International Forum of Educational Technology & Society

How Students can Effectively Choose the Right Courses

Author(s): Hui-Tzu Chang, Chia-Yu Lin, Li-Chun Wang and Fang-Ching Tseng

Source: *Educational Technology & Society* , January 2022, Vol. 25, No. 1 (January 2022), pp. 61-74

Published by: International Forum of Educational Technology & Society

Stable URL: https://www.jstor.org/stable/10.2307/48647030

**REFERENCES**
Linked references are available on JSTOR for this article:
https://www.jstor.org/stable/10.2307/48647030?seq=1&cid=pdf-reference#references_tab_contents
You may need to log in to JSTOR to access the linked references.

JSTOR is a not-for-profit service that helps scholars, researchers, and students discover, use, and build upon a wide range of content in a trusted digital archive. We use information technology and tools to increase productivity and facilitate new forms of scholarship. For more information about JSTOR, please contact support@jstor.org.

Your use of the JSTOR archive indicates your acceptance of the Terms & Conditions of Use, available at https://about.jstor.org/terms

*International Forum of Educational Technology & Society* is collaborating with JSTOR to digitize, preserve and extend access to *Educational Technology & Society*

JSTOR

This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

Chang, H.-T., Lin, C.-Y., Wang, L.-W., & Tseng, F.-C. (2022). How Students can Effectively Choose the Right Courses: Building a Recommendation System to Assist Students in Choosing Courses Adaptively. *Educational Technology & Society*, *25* (1), 61-74.

# How Students can Effectively Choose the Right Courses: Building a Recommendation System to Assist Students in Choosing Courses Adaptively

**Hui-Tzu Chang[1], Chia-Yu Lin[2*], Li-Chun Wang[3] and Fang-Ching Tseng[4]**
[1]Center for Institutional Research and Data Analytics, National Yang Ming Chiao Tung University, Hsinchu // [2]Department of Computer Science and Engineering, Yuan Ze University, Taoyuan // [3]Department of Electrical and Computer Engineering, National Yang Ming Chiao Tung University, Hsinchu // [4]Electrical Engineering and Computer Science Undergraduate Honors Program, National Yang Ming Chiao Tung University, Hsinchu // simple@nycu.edu.tw // sallylin0121@gmail.com // wang@nycu.edu.tw // claire.eecs07@nctu.edu.tw
[*]Corresponding author

(Submitted March 3, 2021; Revised June 21, 2021; Accepted August 1, 2021)

**ABSTRACT:** In this study, we built a personalized hybrid course recommendation system (PHCRS) that considers students' interests, abilities and career development. To meet students' individual needs, we adopted the five most widely used algorithms, including content-based filtering, popularity-based methods, item-based collaborative filtering, user-based collaborative filtering, and score-based methods, to build a PHCRS. First, we collected course syllabi and labeled each course (e.g., knowledge/skills taught, basic/advanced level). Next, we used course labels and students' past course selections and grades to train five recommendation models. To evaluate the accuracy of the system, we performed experiments with students in the Department of Electrical and Computer Engineering, which provides 1794 courses for 925 students and utilizes the receiver operating characteristic curve (ROC) and normalized discounted cumulative gain (NDCG) as metrics. The results showed that our proposed system can achieve accuracies of 80% for ROC and 90% for NDCG. We invited 46 participants to test our system and complete a questionnaire. Overall, 60 to 70% of participants were interested in the recommended courses, while the course recommendation lists produced by content-based filtering were in line with 67.40% of students' actual course preferences. This study also found that students were more interested in courses at the top of the recommendation lists, and more students were autonomously motivated than held extrinsic informational motivation across the five recommendation methods. These findings highlighted that the proposed course recommendation system can help students choose the courses that interest them most.

**Keywords:** Course recommendation, Course selection, Learning aids, Personalized learning

## 1. Introduction

Studying at a university involves taking a wide variety of optional courses, especially for students in larger departments, and students have to carefully consider which of the numerous optional courses would be best for them to take. Course options are important for fulfilling degree requirements and determining future careers (Farzan & Brusilovsky, 2006; Kurniadi et al., 2019). Given the large number of optional courses, students may need to dedicate a great deal of time to researching information for each course to select the best options for their situation. Since students do not always have enough information, it can be challenging for them to make the right decision (Chang et al., 2020; Wang et al., 2020); students are often influenced by the opinions of other students. Under these conditions, it is important to collect student and course information and then perform further analysis to determine which courses might meet each student's personal needs. One solution would be through a course recommendation system that helps students make a good decision (Iatrellis et al., 2017; Sawarkar et al., 2018).

Course recommendation systems use different techniques to collect students' past educational data and then automatically provide course match predictions and recommendations by analyzing the data (Aguilar et al., 2017; Romero & Ventura, 2013). The collaborative filtering method (Chang et al., 2020; Wang et al., 2020), demographic-based filtering method (Dwivedi & Roshni VS, 2017; Zhang et al., 2015), content-based filtering method (Apaza et al., 2014; Esteban et al., 2020), and knowledge-based filtering method (Aher & Lobo, 2013; Kurniadi et al., 2019) are common methods used in the existing recommendation systems, although no existing course recommendation system uses more than one of these methods. Since each student has different motivations and different needs from optional courses, different recommendation methods should be combined into a single recommendation system. In addition, all recommendation methods have positive and negative aspects. To mitigate any disadvantages, many systems choose to use hybrid recommendation methods (Çano & Morisio, 2017; Zhang et al., 2015). Therefore, in this paper, we propose a personalized hybrid course



ISSN 1436-4522 (online) and 1176-3647 (print). This article of the journal of *Educational Technology & Society* is available under Creative Commons CC-BY-NC-ND 3.0 license (https://creativecommons.org/licenses/by-nc-nd/3.0/). For further queries, please contact Journal Editors at ets.editors@gmail.com.

This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

recommendation system (PHCRS) that integrates five recommendation methods for formal offline courses to consider the different learning needs of students.

The goal of the PHCRS is to provide information based on students' preferences; however, current systems mostly focus on how to improve students' grades (Esteban et al., 2020) and help students achieve their long-term career goals (Farzan & Brusilovsky, 2006). These results-oriented PHCRSs do not consider factors that affect students' course-selection process. If a system aims to provide personal recommendations, it is important to fully understand the factors affecting the reasoning behind optional course selection (Han et al., 2016) and then provide many recommendation methods for the students to choose from. Thus, the main purpose of this study is to construct a PHCRS that takes students' interests, abilities, and careers into consideration and then provide a course recommendation list based on their preferred fields to satisfy the need to select optional courses. Our study also evaluated the accuracy of the recommendation model and then empirically assessed whether students were interested in the course recommendation list provided by numerous recommendation methods and the factors affecting that interest. We will eventually expand and modify the system functionality to fit the needs of the students.

