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An Intelligent Course Decision Assistant by Mining and Filtering Learners' Personality Patterns

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Featured Application: This work has already been implemented in the course selection system of the Department of Information Management at Cheng Shiu University, Taiwan.

Abstract: For a student, determining how to choose from a set of courses is an important issue prior to learning. An appropriate learning guide can direct students toward an area of interest. The learning results produced by the student in this case are superior due to their strong interest in the subject matter. Although a number of methods have been proposed to address this issue, the effectiveness remains unsatisfactory. To this end, we created an effective system, called the personality-driven course decision assistant, to help students determine the courses they should select by mining and filtering learners' personality patterns. For learner pattern mining, the relationships between the students' learning results and the referred personalities are discovered to provide the learners with valuable information before learning. For filtering learner personality patterns, students with similar personality patterns are filtered to predict the potential learning results. Through the actual system, a number of subjective and objective evaluations were conducted, and the evaluation results reveal that the proposed system is highly effective and reliable.

Keywords: data mining; personality pattern mining; course decision support; learner filtering; computational intelligence

1. Introduction

Advances in artificial intelligence (AI) have allowed the world to be automatic, intelligent, and interconnected. Therefore, people's careers might be changed, for example, investment portfolios can automatically be predicted without manual costs [1]. These changes have a serious impact on learning. Typically, as shown in Figure 1, learning can be decomposed into three stages: before learning, learning, and after learning. In these three stages, three main issues include what to learn, how to learn, and how to apply, respectively. The attention in most recent e-learning systems is focused on how to learn and how to apply. Although a number of works have contributed to how to learn and how to apply, for a student, knowing what courses they might prefer is also an important issue in addition to how to learn and how to apply [2]. A junior student may not understand or know their learning interests. Therefore, a guideline or suggestions about what to learn is necessary. Basically, the major idea relies on three factors, namely, personality, preference, and achievement. For "personality and preference", Jessee et al. [3] presented that a relationship exists between personality and preference. For "personality and achievement", Khatibi et al. [4] focused on the effect of personality on learning styles of students and also briefly discusses the relationship between learning styles and culture. That is, different personalities will yield different learning styles, and then different learning styles will yield different learning results. Based on the educational points, our intent is to find the implicit associations among personalities, preferences, and achievements. To address this intent, in this paper, we propose an effective system, called a personality-driven course decision assistant, to provide helpful information for courses of potential interest. Learning is easier and more effective when a student takes courses in which they are interested.

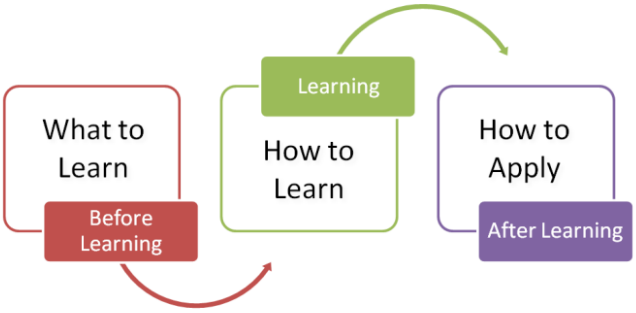

Figure 1. Steps in learning and issues.

To increase the effectiveness of learning, the main contributions of this paper can be summarized as follows.

- From an educational point of view: in fact, a good learning result is strongly related to a strong interest in the subject matter [4,5]. Therefore, in this paper, an intelligent course assistant is proposed to bridge the gap between learning interest and learning direction. Through this assistant, the main goal of this study is to help the students clarify what courses they potentially prefer, thereby enhancing learning motivation and improving learning results.
- From a technical point of view, to identify the courses of potential interested, in this study, the learners (also called "users" in this paper) are modeled and filtered based on the personalities. In terms of learner modeling, the learning results and learner personalities are associated using association mining technology. With the discovered associations, the relationships between learning results and learner personalities can be clarified for researchers from a psychological viewpoint. In terms of filtering learners, the learners with relevant personalities are filtered to predict the potential learning degrees. With the potential learning degrees, the learners' course decisions are directed toward the area of potential interest.

To evaluate the proposed idea, a number of experiments were conducted using the online course assistant system constructed in this work. Through the real system constructed, the objective and subjective evaluation results revealed that the proposed method is effective and reliable.

The remainder of this paper is organized as follows. A brief review of past studies is outlined in Section 2. In Section 3, the proposed method of knowledge discovery for course decision support is presented in detail. The experimental results are provided in Section 4 and the conclusions are outlined in Section 5.

2. Literature Review

The main learning issues can be divided into three stages: learning motivation, learning strategy, and learning application. In this study, the main goal is to increase learning motivation using mining and filtering techniques. In the following, the related literature review is shown by three categories: strategies and applications of learning, personality and learning, and AI and learning.

