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Design and Implementation of a Hybrid Recommender System for Predicting College Admission

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***Abstract*- This paper presents a new college admission system using hybrid recommender based on data mining techniques and knowledge discovery rules, for tackling college admissions prediction problems. This is due to the huge numbers of students required to attend university colleges every year. The proposed system consists of two cascaded hybrid recommenders working together with the help of college predictor, for achieving high performance. The first recommender assigns student's tracks for preparatory year students. While the second recommender assigns the specialized college for students who passed the preparatory year exams successfully. The college predictor algorithm uses historical colleges GPA students admission data for predicting most probable colleges. The system analyzes student academic merits, background, student records, and the college admission criteria. Then, it predicts the likelihood university college that a student may enter. A design for prototype system is implemented and tested with live data available in the On Demand University Services (ODUS-Plus) database resources, at King Abdulaziz University (KAU). In addition to the high prediction accuracy rate, flexibility is an advantage, as the system can predict suitable colleges that match the students' profiles and the suitable track channels through which the students are advised to enter. The system is adaptive, since it can be tuned up with other decision makers attributes performing trusted needed tasks faster and fairly.**

Keywords: Recommender systems, student's admission systems, college's admission criteria, Prediction algorithms.

I. Introduction

University educations are an essential part of most people's preparation for working life. An admission to university is therefore became an important challenging topic. Hence, effective university admission prediction services are needed for helping students to enter the right university college. However, due to the huge numbers of students required to attend the university every year, this decision making process became a very complex problem. Since, this process is not merely relying on student test scores but also depends on students' backgrounds and other qualifications weighting criteria that correlate to the performance of their tertiary education.

The aim of this work is to construct a trusted recommender system (RS) based data mining techniques and knowledge discovery rules to achieve the enrollment of student's admission in the university colleges fairly, according to college's standard criteria. These criteria include college capacity, prerequisite courses rates, and student's scores rate in the first year qualified exam. The system also helps university decision makers to provide needed facilities and resources that are required for achieving highly qualified university education. The system is adaptable and trustable, since it allocates students according to their qualifications, hence, achieving student's satisfaction. The following sub-sections explain the data mining approach and the use of hybrid recommender system in the university admission prediction services. This research is an expanded paper for the work explained in [1].

A. Recommender Systems based Data Mining

Data Mining (DM) is the process of collecting, searching through, and analyzing a large amount of data in a database, as to discover patterns or relationships [2, 3]. An RS can provide recommendations about which universities a student should apply to, taking not only the student's secondary school scores but also other related factors onto account. The RS can apply data mining techniques to determine the similarity among thousands or even millions of university applicant's student's data [4]. We use the most commonly DM methods that are used in RS including: student's classification, clustering based on association discovery rules, as explained in section (III). The following steps are followed:

a) *Web Mining*

Web usage mining performs mining on student's web data, particularly data stored in logs managed by the web servers [4]. The web log provides a raw trace of the students' navigation and activities on the site. In order to process these log entries and extract valuable patterns that could be used to enhance the RS system or help in system evaluation, a significant cleaning and transformation phase needs to take place so as to prepare the information for data mining algorithms. The data we use to construct our recommended system is based on *Knowledge Discovery Association Rules (KDAR).*

b) *Recommendation Using KDAR*

One of the best-known examples of DM in recommender systems is the discovery of association rules, or item-to-item correlations [5, 6]. Association rules used to analyze patterns of preference due to students qualifications and their requirements and necessary university criteria. Association rules can form a very compact representation of preference data that may improve efficiency of storage as well as performance. In its simplest implementation, item-to-item correlation can be used to identify "matching items" for a single item, such as *student admission registration process and Students College's allocation process* explained in section (IV).

c) *Students Data Clustering*

Clustering techniques work by identifying groups of students who appear to have similar preferences [7, 8, and 27]. Once the clusters are created, averaging the opinions of the other students in their cluster can be used to make predictions for an individual. Some clustering techniques represent each user with partial participation in several clusters. *The prediction is then an average across the clusters, weighted by degree of participation*, as explained in section (IV).

d) *Students Classification*

Classifiers are general computational models for assigning a category to an input [9-10]. The inputs may be vectors of features for the items being classified or data about relationships among the items. The category is a domain-specific classification such as approve/reject for applicants requests. To build the RS using a classifier is to use student's information as the input, and to have the output category represent how strongly to recommend the suitable college to the students, *this process is explained in section (IV).*

II. College Admission Prediction Methods

University education is an important part of our day working life. Admission to university is therefore a topic of importance. How a student chooses a university, and conversely how a university chooses a student, determines the success of both sides in carrying through the education. Table1 illustrates the most existing studies of college admission techniques. Where, universities admissions are faced annually with a tremendous quantity of student applicants. The size of the applicant pool taxes the resources of the admissions staff. University admission prediction methods are therefore used for categorizing student applicants and determining the likelihood that they will enroll at an institution if accepted. This evaluation process

in the past was attempted by several admission prediction methodologies as explained briefly in the comparison shown in Table 1.

