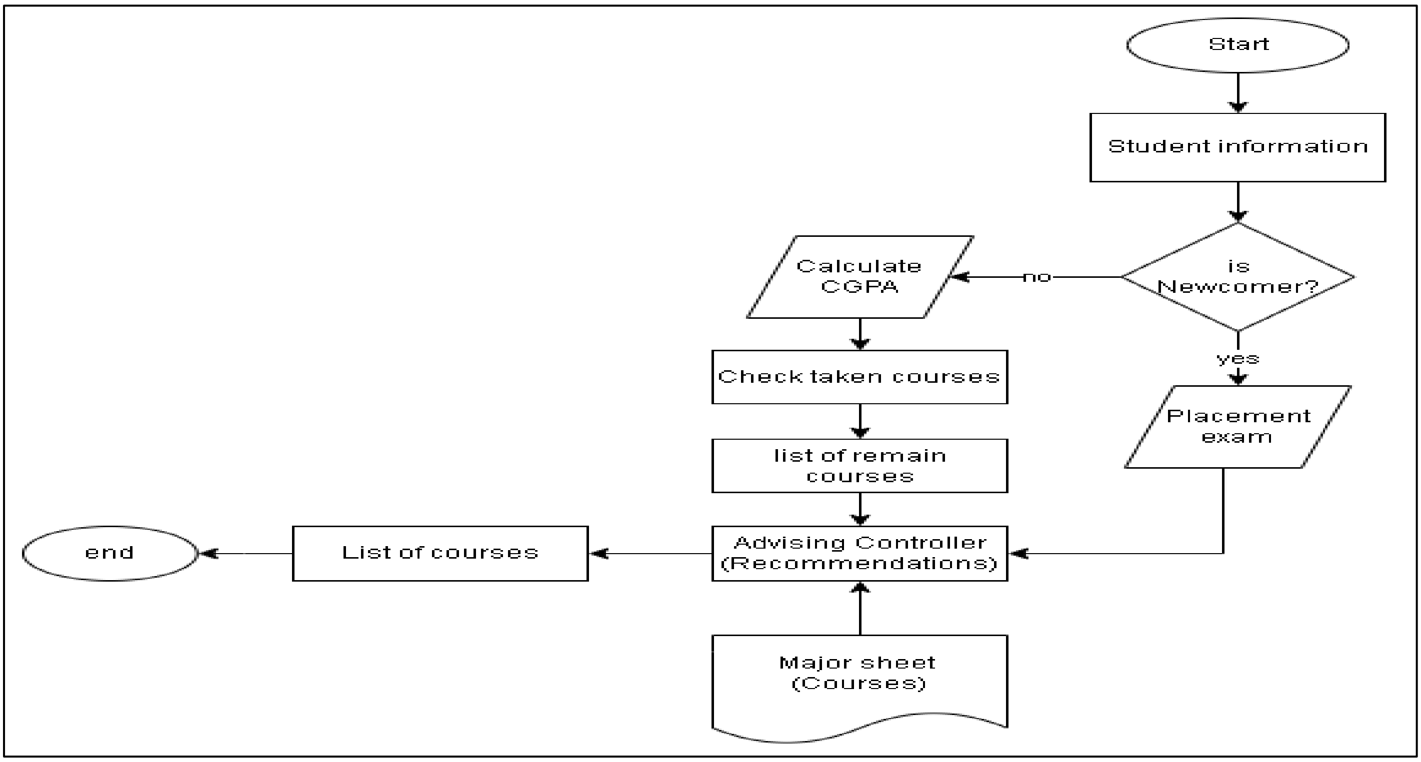

Fig 2: Academic Advisor Data Flow

The model supposes to check the student academic record to get the CGPA and student level. After that those data are taken to the recommendation process. The student data are passed over the Course Rate Dataset (CRD) and then a recommend list of courses is displayed to the student to make the advising.