2.1. Strategies and Applications of Learning

Learning effectiveness relies heavily on the learning strategy [6–8]. A good learning strategy always yields a good learning result. Altun [9] studied the effect of learning cooperation effectiveness on achievement and views of science and technique classes. In Huang et al. [10], a jigsaw-based cooperative learning method was proposed to improve the performance of mobile situated learning. Idress et al. [11] integrated the jigsaw method and the student team achievement divisions for well stimulation technique course. Jee et al. [12] implemented an authoring tool using an augmented reality technique. To encourage students, Laguador [13] proposed an idea for adopting a cooperative learning method as a teaching and learning strategy. Magen-Nagar et al. [14] investigated the effectiveness of the proposed online collaborative learning strategy. Pintrich et al. [15] presented a self-report instrument via a questionnaire from a motivation point of view. Sung et al. [16] used a contextual science inquiry approach to enhance deep-strategy behaviors and the positive learning performance of scientific inquiry.

2.2. Personality and Learning

In addition to the learning strategy, personality is another impact factor affecting learning [17,18]. Personality not only influences how to learn but also what to learn. That is, different personalities are related to different learning interests and learning strategies [19,20]. Others [21,22] studied the impacts of personality and learning approaches on academic performance. Garrison [23] presented a comprehensive theoretical model fusing self-monitoring, self-management, and entering-task dimensions to achieve high-quality of self-directed learning. Komarraju et al. [24] researched the big five traits, conscientiousness, and agreeableness, which are positively related to learning styles and academic performance. Li et al. [25] investigated the relationships between personality and learning style in international managers. Lange et al. [26] analyzed the profiles of open learning students and investigated the associations between characteristics and performance. Premlatha et al. [27] classified learners based on their performance and knowledge level by analyzing the learner profiles. Sun et al. [28] explored the personal characteristics and mobile usage behavior in terms of mobile learning. Trapmann et al. [29] performed a meta-analysis of the correlation coefficients between the big five personality factors and academic achievement. The relationships between personal characteristics and self-directed learning have also been studied [30].

2.3. Artificial Intelligence and Learning

To increase the effectiveness of learning, a number of studies [31] focused on how to learn. Stojanovska et al. [32] predicted student academic performance in game-based learning strategies, flip teaching techniques, and video conferencing sessions by mining personality traits, learning style, and satisfaction. Almohammadi et al. [33] examined AI techniques used in learning platforms. Andriessen et al. [34] investigated the relationship between education and AI. Basavaraju et al. [35]. implemented android apps by supervised learning. Pradhan et al. [36] used Wikipedia data and queried the ontology-based data using SPARQL Protocol and RDF Query Language. Shi et al. [37] calculated user ratings similarities to estimate unknown ratings. Commonsense knowledge (CSK) in machine intelligence was proposed to discuss open issues of CSK acquisition, CSK in natural language, and applications of CSK [38]. Woolf et al. [39] discussed the future challenges of AI in education. Xu et al. [40] proposed a machine learning method to track and predict student performance in degree programs.

3. Proposed Methods

3.1. Basic Concept

Because the existing student course selection systems cannot provide appropriate suggestions aligned with learning interests, the goal of this study is to propose a course decision assistant that associates learning interests with courses by mining personality patterns. To this end, the main techniques contributed by this study are modeling and filtering of personalities. From a psychological viewpoint, learning interest is hidden within a personality [4,5]. Based on this viewpoint, our intent is to discover the relationships between personalities and learning interests using a data mining algorithm. With these patterns mined, the learners will make appropriate selections from a number of courses. In addition to mining the patterns, the other main contributed technique is predicting the degrees for the courses of potential interest. With this technique, learner interest is represented by a performance degree ranging from 1 to 5. Then, learners are filtered by calculating the personality similarities. The active learner's course degree can be predicted by the degrees of the filtered learners to help the learner further identify the predicted degree of the potentially interested course. In summary, through the proposed system, the learner can first identify the courses of potential interest via modeling patterns. Then, the learner can further understand the related degrees determined by the degree prediction algorithm. Finally, the learner will make the appropriate decision when choosing unknown courses. Accordingly, learning performance will increase.

3.2. Overview of the Proposed Method

As discussed in the previous section, the main goal of a good course selection system is to provide appropriate support when choosing courses. To address this concern, in this paper, a course decision assistant is presented to associate the learner interests with the available courses by mining personalities. For this purpose, the proposed system is divided into two stages: offline data engineering and online prediction, as shown in Figure 2.