One of the main problems faced by university students is to take right decision in relation to itinerary based on the available information [19]. In recent years, recommender systems have played an important role in reducing the negative impact of information overload [20]. Moreover recommender systems are important tools that overcome the information overload by sifting through the large set of data and recommending information relevant to the user [21]. So, the recommender systems are increasingly being used in several domains to assist the user in making his choice and in his decision making processes [22]. On the other hand, different functions are proposed for recommender systems such as, recommender systems are used to recommend potentially interesting items to users in different domains [23, 28].

In this paper, we propose a new college admission prediction technique based on using two cascaded hybrid recommenders and use of data mining discovery knowledge rules for achieving student's college admission with high performance fairly and accurately, as explained in next sections.

III. Proposed System Design

Figure 1 shows the components of a proposed Hybrid Recommender System for Predicting College Admission (HRSPCA). System operation steps are numbered from 1 to 10. The system consists of the following components:

A. *Students Web-Portal*

It is an interactive visualization web module that allows communications between students and the system, by specifying a query or task, providing information to help focusing the search. It mapped data onto graphical primitives, search for patterns, irregularities, and relationships among data, and find interesting regions and suitable parameters for further quantitative analysis. This web portal allows entering students who have high school certificates and they desire to continue their study in KAU. Entry screens are used for inputting these data using the web portal. When a student accesses the web site, he can deal with four essential types of data, which include the following:

1. *Personal Data*

A new student is allocated an ID number and user password. After that he will be able to enter his own personal data include: Name (in Arabic and English), Identity number, Nationality, Birth place, Birth Date, Address, Social Status, eMail, Mobile Number, Disability Status, and Get a Subsidy.

2. *High School Data*

It includes Type of study (scientific or literary), its Date and City, Cumulative Grade Point Average (GPA).

3. *University Programs Available*

In this field, a student selects his desires from the university programs available. Six options have to be entered according to the student required desires in priority. Students are advised to follow up recommendations they can get by accessing College Predictor (CP), explained next.

4. *Capabilities Data*

These include, Degree of Achievement, Degree of Capacity, Weighted Literary Rate, and Weighted Scientific Rate, explained in section (IV).

B. *Enrollment Stage*

Once, a student entered his data. He will be registered in the system and will be given an ID number and a password. So that he can access the system and continue entering necessary data required for admission processes.

C. *The Auditing Process*

In this stage, data clearing is accomplished. The essential student's data are compared with the students data documented in the ministry of education. This operation is to verify the corrections of student's names, grades, and nationality. A feedback SMS messages and e-mails will be sent to students in case of finding any data mismatch. The students validated data then stored in the system database.

D. *Track Recommender (TR)*

The TR is used for sorting the preparatory year scientific tracks recommended for fresh students. It contains a sorter and a filter. The sorter used to sort students to several university study tracks available. The filter is used to re-arrange students onto two categories. Students who passed all courses successfully will go to college recommender to be allocated to suitable colleges. Students who failed in any course are rejected and postponed for services when they are succeeded. The track recommender uses knowledge discovery rules explained in section (IV).

E. *College Recommender (CR)*

The college recommender contains two internal components; a Classifier and Allocator, respectively. The CR services students who succeeded in all preparatory year courses. It allocates students into colleges fairly according to the GPA and prerequisite qualified courses stated by specialized colleges. The classifier is used to categorize students according to their gender and their qualifications. The CR carries out data processing using pattern discovery rules. The pattern discovery rules distinguish resident citizen students (Non Saudi), which are allowed for admission by ratio from 5% to 10% of the total offered university capacity. The CR uses the pseudocode of feature selection and knowledge discovery rules explained in section (IV).

Table 1. Comparison of College Admission Prediction Methods.

