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Developing a Method of Recommending e-Learning Courses Based on Students' Learning Preferences

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Abstract. In designing e-learning, it is desirable that individual learner's learning style is considered. This study proposes a way to present the information about the expected adaptability of the course, in which a student wishes to enroll, based on the student's responses to the learning preference questionnaire administered at the beginning of the course. As the result of applying the real data to the model derived, it was confirmed that it would be possible to estimate the course adaptability before taking the course and to provide the information for the student to improve his/her course adaptability based on the student's responses to the learning preference questionnaire.

Keywords:e-learning, learning preferences, e-learning adaptability, recommending courses, multiple regression analysis

1 Introduction

In the period when learner-centered teaching and learning has been called for, it is important to think about providing learning environments that are suitable to learner's individual style and ability of learning. In the early days of e-learning, the learning materials tended to be limited to text and images due to the bandwidth and hardware constraints. As the improvement has been made in the information infrastructure of e-learning in general, nowadays audio, video, and animation are being used in e-learning materials in addition to text and images.

In terms of learning methods and environments, self-study with materials was a very common method in the early days of e-learning. In addition to the types of learning materials, the pedagogy of e-learning has started to change as more constructivistic methods of teaching and learning such as collaborative learning and project-based learning are being introduced to e-learning[1].

The functionalities of learning management systems (LMS) have also improved to allow active learning for students by enabling communication between instructors and students with the interface familiar to them [2], the use of audio and video, information sharing in virtual environments [3].

As stated above, thanks to the development of learning materials and pedagogies, it has become possible to provide learning materials, methods, and environments that are suitable to individual learner's learning style and preferences. However, it is not easy for a student to understand his/her own learning style and select suitable courses or materials among a vast number of choices. This paper looks at the learning style of e-learning learners and discusses the method to recommend suitable e-learning courses for the learners.

2 The Learning Management System in Consideration of Learning Styles

2.1 Research on Learning Styles in e-Learning

Previously some studies were conducted using the Kolb's learning style [4] in developing computer-based training (CBT) [5] and examining the influence of learning styles on the "flow" experience and learning effectiveness in e-learning [6]. Other studies used GEFT (Group Embedded Figure Text) [7] to see the influence of learning styles and learning patterns on learning performance [8] and the instrument developed by Dunn, Dunn and Price [9] to build a system which provides learning environment suitable to the student's learning style [10].

E-learning has the potential to provide "learner-centered learning" and tends to be designed based on the pedagogy of providing learning environments according to the learners' needs, abilities, preferences and styles rather than providing uniform education without any consideration of individual needs and differences. Therefore, it is meaningful to provide students and teachers with information about the students' adaptability to e-learning courses by using a questionnaire on learning preferences in e-learning. Here we use the term "learning preferences" instead of "learning styles" as the term, "preferences" connotes more flexibility than "styles."

This study looks at learning preferences of students and the adaptability in e-learning courses.

2.2 e-Learning Course Recommendation Based on Learning Preferences

Asynchronous learning and the use of ICT (information and communication technologies) are typical characteristics of e-learning. As e-learning is usually conducted asynchronously, it requires more self-discipline of students in comparison with face-to-face classes. E-learning might be easier for students who want to learn at their own pace to continue and complete a study. However, it can be challenging for those who do not like studying on their own and prefer doing in face-to-face classes.

The use of learning management systems (LMS) can ease the distribution of course materials and the communication among students or between students and teaching staffs. However, the use of LMS in e-learning tends to become complex as its functionality increases and may discourage those students who are not familiar with the ICT use. Accordingly, those who do not like asynchronous learning or the use of ICT may have the tendency to drop out in the middle of e-learning courses [11].

E-learning allows student-centered learning in which students themselves, instead of instructors, set the time, place and pace for their study. Therefore, it is desirable that students and their teachers know the students' learning preferences and their adaptability of e-learning courses in advance [12].

As shown in Fig. 1, therefore, we proposed a extended LMS that recommends e-learning courses suitable to a student based on his/her learning preferences. To investigate the learning preferences in e-learning, we developed learning preference questionnaire items asking preferences in studying, understanding, questioning, and doing homework [13]. To establish a learning environment that matches the learning preference of the student, we confirmed through multiple regression analyses that the adaptability to an e-learning course can be estimated before the student's taking the course based on his/her answers to the learning preference questionnaire [14].

In previous studies, the authors estimated the overall course adaptability of a student (instead of the adaptability for each individual course) based on the student's learning preferences [15]. However, in that way, though it could be determined whether the student is suitable for e-learning courses in general, neither it could estimate his/her adaptability to a particular e-learning course, nor it could suggest a suitable course for the student. In other words, the previous model could not provide detailed information to help students decide on which e-learning courses to take.