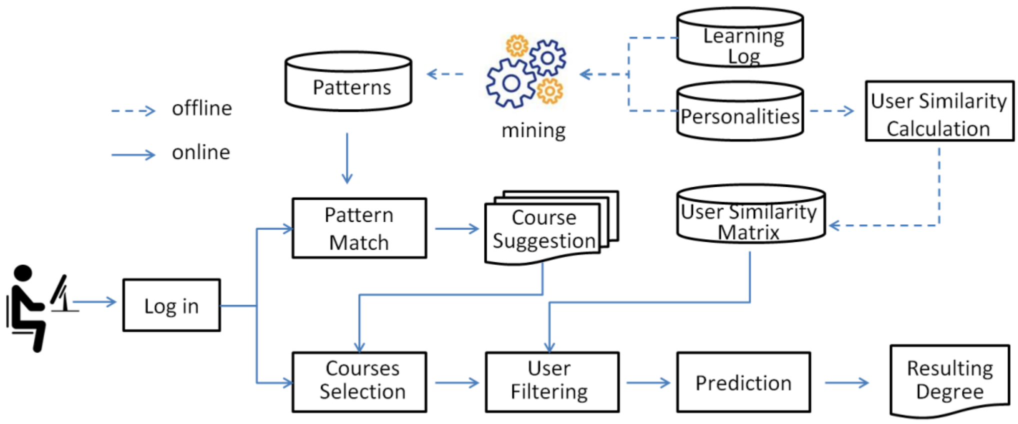

Figure 2. Framework of the proposed method.

- Offline Data Engineering

This stage can also be viewed as a knowledge discovery stage that contains two main processes: mining personality patterns and construction of the user–similarity matrix. For mining personality patterns, the learning log and user personalities are integrated into the transaction table. Thereby, the mining algorithm mines the patterns between the learning log and user personalities. The user similarities are then calculated, and the user–similarity matrix is constructed. These two processing results are the base of the online prediction.

- Online Prediction

Online prediction is triggered by an active user visit. The system searches the patterns by matching the active user's personality and the patterns in the database. Then, the highly confident courses are returned. The user can select the courses of interest to determine the predicted degrees. Once a course is selected, the prediction algorithm predicts the course degree of interest. Consequently, the user selects the courses with high degrees or high interests.

3.3. Offline Data Engineering

As mentioned above, offline data engineering involves two processes, namely mining of personality patterns and construction of the user–similarity matrix, which are described below.

3.3.1. Mining of Personality Patterns

Until now, retrieving the learning interests to facilitate learning has been a challenge. In previous work [4,41], learning interest can be represented by a person's personality. Therefore, the goal of this offline process is to discover the relationship between learning interest and personality. In this process, the user learning log and the user personalities are incorporated into a transaction table. In this work, the learning log indicates the degrees of the learning courses. That is, a transaction in this transaction table contains a user personality, a learning course, and a related degree, which can be defined as follows:

<*user personality*, <*course*, *degree*>>

where *user personality* is a set shown in Table 1 and *degree* indicates the learning degrees ranging from 1 to 5. Note, the main intent for determining the personalities in Table 1 is based on [42] personality being represented by three bipolar dimensions: [41] extroversion–introversion (EI), sensing–intuition (SN), and thinking–feeling (TF), or the five senses [3]. Because the personalities are shown to be closely related to learning preferences, these personalities can further impact learning achievement. Therefore, the determined personalities in Table 1 are included in these three aspects and five senses. For example, a transaction

<{Male, A, Capricorn, Reading, White, Winter, Orange, Pop, Romance, Cake,
<{Nature, Window, Paint, Yes, Well Organized}, {System Development, 4}>

indicates that the degree of system development for a well-organized male with blood type A and astrological sign Capricorn, who likes reading, the color white, winter, orange, pop music, romance movies, cake, nature tours, the window seat, prefers a paint background on the desktop, and is interested in new ideas, is frequently 4 in the transaction table.

Table 1. User personality.

Personality	Items
Sex	{Male, Female}
Blood type	{A, B, O, AB}
Astrological sign	{Aries, Taurus, Gemini, Cancer, Leo, Virgo, Libra, Scorpio, Sagittarius, Capricorn, Aquarius, Pisces}
Hobby	{Reading, Exercise, Music, Science, Art, Vogue}
Preferred color	{Brown, Grey, Red, Yellow, White, Black, Blue, Pink, Green, Purple}
Preferred season	{Spring, Summer, Fall, Winter}
Preferred fruit	{Apple, Banana, Grapes, Cherry, Coconut, Sakya, Orange, Papaya, Peach, Pear, Mango, Pineapple}
Preferred music	{Love, Hip Hop, Rock, Pop, Dance, Classic, Tec, Korea Style}
Preferred movie	{Action, Science Fiction, Romance, Horror, Animation, Comedy, Documentary, War}
Preferred food	{Beef Soup Noodles, Surf & Turf, Pizza, Fired Chicken, Cake, Hong Kong Style, Rice Porridge/Congee}
Preferred tour	{City, Nature, Festival, Challenging, Pilgrimage}
Preferred seat position	{Window, Middle, Aisle}
Preferred desktop background	{Nature, Model, Animal, Paint}
Interested in new ideas	{Yes, No}
I am . . .	{Optimistic, Frank, Well Organized, Accommodate}

After generating the transaction table, the mining algorithm is run to mine the rules, which can be defined as:

{*user personality*}→{*course*, *degree*}.

For example, a rule

{Male, Exercise, Yellow, Summer, Rock, Action, Aisle}→{Programming, 3}

indicates that a programming degree for a male liking exercise, yellow, summer, rock music, action movies, and the aisle seat is always 3. These mined rules provide support for online prediction.