Authors	Year	Approach	Characteristics
J. A. Freeman [11]	1991	Neural networks (NN)	Performing pattern recognition and categorization. However, training a neural network consume a long time.
E. Gottlieb[12]	2001	Linear programming models	Admission problem is solved as a simple yes or no decision.
I. Hatzilygeroudis, [13] J. S. Moore [14]	2004	Expert System	A rule-based system that uses a type of certainty factors. The values of the parameters (weights) are determined via training, before the system is used.
S. Vinnik [15]	2005	Decision Support System	Assessing educational capacity and planning its distribution and utilization in universities.
L. Chang[16]	2006	Data Mining	Predictive modeling was applied to enhance the prediction of enrollment behaviors of admitted applicants at a large state university.
S. Fong [17], W. C. Lou [18]	*2009*	Hybrid Model NN and Decision Tree (DT) Classifier.	The recommender predictions based on students' histories. Combining NN and DT improves recommendation output.
A. Ragab, etal	This paper	Cascaded hybrid Recommender and DM.	Use rules and DM achieving student's admission fairly, and accurately prediction and allocation, with high performance.

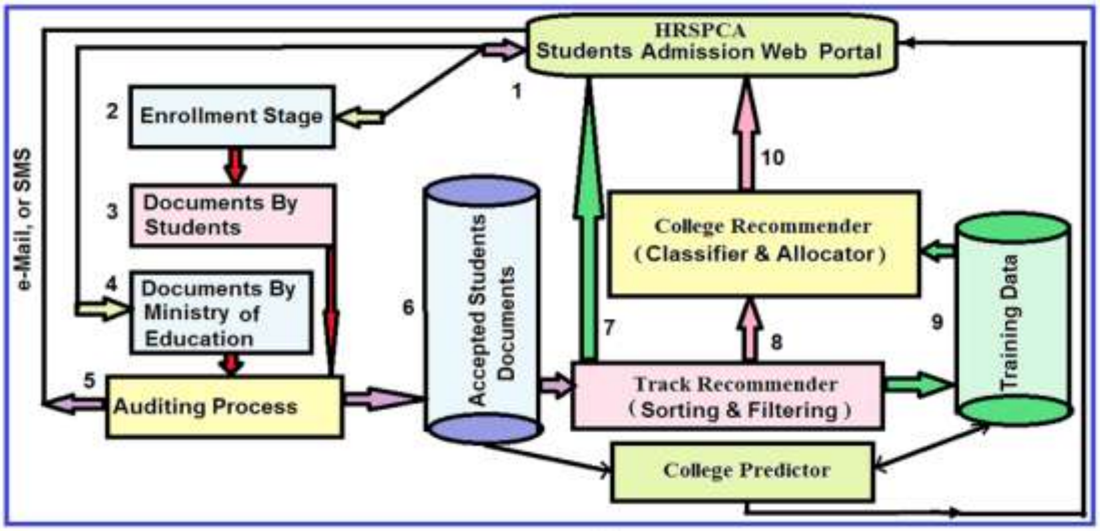


Figure 1. HRSPCA System Components.

Table 2. HRSPCA knowledge discovery rules.

Rules (A)	***Preparatory Year Admission Criteria***	***Rules (B)***	***General Standards College's Allocation Criteria***
R1.1	Demographic student information.	***R2.1***	Passing all preparatory year courses.
R1.2	Weighted degree- Scientific Track.	***R2.2***	Relative rate for college allocation.
R1.3	Weighted degree- Literary Track.	***R2.3***	Capacity of each college.
R1.4	Weighted degree- Affiliated Track.		
R1.5	Colleges with No preparatory year.		
Rules (C)	*Medical colleges: Medicine, Dentist , Pharmacy (Student should get B+ in the following courses).*	***Rules (D)***	*Faculty of Engineering (Student should get B in the following courses).*
R3.1	English	***R4.1***	English
R3.2	Biology	***R4.2***	Math
R3.3	Chemistry	***R4.3***	Physics
R3.4	Physics	***R4.4***	Statistics
R3.5	Interview		
Rules (E)	*Faculty of Computing and Information Technology (Student should get B in the following courses).*	***Rules (F)***	*Faculty of Applied Medical Sciences (Student should get B in the following courses).*
R5.1	English	***R6.1***	English
R5.2	Computer Skills	***R6.2***	Biology
		R6.3	Chemistry
		R6.4	Physics

Figure 2 HRSPCA Web-portal helps students to predict suitable track and college using the College Predictor (CP).