## 2. Literature review

### 2.1. Students choosing courses

Course selection is regarded as an important aspect in student's experiences of university. Students need to make a series of course selection decisions before the semester starts and these decisions have a decisive effect on their future life, education, and employment opportunities (Babad & Tayeb, 2003). The course decision-making process is affected by many factors, and there is usually no perfect combination of courses, as some factors may lead to conflicting demands (Lang, 2010). The resulting issues may interfere with students' judgment, as students commonly use their instincts or information provided by others to choose their courses (Babad et al., 2004), and these decisions affect their learning experiences. Choosing a major is the most important decision when entering university (Begs et al., 2008). Perera and Pratheesh (2018) found that major selection is affected mostly by career factors, and academic quality, personality, and ability also affect this decision. This results in students not always choosing majors they are interested in. Zare-ee and Shekarey (2010) also found that family, social, and personal factors, such as parental educational level, household income, media use, GPA, and personal interests, may force students to change their minds.

After students have decided their majors, they choose the courses they will take each semester in accordance with school regulations. Babad et al. (2004) proposed a theory of students' course selection as a decision-making process using the dimensions of learning values, learning styles, and course difficulty. Babad et al. (2004) found that the importance of academic intelligence and teachers' lecture style are key components affecting students' course selection. Babad (2001) also found that students' first course selection decisions are based mostly on the course's content, lecture quality and potential value for future careers. Conversely, the last course selection decisions are usually based on course difficulty (the easier the better), and a comprehensive course selection strategy may reduce risk in course selection. On the other hand, determining course selection motivations is a more complicated process and includes both autonomous motivation and extrinsic informational motivation (Lee & Sun, 2010). The former is a spontaneous behavior generated by the self-motivated interest, curiousness or career planning of an individual, and the latter is a behavior influenced by the external environment, such as the desire for certain grades, rewards or ratings. Students who select courses based on their autonomous motivation tend to be more devoted to studying than those who select courses based on extrinsic informational motivation (Lee & Sun, 2010). Thus, it is clear that when students select courses, major, course importance and difficulty, and course selection motivations are their main concerns.

### 2.2. Recommendation system

Recommendation systems originated in e-commerce recommend products based on user preferences (Burke, 2002). These have become a fundamental part of e-commerce, requiring massive information collection, analysis, and prediction. Recommendation systems help users choose the most appropriate products on the basis of their demands and preferences (Resnick & Varian, 1997; Xiao et al., 2018). Notable examples are the systems used by Netflix, Google News, and Amazon (Han et al., 2016). These enterprises use recommendation systems to discover the latent relationships between their items and users and to exploit potential customer demands. They



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

have successfully connected information with sales and helped customers find items they are interested in while also raising the total revenue of the enterprise.

Several recommendation techniques based on different user needs are employed in recommendation systems. (1) Collaborative filtering: This analyzes the similarity between users and items to predict what content users may be interested in (using population characteristics or search history) and recommend it to the user (Burke, 2002; Salehudin et al., 2019). (2) Demographics-based recommendation: This utilizes users' basic information to identify user similarities and then recommends items that have been recommended to users with similar characteristics, such as age and gender (Aguilar et al., 2017; Burke, 2002). (3) Content-based filtering: This system matches item characteristics and user attributes and then searches for items similar to those users expressed previous interest in. This is known as item-to-item similarity (Schafer et al., 1999). (4) Utility-based filtering: These recommendations are based on the match between the demands of a user and available items (Burke, 2002). (5) Knowledge-based filtering: This is an inferencing technique that is based not on user demands or preferences but on differences in functional knowledge. The development of this system requires catalog knowledge, functional knowledge and user knowledge (Aguilar et al., 2017; Kurniadi et al., 2019).

### 2.3. Recommendation systems in education

Course options in universities are highly related to career development. In the institutional education process, college is an important transition period for students. Seventy-five percent of college students have not decided what career they want to pursue in the future or even what they want to gain expertise in. Fifty to 75% of students change their major at least once during their time in university (Cuseo, 2003; Gordon, 2007). The main challenge in developing a suitable recommendation system for selected courses is that it is hard to integrate data from different sources. It is also difficult to find effective, useful and precise information online about students' study plans (Obeid et al., 2018). Many students select optional courses without seeking help or advice from outside educational services, which may lead to their skills, interests, and career development plans not aligning with the courses they select, subsequently leading to a decreasing retention rate (Kongsakun et al., 2010). Archer and Cooper (1998) pointed out that university-provided advisory services are important for student success. These services help students determine a study plan, provide career guidance, assist with interpersonal relationship management, and provide an understanding of the physical and mental status of students (Urata & Takano, 2003). Most higher education institutes lack sufficient human resources and talent (Kongsakun et al., 2010). Some schools have asked staff to take on more responsibilities, but they usually do not have enough time to provide complete advisory services, nor do they have enough tools to help needy students (Salehudin et al, 2019). To solve this problem, many schools have tried to utilize recommendation systems to provide support for students' decision making (Aher & Lobo, 2013; Bendakir & Aïmeur, 2006; Romero & Ventura, 2013).

As technology progresses, learners will contribute more to data collection through learning platforms by browsing courses, interacting with the interface, and requesting records. The large amount of data collected contains information on the implicit intentions, interests, and educational performance of students. If the recommendation system can utilize these data to guide students toward suitable learning opportunities, it can help meet students' learning needs (Aguilar et al., 2017). In recent years, course recommendation systems have been developed. A course recommendation system analyzes the selected data and then combines it with past student data to automatically predict preferences and provide recommendations through education data analysis (Aguilar et al., 2017).Using recommendation systems to guide students in their educational decisions has a significantly positive effect (Kurniadi et al., 2019).

Xu (2016) proposed a course sequence recommendation system to reduce students' time to graduation and maximize their performance. This system analyzed the prerequisite dependency among courses to adaptively recommend online learning course sequences to students. Hou et al. (2018) designed a contextual recommendation system to solve heterogeneity issues in large-scale user groups and sequencing issues regarding online learning courses. In the paper (Mondal et al., 2020), the authors combined K-means clustering and collaborative filtering techniques to propose an online course recommendation system based on grades. These studies chose certain online learning university courses such as massive open online courses (MOOCs) for which to implement recommendation systems since online learning is much easier to collect data about than formal higher education courses. However, formal offline courses are more important than online learning courses to students. The variety of formal offline courses offered by universities and the range of skills they teach are wider and more complete than those of online courses. Thus, students have a greater need for recommendation systems when choosing formal offline courses. Yao (2017) developed an intelligent personalized context-aware recommendation (PCAR) learning system to recommend suitable learning materials from various learning environments. Huang et al. (2019) designed a cross-user-domain collaborative filtering algorithm to recommend



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

optional courses for college students by accurately predicting the interest they would have in optional courses. Pardos et al. (2020) built course2vec models based on course catalog descriptions and enrollment histories to prepare an appropriate recommendation system for the university context. Ultimately, all of these works implemented recommendation systems for formal offline courses.