3.3.2. Construction of the User–Similarity Matrix

In addition to mining patterns, the other main process is the construction of the user–similarity matrix. The main purpose of this process is to compute the user personality similarities that support the online course degree prediction. That is, the users on similar personalities will be considered while predicting the unknown degrees. Hence, all user personalities are transformed into a binary vector. For example, assume the personality only contains two main sets: sex = {Male, Female} and blood type = {A, B, O, AB}. If the sex and blood type for a user are female and O, respectively, the binary vector for {{Male, Female}, {A, B, O, AB}} is {0, 1, 0, 0, 1, 0}. Accordingly, the user similarity in this paper is defined in Definition 1.

Definition 1. *Assume z unique personalities exist in the personality table. Given two users {x, y} with bit vectors* $\{p_{x,1}, p_{x,2}, \ldots, p_{x,z}\}$ *and* $\{p_{y,1}, p_{y,2}, \ldots, p_{y,z}\}$*, where* $p \in \{0, 1\}$*, the user similarity* $S_{x,y}$ *is defined as*

$$S_{x,y} = \frac{\sum_{0\le i\le z} p_{x,i} \times p_{y,i}}{\sqrt{\sum_{0\le i\le z}(p_{x,i})^2} \times \sqrt{\sum_{0\le i\le z}(p_{y,i})^2}} \quad (1)$$

where $p_{x,i}$ and $p_{y,i}$ are the *i*th vectors of users x and y, respectively.

Based on the user similarities, the similarity matrix is constructed to accelerate the online prediction.

3.4. Online Prediction

This step consists of two main parts: course suggestion and course degree prediction. As stated in Section 1, for a learner, what to learn is the most important issue. Hence, the proposed system for an active user's log provides a suggested course list by performing pattern matching. Then, the active user can select the courses to obtain the related degrees estimated by the prediction algorithm. In the following subsections, the details of how to achieve course suggestion and course degree prediction are presented.

3.4.1. Course Suggestion

The goal of this process is to retrieve the courses of potential interest using the personality patterns. Conceptually, this process is based on learners with similar personality patterns producing similar learning performances. Therefore, the key challenge for this process is taking advantage of patterns to suggest appropriate courses. Algorithm 1 shows the algorithm for course suggestion. First, the active user's personality is found from the personality database *PDB* in Step 1. In Step 2, the system performs the operation of matching rules. The matching rule is defined in Definition 2.

Algorithm 1. Algorithm of course suggestion.

Input: A set of unique courses *C*, a personality database *PDB*, a personality rule database $PRDB = \cup r_j$, an active user *a*; //P_i indicate the *i*th user's personality set and r_j indicates the *j*th rule;
Output: A suggested course list;
Algorithm: *Course_Suggestion*()
1. retrieve the personality set R_a of the active user *a*;
2. find the matching rule set *MR* to *a* from *PRDB*;
3. **for** each $course_c \in C$ **do**
4. **for** each $r \subseteq MR$ **do**
5. **if** $course_c$ in *r* and $r.course_c.degree$>2 **then**
6. $pd_c = pd_c + r.conf$;// pd_c indicates the accumulated confidence of a positive course and *r.conf* indicates the rule confidence;
7. **else**
8. $nd_c = nd_c + r.conf$;// nd_c indicates the accumulated confidence of a negative course and *r.conf* indicates the rule confidence;
9. **end if**
10. **end for**
11. **if** $(pd_c\text{-}nd_c) > 0$ **then**
12. $SC = SC + course_c$; //*SC* is the suggested course list.
13. **end for**
14. **return** *SC*.

Definition 2. *Given a rule r and a personality p, the matching rule is defined as:* $r \subseteq p$.

Note, in this part, the whole idea is oriented from an aspect [3,4,41,42]: the personalities represented by three bipolar dimensions and five senses are related to the preferences, and the preferences will further impact the achievement. That is, high preferences will result in high performances. Hence, the main scientific intent behind this aspect is to mine the rules between the personalities and the achievements, where the personalities indicate the adopted personalities and the achievements indicate the course degrees. If a rule implies a high degree, the related course can be viewed as a positive course to suggest.

For mining rules, the major idea is motivated from data mining theory [43–48] that, an association rule A = > B indicates that transactions in the database containing an item set A tend to contain an item set B, and the related confidence exceeds the threshold. From another viewpoint, a rule can be viewed as a high confident rule. In this paper, the association rules are mined by the well-known algorithm Apriori [43,48], which is a level-wise scan for frequent itemsets. It uses frequent *k*-itemsets to generate candidate $(k + 1)$-itemsets and prunes non-promising candidates to speed up the frequent itemsets generation. Based on this idea, in our proposed method, a rule < personality = > course, degree > indicates a personality set with a higher frequency larger than the threshold implies a course degree. According to these mined rules, a course confidence is the one accumulated by matching rules' confidences, where the matching rules with higher frequencies are larger than the threshold. That is, in the proposed system, the discovered rules are confident because the related frequencies should be greater than the threshold. That is, the suggested courses are confident by using the confident rules.