F. *College Predictor (CP)*

This software component is available as an optional to help students how to arrange their desired scientific tracks and colleges. It compares current student data with available previous historical data in the system and hence predicts the most suitable colleges for a student [24]. The CP predicts the most probable student colleges to attend, according to his GPA and his qualified exam marks in the preparatory year. After that the student is advised to follow up this information for arranging his desires, in priority, in the entry screen shown in Figure 2. This process help students and university admission department to judge about the trustability of the system as explained in section (V).

IV. HRSPCA System Knowledge Discovery Rules (KDR)

Two cascaded hybrid RS as explained above are used for carrying out the HRSPCA system students' admission processes. The cascaded hybrid recommenders achieve their tasks with high performance, as explained in [25, 26]. The proposed HRSPCA system KDR is implemented using 23 rules that are classified into six groups (A to F), as shown in Table 2. Rules group (A) illustrates preparatory year admission criteria; they include five criteria from *R1.1* to *R1.5*. Rules (B) illustrate general standards college's allocation criteria, and they include three criteria named *R2.1*, *R2.2*, and *R2.3*. Rules (C) show special based criteria rules for some highly demanded colleges, where student must get B+ mark. They include five criteria; from *R3.1* to *R3.5*. Some colleges require certain results for some qualified prerequisite courses. Medical colleges include Medicine, Dentist and Pharmacy. Rules (D) show Faculty of Engineering criteria, where a student has to get B mark. These rules include four criteria; from *R4.1 to R4.4*. Rules (E) show faculty of computing and information technology criteria, where a student must get B mark. These rules include two criteria *R5.1* and *R5.2*, respectively. Rules (F) show Faculty of Applied Medical Sciences criteria, where a student has to get B mark. These rules include four criteria, named from *R6.1 to R6.4*. Table 3 illustrates an example for computing the "Weighted Relative Rate", and its defined formula.

Table 3. An example for computing the "weighted relative rate".

Courses	Degree	Hours	Weight of Course
Math	82	3	246
Physics	75	3	225
English1	85	0	0
English2	70	3	210
Communication	92	3	276
Computer	95	3	285
Total		15	1242
Weighted Relative Rate = 1242 / 15 = 82.8			

*Weight of Course = Hours * Degree*
Weighted Relative Rate = Total Weight of Courses / Hours

A. *Track Recommender (TR) Rules*

The TR uses the rules group (A) shown in Table 2. Where, student's data are preprocessed and filtered due to applying the *four main rules: R1.1, R1.2, R1.3, and R1.4,* as shown in Figure 3a. The track recommender output allows students to be accepted; and clustered; in the following five tracks: 1- Scientific Track (SCT), 2- Literary Track (LCT), 3- Affiliated Track (ACT), 4- Colleges with no preparatory year (NPY), and 5- Rejected Track (RT). Figure 3b shows the pseudocode of the TR for the classification processes.

B. *College Recommender (CR) Rules*

Figure 4 illustrates the pseudocode used by the college recommender to perform the clustering processes. The CR uses the rules shown in Table 2. The standard criteria that govern college allocation are based on fulfilling the following four criteria: (1) Success of all preparatory year courses, *R2.1*, which are shown in Table 2 is satisfied. (2) Minimum score of college prerequisite courses, one of these rules *R3*, *R4*, *R5*, *or R6*, shown in Table 2, must be satisfied. (3) Weighted Relative Rate, *R2.2*, shown in Table 2, must be satisfied. And (4) College capacity, *R2.3*, shown in Table 2, must be valid.

C. *College Predictor (CP) Operations*

Figure 5 shows the flow chart illustrating how the CP works**.** Accepted qualified students has high probable admission chances, others students may has "probable possibility" in case of increasing allowed admission capacity, some students may have no chances for attending colleges such as computing, engineering, or medical.

The CP consists of three main stages. The first stage is collecting data from student's data base. The second stage is to predict suitable colleges according to students GPA and their college's selection desires. The final stage is displaying results on the student's portal web site.

R1.1 = govern the demographical data fields documented in the students personal data.
R1.2 = (High School Degree * 50%) + (Aptitude Degree* 30%) + (Achievement Degree * 20%).
R1.3 = (High School Degree * 60%) + (Aptitude Degree* 40%).
R1.4 = (High School Degree * 50%) + (Aptitude Degree * 30%) + (Achievement Degree * 20%).

Figure 3a. the Track Recommender defined criteria rules.