The above works show that common methods for developing the recommendation system are as follows:

- Collaborative filtering. This includes both item-based and user-based filtering methods. Item-based filtering uses students' grades in other subjects to recommend courses (Chang et al., 2020; Dwivedi & Roshni VS, 2017; Wang et al., 2020). User-based filtering matches a student's course selection route with alumni who shared a similar route and recommends the course list of the alumni to the student (Bendakir & Aimeur, 2006; Perugini et al., 2004; Zhang et al., 2015).
- Demographic-based filtering. This method draws upon population characteristics to classify recommendation demands of different groups. It recommends courses that a group may be interested in on the basis of the age, gender or intended or previous profession of the students. This method is mostly used in MOOC open courses (Dwivedi & Roshni VS, 2017; Zhang et al., 2015) and lifelong learning courses (Han et al., 2016; Tuckman, 1999).
- Content-based filtering. This method is based on characteristics listed in course syllabi, such as the subject field and lecture content. The system is able to provide a course list to a student that is similar to his/her past course list (Apaza et al., 2014; Esteban et al., 2020; Herlocker et al., 2000).
- Knowledge-based filtering. This may use students' past grades to determine courses for which they might receive similar results. Alternatively, it may analyze the students' overall GPA and then use the recommendation results to predict students' future grades or likelihood of graduation. Based on the results, the system then provides a list of the most suitable courses to students (Aher & Lobo, 2013; Kurniadi et al., 2019).

However, each of the currently existing formal offline course recommendation systems uses only one of these recommendation methods. A robust recommendation system should combine different recommendation methods to provide diverse suggestions since each student has different motivations and preferences when choosing courses. Additionally, all recommendation methods have both positive and negative aspects. To mitigate any disadvantages, many systems use hybrid recommendation methods (Çano & Morisio, 2017; Zhang et al., 2015). Of all methods available, the collaborative filtering & content-based filtering hybrid recommendation method is the most common (Esteban et al., 2020). It overcomes the limitations of both collaborative filtering and content-based filtering methods and increases predictability while also decreasing the degree of sparsity and loss of information. Therefore, we propose a PHCRS including five recommendation methods for formal offline courses to consider the different learning needs of students.

Based on the literature mentioned above, students' final course decisions are affected by their major and motivation as well as school requirements. Esteban et al. (2020) suggest that students' personal characteristics, such as major, learning goals, and desires, should be taken into consideration when developing a course recommendation system in order to provide tailored course recommendations to students. This research proposes four hypotheses to verify the effectiveness of the PHCRS:

- Hypothesis 1: Students' degree of interest in the courses recommended by the five recommendation methods will differ among the undeclared field and three optional fields.
- Hypothesis 2: Students' degree of interest in the courses recommended will differ according to the order of the recommended courses.
- Hypothesis 3: The degree of interest in the courses recommended to a student will be affected by the student's internal and external motivations for taking a course.
- Hypothesis 4: The degree of interest a student has in the recommended courses will vary with the recommendation methods used and their degree of suitability for the student.

## 3. Development of a system for recommending adaptive courses

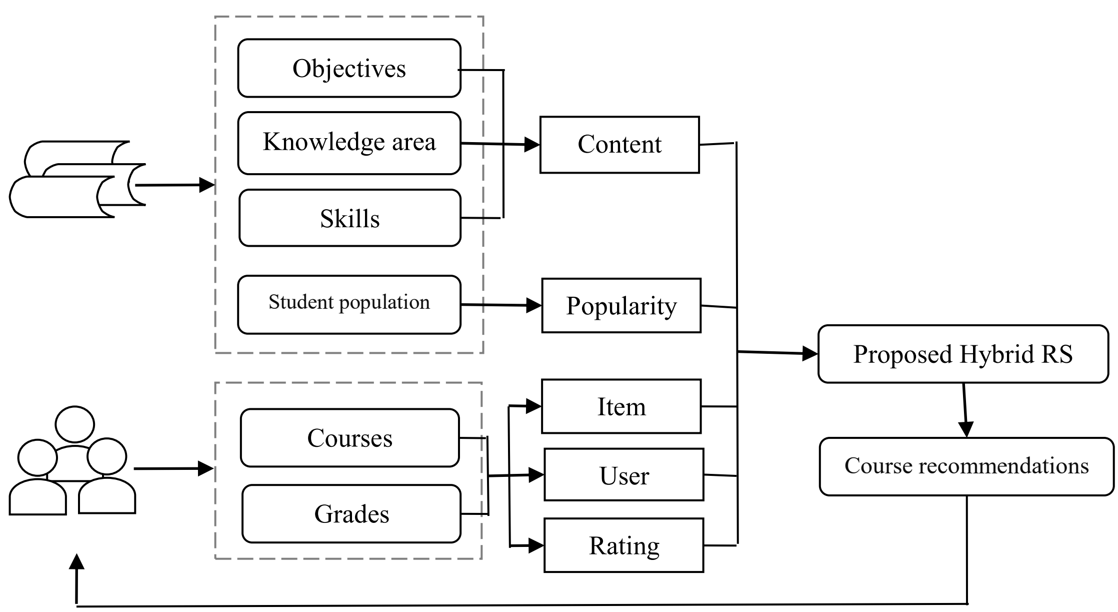
This research proposes a PHCRS, as shown in Figure 1. We use courses and student data from the Big Data Research Center in National Yang Ming Chiao Tung University (NYCU) to train the recommendation system. These data contain information on 386 different courses from the Department of Electrical and Computer Engineering, and a total of 2985 courses were provided from the fall 2011 semester to the fall 2020 semester. For student information, a total of 1824 students from the Department of Electrical and Computer Engineering who



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

were enrolled between 2011 and 2020 were selected. To prepare the training data, the researchers collected the course outlines and interviewed the teachers via telephone. The two researchers discussed and agreed upon the labeling rules and then compared the similarities and differences in the labeling results after making the labels. In cases of disagreement, the scorers discussed the issue until a consensus was reached. The interrater reliability fell between .7 and .8. The attributes of each course was labeled as follows. (1) Course objectives: This label indicates what the course mainly teaches students, such as signal processing or communication systems. There are a total of 44 possible labels. (2) Knowledge areas: This label is based on the theories, methods or empirical theories from the field of electrical engineering that are taught to students, such as information and communication, system-on-chip, and 13 other areas. (3) Skills: This label is based on the relevant technologies, resources or tools used in each course, such as Python or MOSFET. There are a total of 203 possible labels. After the data preparation, five recommendation methods were implemented in HPCRS for students with different learning needs as follows:

*Figure 1*. PHCRS




### 3.1. Recommendation model construction

- Content-based Filtering: Content-based filtering recommends similar courses based on the characteristics of students' past courses (Esteban et al., 2020). In the first step, the feature vectors of the courses is extracted. The course feature vector indicates which domains the courses belong to and which objectives the courses contain. To calculate the feature vectors of *student x* for *course i,* the feature vector of *course i* is multiplied by the score of the *student x* on *course i*. We add up all the feature vectors of *student x* on each course and define this value as the feature vector of student *x*. To recommend *course j* to *student x*, we use the feature vector of student *x* and the feature vector of *course j* to calculate cosine value ($\cos\theta = \frac{\vec{i}\cdot\vec{j}}{||\vec{i}||\cdot||\vec{j}||}$) as the similarity. If the similarity is close to 1, *student x* is more likely to like *course j*.
- Popularity-based Method: Popularity-based method counts the number of students in each course, and recommend the course with the largest number of students. (Burke, 2002).
- Item-based Collaborative Filtering: Item-based collaborative filtering calculates the similarity score between courses and recommend similar courses (Sarwar et al., 2001). We find the students who have taken these two courses and calculate the difference of their scores in the two courses. The smaller the difference, the higher the similarity. The similarity is represented as $w_{i,j}$ and is shown in (1), where A are the set of students who have taken *course i* and *course j*. Assuming *student x* has taken *course i*, if PHCRS want to recommend *course k* to *student x*, the predicted score is calculated by formula (2). The numerator is equal to the product of $w_{i,k}$ and the student's grade in *course i*. The denominator is the summation of the similarity between *course i* and *course k*.