In Algorithm 1, the suggested course list is generated in Steps 3–13. In these steps, for each unique course in the database, the related rules are determined first. Then, for each related rule, if the course degree is greater than 2, the course is identified as a positive course and the related rule confidence is accumulated as a positive confidence. Otherwise, it is identified as a negative course and the related rule confidence is accumulated as a negative confidence. Finally, if the positive confidence is larger than the negative confidence, this course is added to the suggested course list. That is, a suggested course indicates a confident course with a positive confidence from data mining point of view. In summary, in this paper, a suggested course can be regarded as a confident course with a high relation confidence among personality, preference, and achievement based on scientific works [3,4,41–43,48].

3.4.2. Course Degree Prediction

The goal of course degree prediction is to provide a reference for the courses of interest within the suggested course list. A learner might obtain a set of courses of interest generated by the course suggestion operation, but is confused when making a final choice. Hence, they can perform the course degree prediction to understand the estimated degree. Conceptually, the estimated degree can be viewed as the potential performance, which provides helpful information for making a final course decision. Algorithm 2 depicts the algorithm for course degree prediction. In this algorithm, the top k relevant users have to be determined first using the user similarity matrix *SM*. Note, this step can be completed efficiently because the user similarities have been calculated offline. Next, the degrees can be computed in Steps 2 to 8, which are defined in Definition 3. Finally, the resulting degree is returned to the active user.

Algorithm 2. Course degree prediction.

Input: A user-similarity matrix *SM*, a user-to-course degree matrix *DM*, an active user a, an unknown course c;
Output: The degree of c;
Algorithm: *Degree_Prediction*()
1. determine the top k relevant users from the *SM*;
2. **for** each relevant user u **do**
3. retrieve the referred degree $d_{u,c}$ of c from *DM*;
4. retrieve the referred similarity $s_{u,\mathrm{a}}$ between u and a from *SM*;
5. $sum_d = sum_d + (d_{u,\mathrm{c}} * s_{u,\mathrm{a}})$;
6. $sum_s = sum_s + s_{u,\mathrm{a}}$;
7. **end for**
8. $pd_c = sum_d/sum_s$;
9. **return** pd_c.

Definition 3. *Given a user similarity matrix $SM_{u\rightarrow u}$, a user-to-course degree matrix $DM_{u\rightarrow c}$, and an active user a, assume that the system retrieves the most k relevant users for the active user a. The degree of an unknown course c for user a is defined as*

$$pd_c = \frac{\sum_{0<i\leq k} d_{i,c} \times s_{i,a}}{\sum_{0<i\leq k} s_{i,a}} \tag{2}$$

where $d_{i,c}$ indicates the degree of course c for user i and $s_{i,\mathrm{a}}$ indicates the similarity between user i and active user a.

Table 2 provides an example of a user-to-course degree matrix and Table 3 provides an example of similarities between user 5 and all users. Based on 2, the three most relevant users are users 1, 3, and 4, where k = 3. Because the degree of course 2 for user 2 is unknown, user 2 is excluded from the relevant user set in this example. Assume the degree to predict is course 2 for user 5. From Tables 2 and 3, the related degree is (3 × 0.75 + 3 × 0.75 + 3 × 0.5)/(0.75 + 0.75 + 0.5) = 3.

Table 2. Example of similarities between user 5 and all users.

	User1	User2	User3	User4	User5
user5	0.75	0.75	0.75	0.5	1

Table 3. Example of a user-to-course degree matrix.

	Course 1	Course 2	Course 3	Course 4	Course 5	Course 6
user 1	0	3	0	0	1	0
user 2	4	0	2	5	4	2
user 3	0	3	0	2	2	3
user 4	4	3	3	2	3	0
user 5	0	?	0	0	0	0

4. Empirical Study

To evaluate the effectiveness of the proposed idea, a number of experiments were conducted, which can be summarized into two categories: (1) objective evaluations of the course degree prediction and (2) subjective evaluations of the whole system. The experiments were performed on a PC with 16 GB RAM and Intel Core i7–4790, running on 64 bits Windows 7. In the experiments, all prediction algorithms and data engineering were coded by the authors in this paper. Note, the course suggestion and course degree prediction can be finished within 1 s because the patterns and user similarities have been completed in the offline stage.

4.1. Objective Evaluations

4.1.1. Experimental Settings for Objective Evaluations

The experimental data for objective evaluations were obtained from the Department of Information Management at Cheng Shiu University, which consists of 460 students and 17,438 course degrees. From the 17,438 course degrees, 6612 professional course degrees were selected, including 145 unique professional courses. From the 6612 degrees, 1539 degrees were randomly selected as testing degrees (unknown degrees) and the others were selected as training degrees (known degrees). The degrees ranged from 1 to 5, where 1 indicates an original score lower than 60, 2 indicates an original score between 60 and 69, 3 indicates an original score between 70 and 79, 4 indicates an original score between 80 and 89, and 5 indicates an original score greater than 89.