Track Recommender Decision Rules for Students Sorting Process using criteria shown in Table 2:
if R1.1 = TRUE and
if R1.2 = TRUE and Gender = female Then allocate student to SCTF female track, SCTF=SCTF + 1,
if R1.2 = TRUE and Gender = male, Then allocate student to SCTM male track, SCTM=SCM+1,
if R1.3 = TRUE and Gender = female Then allocate student to LCTF female track, LCTF=LCTF + 1,
if R1.3 = TRUE and Gender = male, Then allocate student to LCTM male track, LCTM=LCTM+1,
if R1.4 = TRUE and Gender = female Then allocate student to ACTF female track, ACTF = ACTF + 1
if R1.4 = TRUE and Gender = male, Then allocate student to ACTM male track, ACTM = ACTM +1,
if R1.5 = TRUE and Gender = female Then allocate student to NPYF female track, NPYF = NPYF + 1
if R1.5 = TRUE and Gender = male, Then allocate student to NPYM male track, NPYM = NPYM +1,
else allocate student to Reject Track, RT=RT+1,
total admission capacity for female TACF = SCTF+LCTF+ACTF+ NPYF,
total admission capacity for male TACM = SCTM+LCTM+ACTM+NPYM,
total admission capacity TAC = TACF+TACM,
if TAC ≥ TUC (University Total Capacity) Then STOP, else continue

Figure 3b. Pseudocode of the Track Recommender classification processes.

College Recommender Decision Rules for Students Clustering Process, using criteria shown in Table2:
if R2.1 and R2.2 and R2.3 = TRUE and
if R3.1 and R3.2 and R3.3 and R3.4 and R3.5 = TRUE
then allocate student to Medical College, MC = MC +1,
if R4.1 and R4.2 and R4.3 and R4.4 = TRUE
then allocate student to Engineering College, EC = EC +1,
if R5.1 and R5.2 = TRUE
then allocate student to Computing College, CC = CC +1,
if R6.1 and R6.2 and R6.3 and R4.4 = TRUE
then allocate student to Applied Medical College, AMC = AMC +1,
else allocate student to Normal Colleges NC = NC +1,
total capacity TC = MC + EC + CC + AMC + NC,
if TC ≥ CCAP (Colleges Capacity) Then STOP, else continue

Figure 4. Pseudocode of the College Recommender for clustering processes.