$$\text{Similarity between } course\ i \text{ and } course\ j\ (w_{i,j}) = \frac{1}{1+\sqrt{\sum_{A\epsilon M(i)\cap M(j)}(grade(A,i)-grade(A,j))^2}} \quad (1)$$



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

$$\text{The prediction score of } \textit{course } k \text{ for } \textit{student } x = \frac{\sum_{w_{i,k}>0} grade(x,i) * w_{i,k}}{\sum_{w_{i,k}>0} w_{i,k}} \quad (2)$$

- User-based Collaborative Filtering: User-based collaborative filtering utilizes students' past course data to calculate the similarity between students and recommend courses taken by similar students (Han et al., 2016). To calculate the similarity between two students, we have to find out the courses the students have both taken. We utilize the scores of two students in the courses to calculate the similarity. The similarity of *student x* and *student y* is represented as weighted value ($w_{x,y}$) and is shown in (3), where *N(x)* are the courses that *student x* has taken, and *N(y)* are the courses that *student y* has taken. If the scores are closer, the similarity of two students is higher. If PHCRS want to recommend *course k* to *student y*, the similarity of *student x* and *student y* is multiplied by the scores of *student x* on *course k*. The average of weighted value is the predicted score, as shown in (4).

$$\text{Similarity of } \textit{student } x \text{ and } \textit{student } y\ (w_{x,y}) = \frac{1}{1+\sqrt{\sum_{i\in N(x)\cap N(y)} (grade(x,i) - grade(y,i))^2}} \quad (3)$$

$$\text{The predicted score for } \textit{student } y \text{ on } \textit{course } k = \frac{\sum_{w_{x,y}>0.2} grade(y,k) * w_{x,y}}{\sum_{w_{x,y}>0.2} w_{x,y}} \quad (4)$$

- Score-based Method: Score-based method calculates the total average score of the class for each course and recommend the course with the highest average score (Sawarkar et al., 2018).

### 3.2. Evaluation of the recommendation results

This study uses the receiver operating characteristic curve (ROC) and NDCG to evaluate the recommendation results.

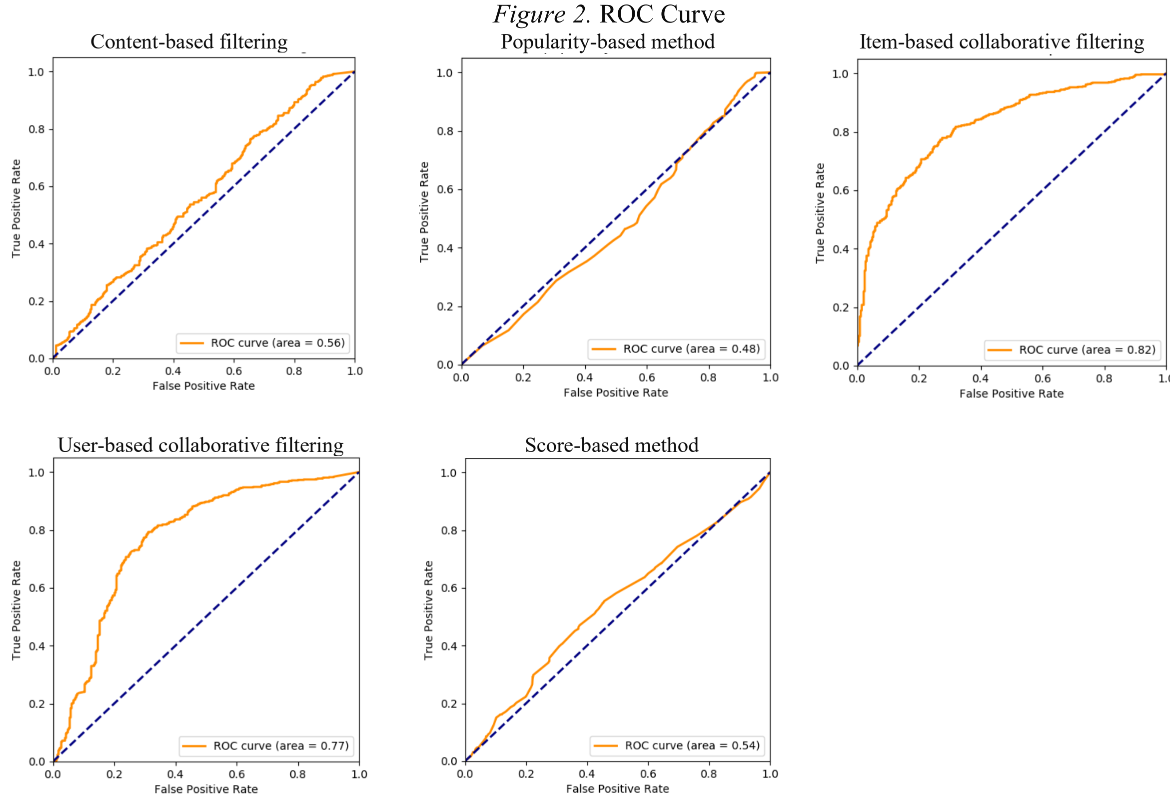
#### *3.2.1. ROC*

ROC is a coordinate diagram analysis tool used to select the best signal detection model and is also often being used for evaluation of recommendation systems (Zweig & Campbell, 1993). We use the grades of students as the evaluation indicator. For each course, we calculate the average score of students who have taken the course. If the grade of a student is higher than the average score, we say that the course is suitable for the student and call it "true value." For each student and each course, the recommendation system predicts a score for the student. For all test data, we will get many predicted scores. We take every predicted score as the threshold to draw ROC. If the predicted score of the course for the student is higher than the threshold, it would be judged as positive. Otherwise, it is negative. Therefore, we can compare the ground truth and the predicated result to get true positive (TP), false positive (FP), true negative (TN), and false negative (FN). The true positive rate (TPR) is TP/(TP+FN). The false positive rate (FPR) is FP/(FP+TN). The ROC curve takes the false positives rate (FPR) as the x-coordinate and true positive rate (TPR) as the y-coordinate. If the area under the ROC curve is above 0.9, the system is highly accurate; whereas if it is between 0.7 and 0.9, this means medium accuracy. If it is between 0.5 and 0.7, this will mean low accuracy and finally poor accuracy can be identified with results below 0.5. This study uses ROC to evaluate the five recommended methods with the best coefficients as item-based collaborative filtering = .82, followed by user-nased collaborative filtering = .77, content-based filtering = .56, score-based method = .54, and popularity-based method = .48 (see Figure 2).