4.1.2. Experimental Results of Objective Evaluations

The goal of this evaluation is to determine the effectiveness of the proposed course prediction. This evaluation is based on the course prediction algorithm shown in Algorithm 2. In this experiment, k is 50. That is, in Step 1 of the prediction algorithm, the 50 most relevant users were determined to calculate the unknown course degrees. Table 4 shows the experimental results, which can be decomposed into five concepts: average, standard error, standard error of averages, relationships, and t-test for paired samples between the predicted set and ground-truth set. For the average, the averaged degrees for the predicted set and ground-truth set are similar. For standard error and standard error of averages, those of the predicted set are lower than those of the ground-truth set, showing that the variance for the predicted set is small. That is, the prediction performance is stable. For the paired sample relationship, the relationship between the predicted and ground-truth sets is close ($p = 0.00$). For the paired sample t-test, because the p-value 0.434 is larger than 0.01, the difference between the predicted and ground-truth sets is very small. In summary, the objective evaluation results show that the proposed prediction algorithm performs well and can provide the learner with a reliable guideline for choosing courses.

Table 4. Experimental results of objective evaluations.

Paired Sample Set	Average	Standard Error	Standard Error of Averages	Relations for Paired Samples	*t*-Test for Paired Samples
Predicted set	3.2121	0.47892	0.01221	$r = 0.336$ $p = 0.000$ ($p < 0.01$)	$t = 0.16751$ $p = 0.434$ ($p > 0.01$)
Ground truth	3.2170	1.23545	0.03149		

4.2. Subjective Evaluations

4.2.1. Experimental Settings for Subjective Evaluations

In addition to course prediction, another aim is course suggestion. For this goal, the 6612 degrees of experimental data were viewed as transactions. The mining algorithm applied is a priori [5,37] and the minimum support is 0.04. Basically, this subjective evaluation is based on the questionnaire. Table 5 outlines the hierarchical questionnaire that is divided into three sets of questions: questions for course selection, for the existing course selection system, and for using the proposed course decision assistant. The first and second sets are related to the motivations for the proposed idea, whereas the third set is related to the overall satisfaction with the proposed system.

Table 5. Questionnaire for subjective evaluation.

Level 1: Questions for Course Selection
1. While selecting courses, is interest important?
2. Before selecting courses, do you want to know the relationships between courses and personalities?
3. Do you know what courses to select?
4. Have you ever selected a course in which you were uninterested?
Level 2: Questions about the Existing Course Selection System
1. Is the existing system sufficiently intelligent to know the courses that would interest you?
2. Does the existing course selection provide course suggestion?
3. Do you want to know the potential course degrees for future learning?
4. Should a good course selection system be intelligent?
Level 3: Questions about Using the Proposed Course Decision Assistant
1. Have you ever used a similar system?
2. Is the proposed data analysis by mining the relationships between personalities and courses important?
3. Will the proposed course suggestion help you choose courses of potential interest?
4. Can the proposed course prediction can help you choose your future learning?
5. Overall, is this system intelligent?

4.2.2. Experimental Results of Subjective Evaluations

This subjective evaluation was mainly conducted to determine the overall satisfaction with the proposed idea, including course suggestion and course degree prediction. To this end, we created and implemented an online course decision assistant system that provides course suggestion and course degree prediction services. Next, we announced the system and invited 226 testing students (called testers hereafter) to answer the questions using ratings. The ratings ranged from 1 to 5, where 1 and 2 indicated negative opinions and 3, 4, and 5 indicated positive perceptions. Figures 3–5 depict the rating results for three levels individually.

- For level 1, Figure 3 shows that,

  I. 85.022% of testers agreed that interest in a course is important.
  II. 92.982% of testers wanted to know the relationships between courses and personalities before selecting courses.
  III. 80.349% of testers did not know what courses they wanted to select.
  IV. 92.609% of testers had selected courses in which they were not interested.

- For level 2, Figure 4 shows that,

  I. 63.717% of testers did not know courses that interested them when selecting courses.
  II. 92.035% of testers wanted course suggestions in the existing system.
  III. 94.69% of testers wanted to know the possible degrees for future learning.
  IV. 94.69% of testers agreed that a good system has to be intelligent.

- For level 3, Figure 5 shows that,

  I. 96.53% of testers have never used a similar system.
  II. 94.273% of testers agreed that the proposed data analysis via mining the relationships between personalities and courses is important.
  III. 94.323% of testers agreed that the proposed course suggestions are helpful for choosing courses of potential interest.
  IV. 96.087% of testers agreed that the proposed course prediction is helpful for choosing future learning.
  V. 97.835% of testers agreed that the proposed system is intelligent.