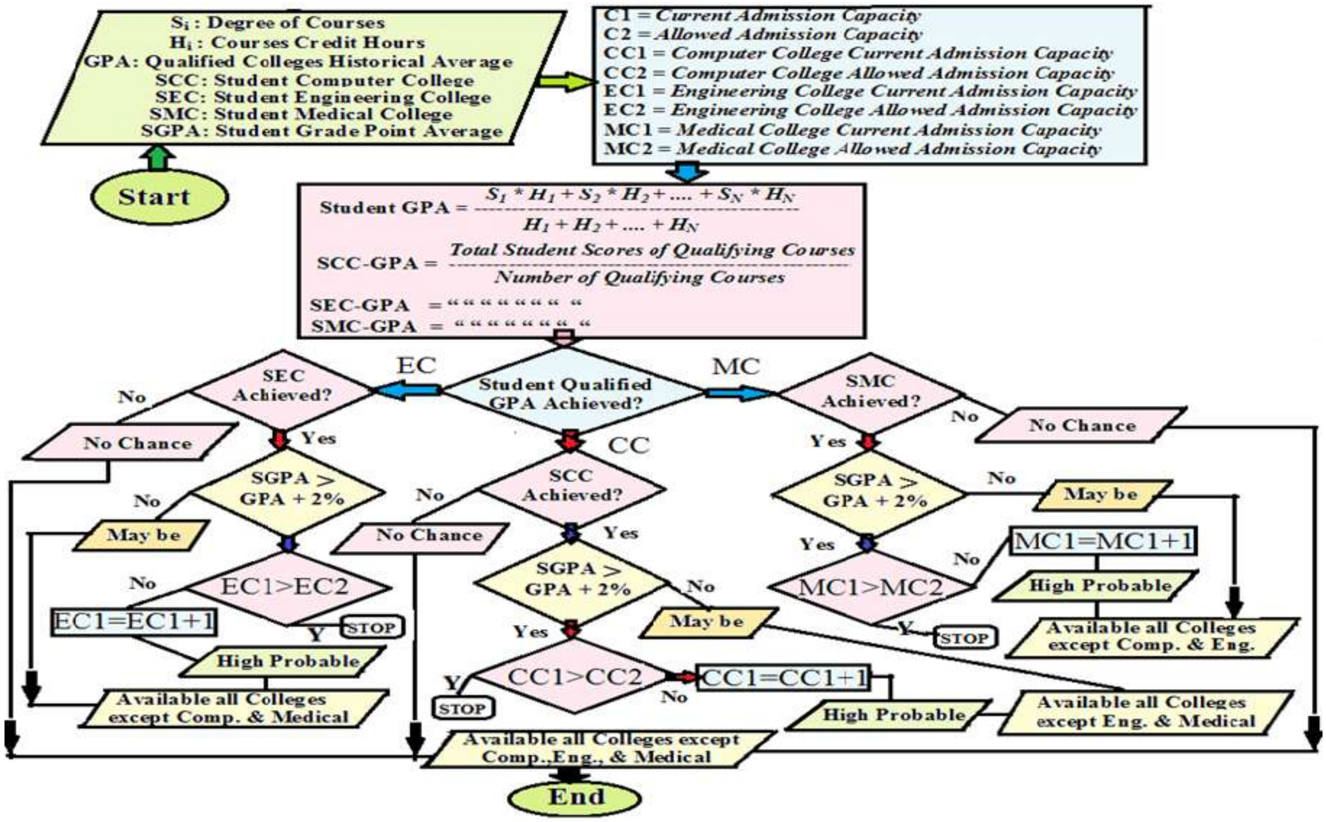


Figure 5. Flowchart to illustrate how the College Predictor works.

V. System Results

A prototype system was implemented using live data available at KAU database resources. The HRSPCA Web-Portal was accessed by about 66 thousands male and female students during year 2012. The recommender admitted about 16 thousands students who achieved the standard university and colleges criteria. Others students who did not pass the standards are rejected, and may be tried again for other chances. The following sections illustrate some outputs of the practical experimental results in details.

A. Track Recommender Outputs

The TR applies university criteria and rules explained in section (IV). It carries out the pseudocode explained in Figure 3b. While, Figure 6 illustrates the output-screen indicating student's marks, according to computed weights during recommender sorting processes. Figure 7 shows the output of students recommended to enter scientific track, students recommended to enter literary track, and students recommended to enter affiliated track for both male and female.

Results show that the scientific college track for male (*SCTM*) achieves the highest admission desires, where it reaches 7078 students. While, the literary colleges track for female gets the second priority, it reaches to 4720 students.

The minimum number of the male students who did not achieve requirements criteria for preparatory year admission (*NPYLM*: No Preparatory Year Literary Male) are 100 students

Other students are allocated colleges tracks as follows:

Affiliated College Track for Female *(ACTF) = 2000,*

Affiliated College Track for Male *(ACTM) = 1500,*

Literary College Track for Male *(LCTM) = 600,*

Scientific College Track for Female *(SCTF) = 2909, and*

No Preparatory Year Scientific Male *(NPYSM) = 500,*

B. College Recommender Outputs

The CR applies university criteria and rules explained in section (IV). It carries out the pseudocode explained in Figure 4. Then, Figure 6 illustrates the output-screen indicating student's marks, according to computed weights during recommender sorting processes. It displays information related to three colleges include: Medicine College, Engineering College, and Computing and Information Technology College, with their courses and students mark. For each of these colleges, the screen displays: student nationality, minimum weighted allowed marks, weighted private marks, proposed accepted number of students (college capacity), the accepted number of students, and the remaining numbers.