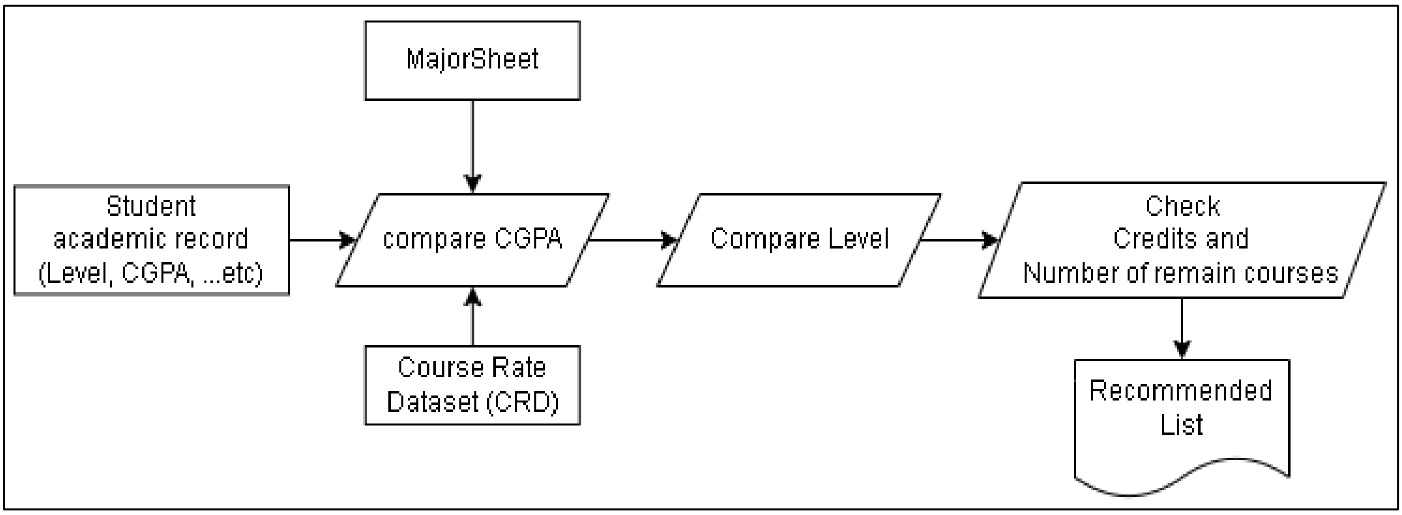

Fig 3: Advising Controller (Recommendation Process)

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1299

In figure 3, the student academic record is pass over the recommendation filters (compare CGPA, Level … etc) and generate a recommendation list for the student when advising begins. The next section shows how to apply the proposed model.

IV. RESULTS

In this section, the system was tested on a major sheet of faculty of Business Information Technology. The dataset is collected form this major sheet contains about 43 courses for whole curriculum study divided into 4 years, in each year the student supposes to study 11 courses on two semesters. The major sheet courses are listed in table 1.

The case study focuses on the return students as they already pass at least one academic year and exposed to the academic life rather than the new-comer who is considered a clean sheet.

Table 1: Level 1 Courses List

Code	**B 101**	**B 102**	**B 103**	**B 104**	**B 105**	**B 106**	**B 107**	**B 108**	**E 101**	**E 102**
Level	1	1	1	1	1	1	1	1	1	1
Credits	3	3	3	3	3	3	3	3	3	3

Table 2: Level 2 Courses List

Code	**B 201**	**B 202**	**B 203**	**B 205**	**B 206**	**B 207**	**B 208**	**B 209**	**B 210**
Level	2	2	2	2	2	2	2	2	2
Credits	3	3	3	3	3	3	3	3	3

Table 3: Level 3 Courses

Code	**B 311**	**B 312**	**B 313**	**B 314**	**B 315**	**B 316**	**B 317**	**B 318**	**B 319**	**EL 302**	**EL 305**
Level	3	3	3	3	3	3	3	3	3	3	3
Credits	3	3	3	3	3	3	3	3	3	3	3

Table 4: Level 4 Courses

Code	**B420**	**B421**	**B422**	**B423**	**B424**	**B425**	**B426**	**B427**	**B429**	**EL405**	**EL406**	**EL407**	**EL408**
Level	4	4	4	4	4	4	4	4	4	4	4	4	4
Credits	3	3	3	3	3	3	3	3	3	3	3	3	3

The courses difficulty rates are collected from graduated students rating which ranged from 0 to 10 where the high score represented the most difficult course. Table 2 shows the list of courses and level of the courses and the difficulty rate.