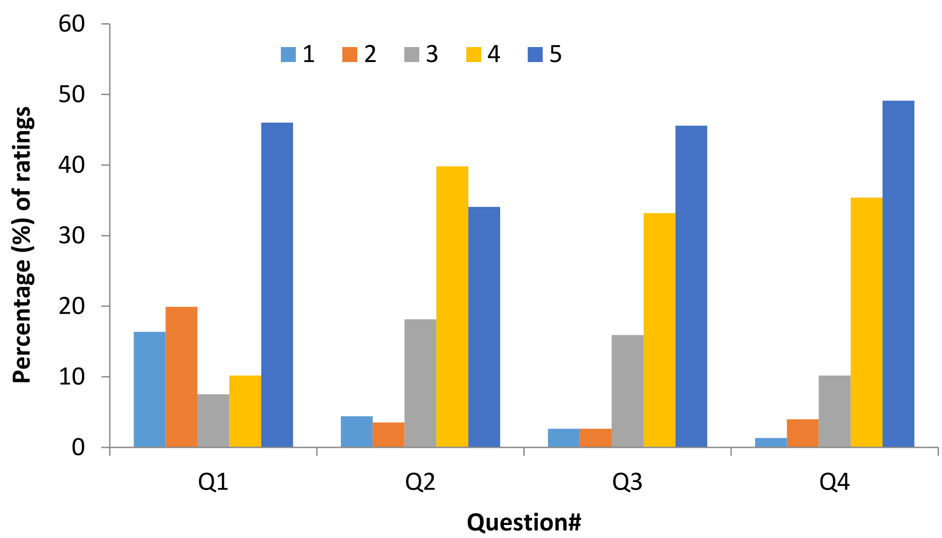

Figure 3. Ratings for level 1 questions.

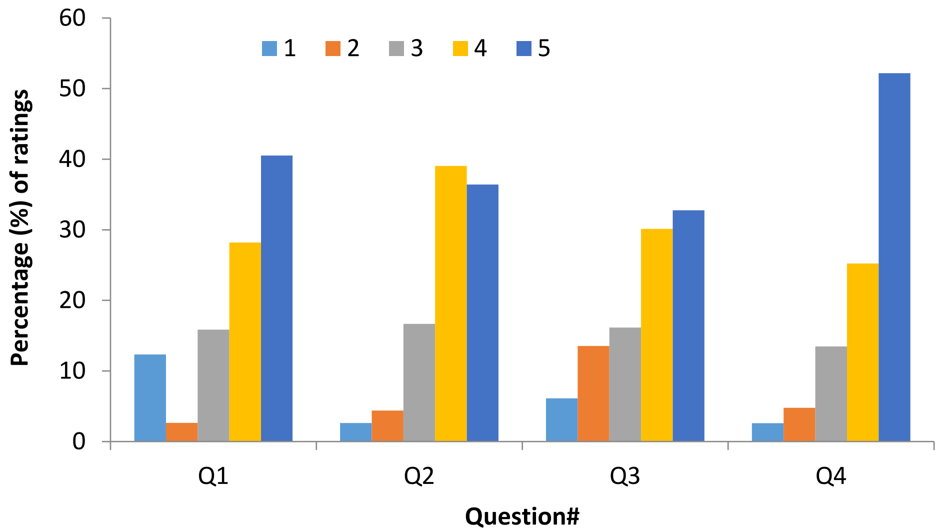

Figure 4. Ratings for level 2 questions.

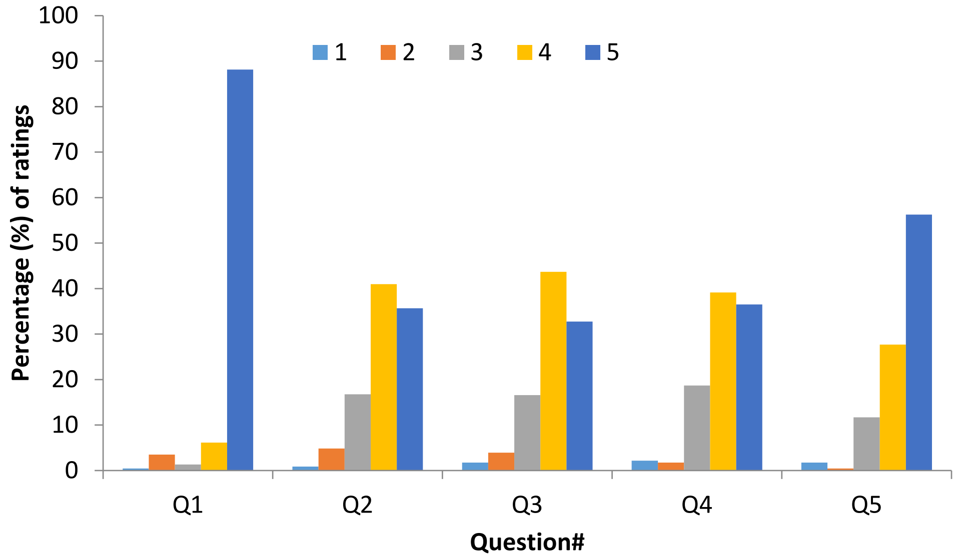

Figure 5. Ratings for level 3 questions.

4.3. Experimental Discussion

To demonstrate the effectiveness of and satisfaction with the proposed system, a number of objective and subjective evaluations were conducted. Here, a set of insightful discovery is discussed as follows.