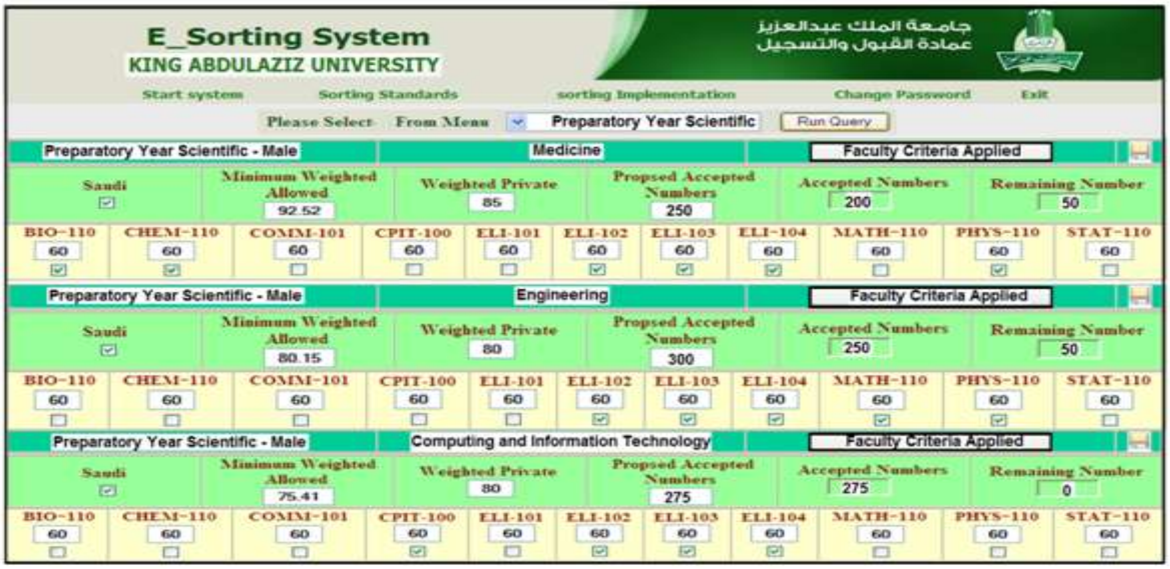


Figure 6. Output-screen indicates student's marks, and computed weights during recommender sorting processes.

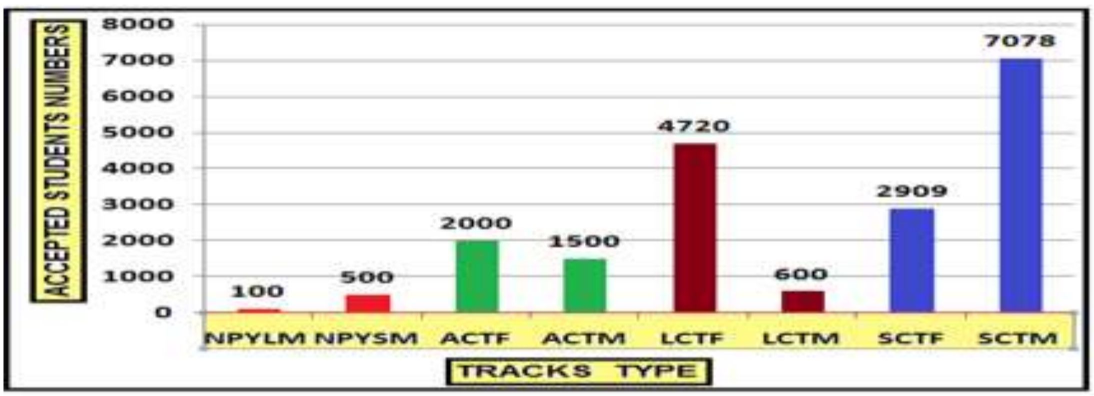


Figure 7. Track Recommender outputs based on students accepted data.

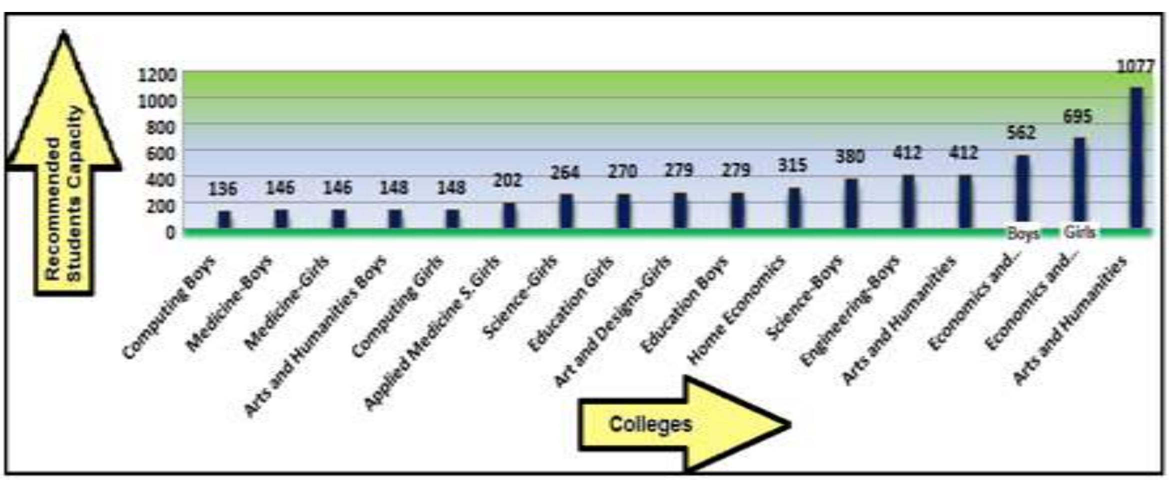


Figure 8. College Recommender outputs based on students accepted data.