Table 5: Level 1 Courses Rate

Code	**B 101**	**B 102**	**B 103**	**B 104**	**B 105**	**B 106**	**B 107**	**B 108**	**E 101**	**E 102**
Level	1	1	1	1	1	1	1	1	1	1
Rate	8	3	5	4	6	3	1	4	2	3

Table 6: Level 2 Courses Rate

Code	**B 201**	**B 202**	**B 203**	**B 205**	**B 206**	**B 207**	**B 208**	**B 209**	**B 210**
Level	2	2	2	2	2	2	2	2	2
Rate	5	6	7	8	4	3	4	5	6

Table 7: Level 3 Courses Rate

Code	**B 311**	**B 312**	**B 313**	**B 314**	**B 315**	**B 316**	**B 317**	**B 318**	**B 319**	**EL 302**	**EL 305**
Level	3	3	3	3	3	3	3	3	3	3	3
Rate	4	5	3	4	5	7	4	5	3	5	4

Table 8: Level 4 Courses Rate

Code	**B420**	**B421**	**B422**	**B423**	**B424**	**B425**	**B426**	**B427**	**B429**	**EL405**	**EL406**	**EL407**	**EL408**
Level	4	4	4	4	4	4	4	4	4	4	4	4	4
Rate	4	5	6	7	8	2	6	5	7	3	4	5	8

The level and CGPA is collected for a sample of 20 return students listed in table 3 after calculating the CGPA for each one to apply the major sheet roles.

Table 9: List of Return Students

Student	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Level	2	4	3	4	3	4	2	3	4	2	4	4	4	2	3	4	3	2	3	2
CGPA	1.4	2.8	1.2	3.3	1.7	2	0.8	2.2	3	1	2.4	2.3	2.8	1.2	1.7	2.8	1.9	1.1	2	0.6

➢ *The Rules of Major Sheet Stat that:*

- Rule 1: The student with CGPA less than 2 to be under academic mentoring (low GPA student), so he will take only 4 courses while the student with CGPA greater than 2 will take the normal load which is 6 courses.
- Rule 2: The student will enroll in courses equal to his level or in the next level only.

So, based on collected data and the major sheet roles, and after applying the major sheet roles on return students, each student will take number of courses as shown in table:

Table 10: Applying the CGPA Major Sheet Rule

Student	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Level	2	4	3	4	3	4	2	3	4	2	4	4	4	2	3	4	3	2	3	2
CGPA	1.4	2.8	1.2	3.3	1.7	2	0.8	2.2	3	1	2.4	2.3	2.8	1.2	1.7	2.8	1.9	1.1	2	0.6
Rule 1	4	6	4	6	4	6	4	6	6	4	6	6	6	4	4	6	4	4	6	4

So according to the previous applied rule the recommendation will be in the range of the available courses to be taken. The proposed model works on recommending the easiest to be first and then arranged till the difficult course and keeps in mind the previous taken and passed courses and the number of remaining courses for the student to finish the major sheet courses.

The steps used in recommendation process as follows:

- Check and avoid old taken and succeeded courses.
- Check total passed number of credits and allowed credits.
- Check number of remain courses for each student.
- Check courses level to be equal to student level or greater than it by 1.
- Compare above results (student academic record) with the dataset to get the number of recommendations.
- Arrange the recommended courses to be advised according to difficulty.
- Display a recommended list of courses to the student.