- Algorithm 2 shows that k is the factor for predicting the course degree. Notably, if k is smaller than 50, the effectiveness decreases. Although the best effectiveness appears when $k > 50$, k cannot be too large or efficiency is affected. This is why we set k to 50.
- The levels 1 and 2 questions can be viewed as the motivation evaluations of the proposed system. Figures 3 and 4 show that over 80% of testers want an intelligent system that can provide course suggestions and course degree prediction services. This result provides evidence that the proposed system is necessary and valuable for student learning.
- Figure 6 summarizes the ratings for all three levels of questions. First, 87.611% and 86.283% of testers assigned positive ratings for levels 1 and 2 questions, respectively. These results show that most testers agreed that the existing system lacks the ability to suggest courses and predict course degrees. Second, 95.664% assigned positive ratings for the level 3 questions. In detail, the proposed

system can provide an effective course selection support. Further, the high positive ratings for the level 3 questions give an evidence that the data mining technique based on References [5,37] works well for bridging personalities, preferences and achievements [9,23,24,27].

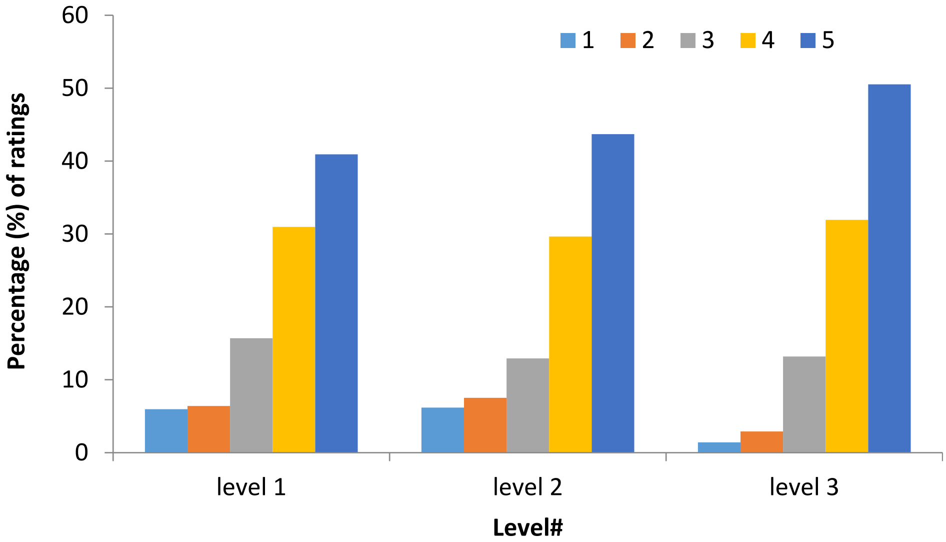

Figure 6. Summary of the ratings of the three levels of questions.

In summary, the basic idea of our proposed idea is based on an educational aspect that personality is an impact factor for preferences, and preferences will have an impact on learning results. Accordingly, our intent is to mine the confident rules between personalities and achievements by data mining techniques. To evaluate the proposed idea, a number of experiments were made. The subjective and objective evaluation results show that the proposed idea is effective by combining data mining techniques and educational aspects.

5. Conclusions and Future Work

Learning is an important aspect of education. Determining how to learn has generally attracted more attention than what to learn in recent learning systems. However, what to learn is more critical than how to learn because a learning direction aligns learning with interests, ensuring learning is more effective and efficient. For this purpose, we designed a novel course decision assistant that provides services of course suggestion and course degree prediction. The contributed technical services and experimental findings are concluded as follows.

- In terms of course suggestion, the relationship patterns between user personalities and course degrees are mined from learning logs. From the mined patterns, the potential high-performance courses are provided as a suggestion list.
- In terms of course degree prediction, the unknown degrees are estimated by the prediction algorithm. In this algorithm, the user similarities are calculated to filter users. By user-filtering, the relevant users can be gathered to provide useful information for predicting unknown degrees.
- In terms of experimental findings, a number of objective and subjective evaluations were conducted to verify the validity of the evaluation. For objective evaluations, the results showed that the prediction results are strongly related to the ground truth data, showing that the proposed prediction algorithm is reliable for the users. For subjective evaluations, the experimental results revealed that most testers wanted an intelligent system that can suggest courses and predict course degrees. After using the proposed system, more than 94% of testers assigned satisfactory ratings to the proposed system, showing that our proposed system can provide useful information for selecting courses.

Although the proposed idea has been applied in a real system, a set of issues remains to be investigated for improvements.

- First, for course suggestion, in addition to personality, other information could be considered, e.g., teacher, teaching type, and so on.
- Second, for course degree prediction, although the prediction results show the prediction algorithm is effective, other prediction methods, such as course filtering, will be tested further. From a course point of view, the unknown degree can be derived by similar courses.
- Third, this study was just the first step of the proposed idea that was realized in a single department. In the future, it will be applied across different departments.

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