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

*Figure 2.* ROC Curve




### *3.2.2. NDCG*

This study uses NDCG to evaluate the five recommendation methods. For k courses, we sort the courses by the recommendation scores and calculate discounted cumulative gain (DCG). The DCG is shown in (5), where $k$ represents the number of courses the system is recommended and $rel_i$ is gain for each recommendation course. In the evaluation, when the recommendation course overlaps the real record, we set the gain $rel_i$ to be 1; otherwise be 0. The ideal course order based on the predicted score is used to calculate ideal discounted cumulative gain (IDCG), as shown in (6). We can use DCG and IDCG to calculate NDCG, as shown in (7).

$$DCG_k = \sum_{i=1}^{k} \frac{2^{rel_i - 1}}{log_2(i+1)} \quad (5)$$

$$IDCG_k = \sum_{i=1}^{|rel_k|} \frac{2^{rel_i - 1}}{log_2(i+1)} \quad (6)$$

$$NDCG_k = \frac{DCG_k}{IDCG_k} \quad (7)$$

The NDCG of five recommendation methods are: user-based collaborative filtering = .96, popularity-based method = .94, score-based method = .94, content-based filtering = .89, and item-based collaborative filtering = .89.

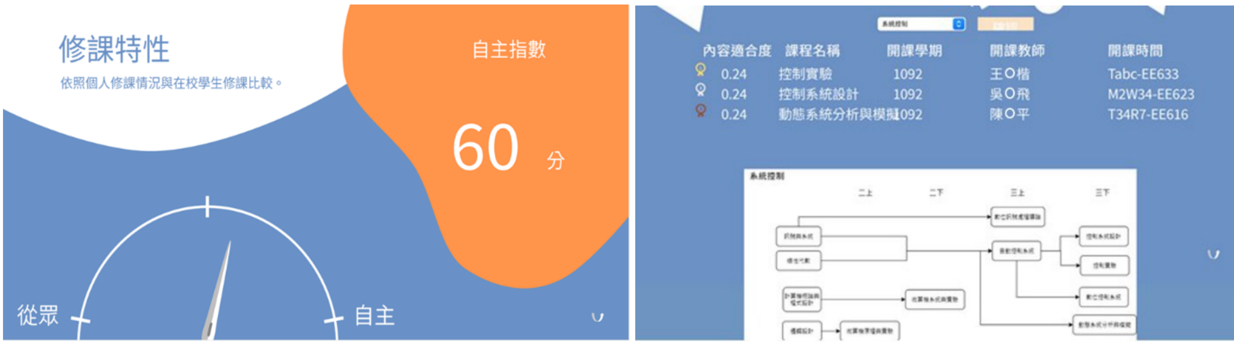
### 3.3. Building a recommendation system website

Our course recommendation website was built using WordPress (WordPress.com, 2021) and is hosted on Xammp (Apache Friends. 2021). The website is embedded in the NYCU portal so that both student and course information data can be updated before the course selection period in each semester. To prevent data overload and to enhance the performance of the website, we imported the data into the website database after it was computed and simplified. The two main features of our website include personal learning analysis and course recommendation services (see Figure 3). The personal learning analysis helps students understand their autonomy index and conformity index in course selection, while the course recommendation feature allows them to search for suitable courses by entering their preferences into the recommendation system. The course recommendation website then indicates the suitability of the courses for the student as well as the course name, lecture time and lecturer name.



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

*Figure 3*. Screenshot of the course recommendation service system




## 4. Research design

This study used a survey method to verify the accuracy of the recommendation system. The survey used nonprobability sampling to invite undergraduates from the Department of Electrical and Computer Engineering, NYCU, who volunteered as participants. As the freshmen's course selection and grade data were not yet completed, they were excluded to avoid interference in the research results. A total of 46 students were selected (15 sophomores, 13 juniors, and 18 seniors; 35 males and 11 females). In this research, recruitment posters were sent out by the Department of Electrical and Computer Engineering. After the students signed up, the researchers explained the research process and parameters via phone or mail. To collect data, students were required to log in to the course recommendation system. After reading the description of each recommendation method, students were asked to evaluate whether the courses recommended by each method were of interest and to provide their reasoning. Students could see the overall results for all knowledge fields, and they could choose up to three fields that most interested them. Finally, they were asked to fill in their personal information and offer suggestions for the system.

This study used a recommendation effect scale defined by our research group. When students browsed the course recommendation list, they were asked to evaluate whether each course was of interest to them and the reasons for their answer. For example, when students answered "yes," they would select from a reasons aligned with "autonomous motivation," which comes from careful consideration and self-determination (Lee & Sun, 2010) and includes reasons such as the practicality of the course content, individual learning plans and personal interests, Or reasons aligned with passive "external information motivation" (Lee & Sun, 2010), which included reasons such as making up for missed credits, the course being easy to pass, and seeing good reviews of the teacher. Conversely, if the student answers "No," he or she must also select the reasons for this choice. The options for "autonomous motivation" include the course not being part of their plan, understanding the course content and having no interest in the course. Options for "external information motivation" include the course being too hard, seeing bad reviews of the teacher, and having peers who did not choose the course. The students' overall choice is indicated by "Yes" or "No," and the students can select multiple reasons.

## 5. Data analysis and results

### 5.1. An analysis of the differences among the degree of interest in the courses recommended by the five recommendation methods in the undeclared and three optional fields

Repeated-measures ANOVA is used in this section. The data followed a normal distribution (skewness between -1.01 and .49; kurtosis between -1.22 and 1.90). Table 1 shows that the score-based method produced significant differences ($p < .05$), with the first field ($M = 73.27$), second field ($M = 63.09$), and third field ($M = 64.64$) being higher than the undeclared field (Non Field, $M = 55.72$). The results indicated that students were more interested in their optional field course than with the undeclared field courses recommended by the ratings-based method.



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

*Table 1.* A differences analysis between the degrees of interest in the courses recommended among the undeclared field and three optional fields

| Recommendation methods | Non field | | First field | | Second field | | Third field | | $F$ | Multiple comparison |
|---|---|---|---|---|---|---|---|---|---|---|
| | $M$ | $SD$ | $M$ | $SD$ | $M$ | $SD$ | $M$ | $SD$ | | |
| Content-based Filtering | 68.12 | 24.82 | 79.88 | 20.92 | 75.06 | 17.38 | 63.54 | 26.77 | 2.62 | - |
| Popularity-based Method | 65.51 | 29.42 | 71.91 | 22.53 | 68.46 | 30.02 | 65.87 | 33.46 | .15 | - |
| Item-based Collaborative Filtering | 64.20 | 25.97 | 67.04 | 25.29 | 64.88 | 33.12 | 62.13 | 28.38 | .14 | - |
| User-based Collaborative Filtering | 61.16 | 28.71 | 77.78 | 25.40 | 67.16 | 24.58 | 65.00 | 21.22 | 2.98 | - |
| Score-based Method | 55.72 | 30.85 | 73.27 | 27.22 | 63.09 | 25.84 | 64.64 | 27.70 | $3.78^{*}$ | First>Non<br>Second>Non<br>Third>Non |

*Note.* $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

**5.2. An analysis of the difference among the students' degree of interest in the courses recommended according to the order of the recommendations**

Repeated-measures ANOVA is used again in this section. The data follow a normal distribution (skewness between .34 and 1.81; kurtosis between -.77 and 3.46).