After applying those steps, the student will find a list of courses to choose from them the recommended courses are comes first.

The algorithm used in this recommendation process can be expressed as:

➢ *Algorithm: Recommender Code*

```
TotalMajsheetCourse = 43;
PassCourses = [A, B, C];
stdrecord = [LVL, CGPA, PassCourses]
remainCoursesNum = TotalMajsheetCourse - PassCourses
ratecourses = ["code"=>Rate]
CoursrRateDataset = [[1v1]=>[ratecourses]]
selectedDataset = sort(CoursrRateDataset[stdrecord->LVL])
if (stdrecord->CGPA < 2){stdAllowedCourses = 4} else {stdAllowedCourses = 6 }
TotalCoursesList = []
foreach(majorsheetcourses as majorsheetcourse):
        if(majorsheetcourse->code not in stdrecord->PassCourses and not in TotalCoursesList)
        if(majorsheetcourse->level <= stdrecord->LVL + 1)
                if(count(CoursesList) < remainCoursesNum)
                        add(TotalCoursesList, majorsheetcourse->code)
endforeach;
foreach(selectedDataset as recommended)
        foreach(TotalCoursesList as coursecode)
                if(count(recommendedList) < stdAllowedCourses)
                if(recommended == coursecode)
                add(recommendedList, recommended)
        endforeach;
endforeach;
output recommended List
```

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24MAR1299

The algorithm is depending on the matching algorithm between the student academic record and the Course Rated Dataset (CRD) plus the original rules on the major sheet. The sequence is moves to select first the available courses to be registered and then apply the recommendation on the available courses to refine the last displayed list.

V. CONCLUSION

In this paper the academic advisor is using recommendation system to make the advising process. As the newcomer and return student did not know how to select courses to study. The dataset is collected from graduated students to develop the proposed model.

The proposed model is loaded with the major sheet and the rules are set to make the model works fine. The advising process is moves through the rules and finally output the refined list for the student to register in the courses.

The proposed model is consisting of a classification filter to classify the courses like level filter and CGPA filter. By applying those filters, it is guaranteed that the student has a most refined list of courses to select from them.

Finally, it supposed to use an automated academic advising to cover the rapidly increasing in the students numbers year by year.

REFERENCES

[1]. Fox, J.R. and Martin, H.E. eds., 2017. Academic advising and the first college year. Stylus Publishing, LLC.

[2]. Howard, F., 2017. Undocumented students in higher education: A case study exploring street-level bureaucracy in academic advising. Accessed from: https://scholarscompass.vcu.edu.

[3]. Lynch, M. (2016). Uncovering the Devastating Impact of World War II on American Education. Retrieved from http://www.theedadvocate.org/uncovering-devastating-impact-world-war-ii-american-education.

[4]. Pazzani, M.J., Billsus, D. (2007). Content-Based Recommendation Systems. In: Brusilovsky, P., Kobsa, A., Nejdl, W. (eds) The Adaptive Web. Lecture Notes in Computer Science, vol 4321. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-72079-9_10.

[5]. Nilashi, Mehrbakhsh & Bagherifard, Karamollah & Ibrahim, Assoc Prof. Dr. Othman & Alizadeh, Hamid & Lasisi, Ayodele & Roozegar, Nazanin. (2013). Collaborative Filtering Recommender Systems. Research Journal of Applied Sciences, Engineering and Technology. 5. 4168-4182. 10.19026/rjaset.5.4644.

[6]. Siegfried, Robert & Wittenstein, Adam & Sharma, Tashi. (2003). An automated advising system for course selection and scheduling. Journal of Computing Sciences in Colleges - JCSC.

[7]. Laghari, M.S. (2014). Automated Course Advising System. International Journal of Machine Learning and Computing, 47-51.

[8]. Sandoval-Lucero, E., Antony, K. and Hepworth, W., 2017. Co-curricular learning and assessment in new student orientation at a community college. Creative education, 8(10), p.1638.