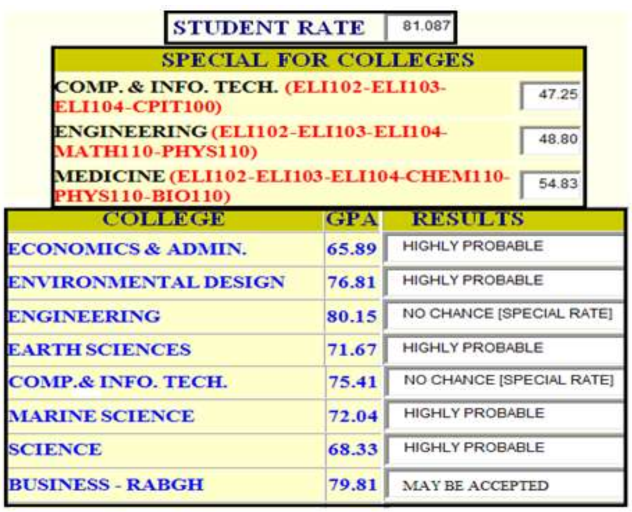
Figure 8 shows the output students recommended to be allocated to all available university colleges, for both male and female. Results show that the college of Arts and Humanities has the highest priority, it gets 1077 students. While, computing college gets 136 male students, and Medicine College of male gets 146 students.

C. System Trustability (ST)

The ST is achieved when students compare their admitted colleges by the HRSPCA system, with the most probable colleges they got from the College Predictor (CP). The positive increased numbers of student's answers are a good measure for insuring that the proposed HRSPCA system is fair and trustable. Figure 9 shows sample output results of the College Predictor and colleges that the student can be admitted.

Results show, for example, that the student who get *GPA=65.89* is highly probable to attend the Economic and Administration College. While, the student who gets *GPA=80.15* has no chance to attend the Engineering College, since he did not achieve the required rate for that college.

The proposed recommender system is adaptive, since the admission rules and the criteria used can be tuned up with the KAU admission decision makers; for example; by suggesting attendance rate to increase or decrease students in a specific college according to the market needs and colleges capacities available.



STUDENT RATE 81.087

SPECIAL FOR COLLEGES	
COMP. & INFO. TECH. (ELI102-ELI103-ELI104-CPIT100)	47.25
ENGINEERING (ELI102-ELI103-ELI104-MATH110-PHYS110)	48.80
MEDICINE (ELI102-ELI103-ELI104-CHEM110-PHYS110-BIO110)	54.83

COLLEGE	GPA	RESULTS
ECONOMICS & ADMIN.	65.89	HIGHLY PROBABLE
ENVIRONMENTAL DESIGN	76.81	HIGHLY PROBABLE
ENGINEERING	80.15	NO CHANCE [SPECIAL RATE]
EARTH SCIENCES	71.67	HIGHLY PROBABLE
COMP.& INFO. TECH.	75.41	NO CHANCE [SPECIAL RATE]
MARINE SCIENCE	72.04	HIGHLY PROBABLE
SCIENCE	68.33	HIGHLY PROBABLE
BUSINESS - RABGH	79.81	MAY BE ACCEPTED

Figure 9. Sample output results of the College Predictor.

VI. CONCLUSIONS

This paper proposed a novel design for college admission hybrid recommender system (HRSPCA). It consists of two cascading hybrid recommenders working together with the help of a college predictor. The HRSPCA system allocates students onto suitable educational tracks as well as suitable colleges. The system provides recommendations about which university colleges a student should be admitted to, taking into consideration not only student's scores but also other university qualified criteria into account. The HRSPCA system was validated using real students data. System experiments showed that the HRSPCA system performs substantially high performance due to allocating admission tasks between two cascading recommenders. The HRSPCA was based on knowledge discovery rules; hence improved recommendation output was achieved fairly and accurately. Also, the proposed system improved admission enrollment quality, since it uses auditing process component for performing student's data verification. The HRSPCA trustability is achieved, since student's responses positively increasing as long as they allocated to the most suitable college which satisfies their desire. And this is performed with the help of the college predictor. Although, real students' data was used from KAU, the design of the HRPCA system is generic and can be applicable to other Saudi Arabian Universities.

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