*Table 2.* A differences analysis between the students' degrees of interest in the courses recommended in the course recommendation order

| Recommendation methods | First course | | Second course | | Third course | | Fourth course | | Fifth course | | $F$ | Multiple comparison |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $M$ | $SD$ | $M$ | $SD$ | $M$ | $SD$ | $M$ | $SD$ | $M$ | $SD$ | | |
| Content-based Filtering | 87.13 | 4.68 | 83.71 | 14.86 | 78.72 | 9.11 | 67.45 | 14.86 | 43.27 | 13.96 | $10.25^{***}$ | First＞Fifth<br>Second＞Fifth<br>Third＞Fifth |
| Popularity-based Method | 83.25 | 5.44 | 72.07 | 3.48 | 76.85 | 9.55 | 68.67 | 9.93 | 65.42 | 10.20 | 2.75 | - |
| Item-based Collaborative Filtering | 79.45 | 8.72 | 71.09 | 7.48 | 71.10 | 7.05 | 68.45 | 8.51 | 56.74 | 4.55 | $5.94^{**}$ | First＞Fifth<br>Second＞Fifth<br>Third＞Fifth |
| User-based Collaborative Filtering | 69.51 | 8.30 | 72.74 | 5.54 | 80.06 | 9.64 | 61.50 | 9.53 | 63.54 | 7.72 | $5.03^{*}$ | First＞Fourth<br>Third＞Fifth |
| Score-based Method | 65.06 | 9.45 | 77.45 | 5.84 | 76.12 | 8.45 | 64.02 | 12.19 | 59.97 | 17.17 | $5.47^{**}$ | Second＞Fifth<br>Third＞Fifth<br>Second＞Fourth<br>Third＞Fourth |

*Note.* $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Table 2 shows that content-based filtering produced significant differences ($p < .05$), with the first ($M$ = 87.13), second ($M$ = 83.71), and third courses ($M$ = 78.72) being higher than the fifth course ($M$ = 43.27). Item-based collaborative filtering produced significant differences ($p < .05$), with the first ($M$ = 79.45), second ($M$ = 71.09),



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

and third courses ($M$ = 71.10) being higher than the fifth course ($M$ = 56.74). User-based collaborative filtering produced significant differences ($p$ < .05), with the first course ($M$ = 69.51) being higher than the fourth course ($M$ = 61.50) and the third course ($M$ = 80.06) being higher than the fifth course ($M$ = 63.54). The score-based method produced significant differences ($p$ < .05), with the second ($M$ = 77.45) and third courses ($M$ = 76.12) being higher than the fifth course ($M$ = 59.97) and the second ($M$ = 77.45) and third courses ($M$ = 76.12) being higher than the fourth course ($M$ = 64.02). Overall, the students were more interested in the courses at the top of the recommendation lists.

### 5.3. The degree of interest in the recommended courses is affected by students' internal and external motivations for taking a course

The Mann-Whitney U nonparametric test is used in this section. The data follow a normal distribution (skewness between .29 and 1.57; kurtosis between -.09 and 2.39). Table 3 shows that the proportion of students with autonomous motivation ($M$ = 44.49%~51.17%) was higher than that of students with extrinsic informational motivation ($M$ = 18.89%~20.59%; $p$ < .05) across the five recommendation methods. The results indicated that most students choose courses according to their plans, interests, or needs.

*Table 3.* A difference analysis of the students' motivation of course-taking in five recommendation methods

| Recommendation methods | Autonomous motivation | | Extrinsic informational motivation | | $p$ | Multiple comparison |
|---|---|---|---|---|---|---|
| | $M$ | $SD$ | $M$ | $SD$ | | |
| Content-Based Filtering | 49.21 | 16.90 | 19.15 | 15.25 | $.00^{***}$ | AM>EIM |
| Popularity-Based | 46.29 | 16.35 | 19.96 | 16.35 | $.00^{***}$ | AM>EIM |
| Item-Based Collaborative Filtering | 51.17 | 23.66 | 19.57 | 17.52 | $.00^{***}$ | AM>EIM |
| User-Based Collaborative Filtering | 45.24 | 20.06 | 18.89 | 15.26 | $.00^{***}$ | AM>EIM |
| Score-Based | 44.49 | 21.18 | 20.59 | 15.84 | $.00^{***}$ | AM>EIM |

*Note.* $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$. Autonomous Motivation = AM, Extrinsic Informational Motivation = EIM.

### 5.4. An analysis of the different degrees of interest in the courses recommended to a student using five recommendation methods and the degree of course suitability for the student

The Kruskal-Wallis nonparametric test is used in this section. The data followed a normal distribution (skewness between -1.01 and 2.09; kurtosis between -1.48 and 3.46). Table 4 shows that the students' interest matched between 60 and 70% of the course recommendation lists across the five recommendation methods, while there were no significant differences in the parameters according to the Kruskal-Wallis test ($p$ > .05). Further analysis of the degree of alignment between student interest and the lists generated by the five recommendation methods showed that there were statistically significant differences in the parameters by the Kruskal-Wallis test ($p$ > .05), and the results were the same for the degree of course list suitability for students. The post hoc comparisons showed that students thought that the results of the content-based filtering ($M$ = 67.40) were more in line with their preferences and needs than other methods (Table 1).

*Table 4.* A difference analysis between the degrees of interest and suitability for student

| Recommendation methods | Degree of interest ($N$ = 46) | | | | Degree of suitability ($N$ = 46) | | | |
|---|---|---|---|---|---|---|---|---|
| | $M$ | $SD$ | $p$ | Multiple comparison | $M$ | $SD$ | $p$ | Multiple comparison |
| Content-based Filtering | 70.14 | 21.58 | .59 | - | 67.40 | 47.40 | $.00^{***}$ | CBF>PB<br>CBF>IBCF<br>CBF>UBCF<br>CBF>SB |
| Popularity-based Method | 66.03 | 25.55 | | | 32.60 | 47.40 | | |
| Item-based Collaborative Filtering | 64.63 | 25.33 | | | 30.40 | 46.52 | | |
| User-based Collaborative Filtering | 65.88 | 23.12 | | | 26.10 | 44.40 | | |
| Score-based Method | 62.39 | 25.99 | | | 28.30 | 45.52 | | |

*Note.* $^{***}p$ < .001. Content-based Filtering = CBF, Popularity-based Method = PB, Item-based Collaborative Filtering = IBCF, User-based Collaborative Filtering = UBCF, Score-based Method = SB.



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

## 6. Discussion

In developing the PHCRS, we used ROC and NDCG to evaluate the system's accuracy. After the students used the PHCRS, the course fields that were only score-based showed obvious differences in the data analysis. This indicates that the students are less interested in the recommended courses when the list produced is not divided by field. In contrast, the students are more interested in their optional courses when the fields are divided in the recommendation list. The results partially support Hypothesis 1, which indicates that if the PHCRS considers the fields that the students are interested in, the recommendation accuracy increases. We also found that for all five recommendation methods, the students were more interested in the courses at the top of the list. This aligns with Babad (2001), who believes that students care most about informativeness, lecture quality and potential value for their future careers when selecting their first course. The courses selected toward the end of their education tend to be easier courses. While the results support Hypothesis 2, they also validate the appropriateness of the course order produced by the PHCRS.

When students referred to the course list provided by the five recommended methods, 44.49 to 51.17% of students chose courses based on autonomous motivation, which aligned well with the study list based on their interests and course content. Additionally, 18.89 to 20.59% of students chose courses based on extrinsic informational motivation, which caused them to consider how easy the course is to pass or earn a high grade in, the style of the lecturer or whether their colleagues are taking the same course. The results support Hypothesis 3 that students choose courses based on internal motivation and after considering their own interests (Barth, 2008; Wolbring & Treischl, 2016). Finally, approximately 60 to 70% of the students were interested in the course lists recommended to them by all five recommendation methods, and 67.40% of students said that content-based filtering produced the best results. Thus partially supporting Hypothesis 4. This indicates that most students choose courses on the basis of the course content, which is in line with previous relevant research that has concluded that content-based filtering is best suited to meet students' needs and are also most frequently used in course recommendation systems because it considers the characteristics of every course using syllabus details to provide course recommendations similar to students' previous courses (Apaza et al., 2014; Esteban et al., 2020).

## 7. Conclusion

This research applied five recommendation methods to build a PHCRS: content-based filtering, a popularity-based method, item-based collaborative filtering, user-based collaborative filtering, and a score-based method. Compared to recommendation systems built based on only one of these methods, our system is more suitable for fulfilling the diverse educational needs of students. We also built a labeling process that transfers text from course syllabi into a database, and a classification rule for information such as the field and objectives of the course and the knowledge, skills and perspectives students encounter or learn. Future studies can use the text database to enhance their course classification accuracy with text mining approaches. This database can also be a reference for other schools when developing a recommendation system for their electrical and computer engineering departments. After the system was built, to enhance the efficiency and make it more interesting for the students to use, the recommendation system website was coordinated with the school course selection website to assist students in selecting their courses before the start of every semester based on their personal needs. To help avoid students blindly selecting courses, we integrated the past course selection data of the student to calculate the ratio of autonomously selected courses to the courses selected using the recommendation list. When students log into the website, their course selection characteristics are automatically shown (Figure 2). Finally, we evaluated the performance of the PHCRS using recommendation metrics and questionnaires. The NDCG of the five recommendation methods is higher than .85, especially for user-based collaborative filtering (which had an NDCG of .96). The ROC of item-based collaborative filtering achieved .82. The results showed that the PHCRS can accurately predict students' needs and recommend suitable courses. In the questionnaires, we evaluated the effectiveness of the PHCRS on the basis of students' major, course selection order, and course selection motivations and the accordance between the recommended courses and the actual course selection. Overall, approximately 70% of the students were interested in the course list recommended by the PHCRS, which would shows that the system can guide students in choosing courses in their major and saves them time in choosing courses outside their major.

## References

Aguilar, J., Valdiviezo-Díaz, P., & Riofrio, G. (2017). A General framework for intelligent recommender systems. *Applied Computing Informatics*, *13*, 147-160. https://doi.org/10.1016/j.aci.2016.08.002



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

Aher, S. B., & Lobo, L. M. R. J. (2013). Combination of machine learning algorithms for recommendation of courses in e-learning system based on historical data. *Knowledge-Based Systems*, *51*, 1-14. http://dx.doi.org/10.1016/j.knosys.2013.04.015

Apache Friends. (2021, June). *XAMPP Apache + MariaDB + PHP + Perl*. https://www.apachefriends.org/zh_tw/index.html

Apaza, R. G., Cervantes, E. V., Quispe, L. C., & Luna, J. O. (2014, September). *Online courses recommendation based on LDA* [Paper presentation]. Information Management and Big Data, Cusco, Peru. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.664.8706&rep=rep1&type=pdf

Archer, J. J., & Cooper, S. (1998). *Counselling and mental health services on campus: A Handbook of contemporary practices and challenges.* Jossey-Bass Inc.

Babad, E. (2001). Students' course selection: Differential considerations for first and last course. *Research in Higher Education*, *42*, 469-492. https://doi.org/10.1023/A:1011058926613

Babad, E., Avni-Babad, D., & Rosenthal, R. (2004). Prediction of students' evaluations from brief instances of professors' nonverbal behavior in defined instructional situations. *Social Psychology of Education*, *7*, 3-33. https://doi.org/10.1023/B:SPOE.0000010672.97522.c5

Babad, E., & Tayeb, A. (2003). Experimental analysis of students' course selection. *British Journal of Educational Psychology*, *73*, 373-393. https://doi.org/10.1348/000709903322275894

Barth, M. M. (2008). Deciphering student evaluations of teaching: A Factor analysis approach. *Journal of Education for Business*, *84*(1), 40-46. https://doi.org/10.3200/JOEB.84.1.40-46

Begs, J. M., Bentham, J. H., & Tyler, S. (2008). Distinguishing the factors influencing college students' choice of major. *College Student Journal, 4*(22), 381-394.

Bendakir, N., & Aïmeur, E. (2006). Using association rules for course recommendation. *American Association for Artificial Intelligence*, *3*, 1-10.

Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User Modeling and User-Adapted Interaction*, *12*(4), 331-370. https://doi.org/10.1023/A:1021240730564

Çano, E., & Morisio, M. (2017). Hybrid recommender systems: A Systematic literature review. *Intelligent Data Analysis, 21*(6), 1487-1524. https://doi.org/10.3233/IDA-163209

Chang, H. T., Wang, L. C., Lin, C. Y., Tseng, F. C., & Jheng, W. B. (2020, October). *LINE study secretary: AI-based personalized learning assistance system* [Paper presentation]. 2020 Conference on Innovation and Design (CID), Taipei, Taiwan. https://id100.chihlee.edu.tw/p/412-1025-3920.php

Cuseo, J. (2003). *Academic advisement and student retention: Empirical connections and systemic interventions*. National Academic Advising Association. Retrieved from http://www.uwc.edu/admin-istration/academic-affairs/esfy/cuseo/Academic%20Advisement%20and%20Student%20Retention.doc

Dwivedi, S., & Roshni V. S., D. K. (2017, August). *Recommender system for big data in education* [Paper presentation]. 5th National Conference on E-Learning & E-Learning Technologies, Hyderabad, India. https://doi.org/10.1109/ELELTECH.2017.8074993

Esteban, A., Zafra, A., & Romero, C. (2020). Helping university students to choose elective courses by using a hybrid multi-criteria recommendation system with genetic optimization. *Knowledge-Based Systems*, *194*(22), 1-14. https://doi.org/10.1016/j.knosys.2019.105385

Farzan, R., & Brusilovsky, P. (2006, June). *Social navigation support in a course recommendation system* [Paper presentation]. International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems, Dublin, Ireland. https://link.springer.com/chapter/10.1007%2F1176801211

Gordon, V. N. (2007). *The Undecided college student: An Academic and career advising challenge*. Charles C Thomas Pub Ltd.

Han, J. W., Jo, J. C., Ji, H. S., & Lim, H. S. (2016). A Collaborative recommender system for learning courses considering the relevance of a learner's learning skills. *Cluster Computing*, *19*, 2273-2284. https://doi.org/10.1007/s10586-016-0670-x

Herlocker, J., Konstan, J., & Riedl, J. (2000). Explaining collaborative filtering recommendations. *2000 ACM conference on Computer supported cooperative work* (pp. 241–250). https://doi.org/10.1145/358916.358995

Hou, Y., Zhou, P., Xu, J., & Wu, D. O. (2018, April). *Course recommendation of MOOC with big data support: A Contextual online learning approach* [Paper presentation]. IEEE Conference on Computer Communications Workshops, Honolulu, HI. https://ieeexplore.ieee.org/document/8406936

Huang, L., Wang, C. D., Chao, H. Y., Lai, J. H., & Yu, P. S. (2019). A Score prediction approach for optional course recommendation via cross-user-domain collaborative filtering. *IEEE Access*, *7*, 19550-19563. https://doi.org/10.1109/ACCESS.2019.2897979



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

Iatrellis, O., Kameas, A., & Fitsilis, P. (2017). Academic advising systems: A Systematic literature review of empirical evidence. *Education Science, 7*(4), 1-17. https://doi.org/10.3390/educsci7040090

Kongsakun, K., Fung, C. C., & Chanakul, T. (2010). Developing an intelligent recommendation system for a private university in Thailand. *Issues in Information Systems*, *11*(1), 467-472.

Kurniadi, D., Abdurachman, E., Warnars, H. L. H. S., & Suparta, W. (2019). A Proposed framework in an intelligent recommender system for the college student. *Journal of Physics: Conference Series*, *1402*, 1-7. https://doi.org/10.1088/1742-6596/1402/6/066100

Lang, C. (2010). Happenstance and compromise: A Gendered analysis of students' computing degree course selection. *Computer Science Education*, *20*(4), 317-345. https://doi.org/10.1080/08993408.2010.527699

Lee, Y. M., & Sun, S. H. (2010). The Relationship between autonomous motivation of course-taking and learning engagement on college students. *Journal of Research in Education Sciences, 55*(1), 155-182. https://doi.org/10.3966/2073753X2010035501006

Mondal, B., Patra, O., Mishra, S., & Patra, P. (2020, March). *A Course recommendation system based on grades* [Paper presentation]. IEEE International Conference on Computer Science, Engineering and Applications (ICCSEA), Gunupur, India. https://ieeexplore.ieee.org/document/9132845

Obeid, C., Lahoud, I., El Khoury, H., & Champin, P. A. (2018). Ontology-based recommender system in higher education. *WWW'18: Companion Proceedings of the The Web Conference 2018* (pp. 1031–1034). https://doi.org/10.1145/3184558.3191533

Pardos, Z. A., & Jiang, W. (2020). Designing for serendipity in a university course recommendation system. *LAK'20: Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 350–359). https://doi.org/10.1145/3375462.3375524

Perera, A. T., & Pratheesh, P. (2018). Factors influence on student course selection: A Case of trincomalee campus. *International Journal of Innovative Science and Research Technology, 3*(5), 579-581.

Perugini, S., Goncalves, M. A., & Fox, E. A. (2004). Recommender systems research: A Connection-centric survey. *Journal of Intelligent Information Systems*, *23*(2), 107-143. https://doi.org/10.1023/B:JIIS.0000039532.05533.99

Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM*, *40*(3), 56-58. https://doi.org/10.1145/245108.245121

Romero, C., & Ventura, S. (2013). Data mining in education. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *3*(1), 12-27. https://doi.org/10.1002/widm.1075

Salehudin, N. B., Kahtan, H., Adbulgabber, M. A., & Al-bashiri, H. (2019). A Proposed course recommender model based on collaborative filtering for course registration. *International Journal of Advanced Computer Science and Applications*, *10*(11), 162-168. https://doi.org/10.14569/IJACSA.2019.0101122

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001). Item-based collaborative filtering recommendation algorithms. *WWW '01: Proceedings of the 10th international conference on World Wide Web* (pp. 285–295). https://doi.org/10.1145/371920.372071

Sawarkar, N., Raghuwanshi, M. M., & Singh, K. R. (2018). Intelligent recommendation system for higher education. *International Journal on Future Revolution in Computer Science & Communication Engineering*, *4*(4), 311-320.

Schafer, J. B., Konstan, J., & Riedl, J. (1999). *Recommender systems in e-commerce*. *EC '99: Proceedings of the 1st ACM conference on Electronic Commerce* (pp. 158–166). https://doi.org/10.1145/336992.337035

Tuckman, B. W. (1999). *Conducting educational research* (5th ed.). Sea Harbor Drive, Orlando: Harcourt Brace College Publishers.

Urata, U., & Takano, A. (2003). Construction of a student counseling system: Collaboration between psychology and college education. *Japanese Journal of Educational Psychology*, *51*, 205-217. https://doi.org/10.5926/jjep1953.51.2_205

Wang, L. C., Lin, J. Y., & Chang, H. T. (2020, June). *A Personalized course recommendation system for college students* [Paper presentation]. Association for Institutional Research Forum, New Orleans, LA. https://www.airweb.org/collaborate-learn/air-forum

Wolbring, T., & Treischl, E. (2016). Selection bias in students' evaluation of teaching. *Research in higher education*, *57*, 51-71. https://doi.org/10.1007/s11162-015-9378-7

WordPress.com. (2021). *WordPress*. https://wordpress.com/

Xiao, J., Wang, M., Jiang, B., & Li, J. (2018). A Personalized recommendation system with combinational algorithm for online learning. *Journal of Ambient Intelligence and Humanized Computing*, *9*, 667-677. https://doi.org/10.1007/s12652-017-0466-8.



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms

Xu, J., Xing, T., & Schaar, M. van der. (2016). Personalized course sequence recommendations. *IEEE Transactions on Signal Processing, 64*(20), 5340-5352. https://doi.org/10.1109/TSP.2016.2595495

Yao, C. B. (2017). Constructing a user-friendly and smart ubiquitous personalized learning environment by using a context-aware mechanism. *IEEE Transactions on Learning Technologies, 10*(1), 104–114. https://doi.org/10.1109/TLT.2015.2487977

Zare-ee, A., & Shekarey, A. (2010). The Effects of social familial and personal factors on students' course selection in Iranian technical schools. *Procedia Social and Behavioral Sciences, 9*, 295-298. https://doi.org/10.1016/j.sbspro.2010.12.153

Zhang, H. R., Min, F., He, X., & Xu, Y. Y. (2015). A Hybrid recommender system based on user-recommender interaction. *Mathematical Problems in Engineering*, *2015*, 1-12. https://doi.org/10.1155/2015/145636

Zweig, M., Campbell, G. (1993). Receiver-operating characteristic (ROC) plots: A Fundamental evaluation tool in clinical medicine. *Clinical Chemistry, 39*(8), 561-577. https://doi.org/10.1093/clinchem/39.4.561



This content downloaded from
150.116.106.122 on Sat, 08 Apr 2023 12:57:31 UTC
All use subject to https://about.jstor.org/terms