As shown in Fig. 1, therefore, this study conducts multiple regression analyses to suggest a student's adaptability to each course based on the past students' data of learning preferences and the adaptability of the course. Using the multiple regression

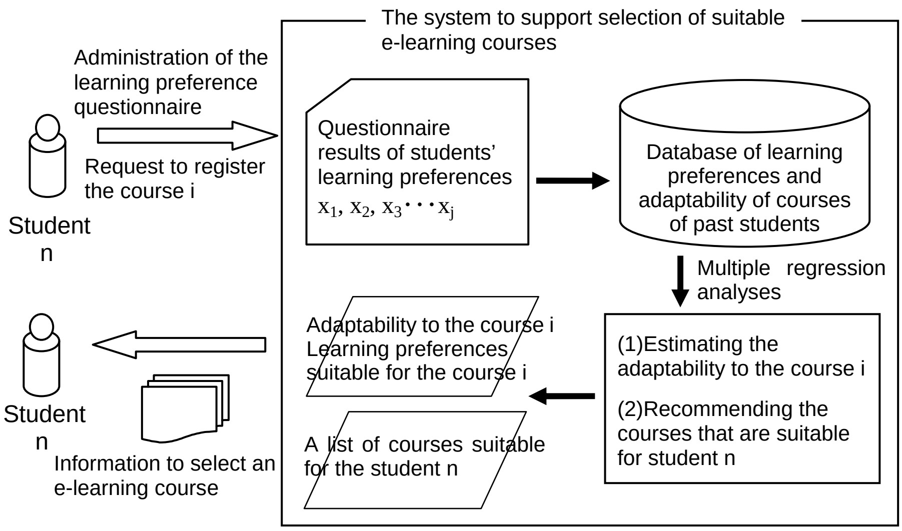

Fig.1. The system of recommending e-learning courses suitable to a student in consideration of the student's learning preferences

model, a student can be informed of his/her adaptability to a particular e-learning course beforehand. At the same time, it can be known which learning preferences are suitable for taking the course successfully. In addition, we examine the ways to suggest the courses that are considered to be more suitable to the student.

3 Predicting e-Learning Course Adaptability Based on Learning Preferences

3.1 Survey on Learning Preferences

eHELP (e-learning for Higher Education Linkage Project) is one of the biggest collaborative e-learning projects in Japan, aiming at credit transfer through e-learning among universities and colleges of technology. As of 2010, 6 universities, 17 colleges of technology and one institution participated in the project and the total of about 1000 students were enrolled in at least one of the 60 full online e-learning courses on engineering subjects. Most of the enrolled students had the experience of using ICT in face-to-face classes, but little experience of taking fully-online courses. The 60 courses offered through eHELP are independent of one another, and no prerequisite is required for taking any course.

The questionnaire on learning preferences was administered to those students who enrolled in the eHELP. Students take a few full online courses offered by other institutions in parallel to taking courses offered by their own institution. In taking an e-learning course, a student studies the content which is equivalent to 15 face-to-face classes (90 minutes per class). For example, the course, Information Society and Information Ethics, followed the cohort base model and the students studied online learning materials (including PowerPoint slides and lecture videos) provided weekly. In another course, e-Management Information Mathematics, the students carried out learning activities such as watching lecture videos using graphics and taking quizzes.

The study discussed here was conducted at the beginning of the spring semester in 2009 and 2010. All the items in the questionnaire were asked with the 7-point Likert-type scale; from 1 being “don’t agree at all” to 7 “agree strongly,” and we obtained valid responses from 77 students. We discarded responses that had marked all the same points regardless of reverse coded (i.e., negatively phrased) items. The questionnaire consists of 33 items asking preferences in studying, understanding, questioning, and doing homework in terms of asynchronous learning (async) and the use of ICT (with ICT) (see Appendix 1). The questionnaire was made available online and students accessed the questionnaire online.

3.2 Survey on e-Learning Course Adaptability

When the learning preference questionnaire was administered, the questionnaire on e-learning course adaptability was also administered to the students who enrolled in eHELP courses. The items in the questionnaire are shown in the Table 1. The questionnaire consists of 10 items asking psychological aspects of learning such as the level of students' understanding and the level of satisfaction. In this study, in order to make the student's course adaptability a single variable, the mean of 10 items was calculated for each student and defined as the adaptability score for the particular course. Then, the method to estimate the course adaptability for another student before taking the course is explored.

The questionnaire (see Table 1) was administered online to the students enrolled in each of the eHELP courses upon their completion of the course and 69 completed responses were obtained at the end of the spring semester in 2009 and 2010. All the items in the questionnaire were asked with the 7-point Likert-type scale; from 1 being "don't agree at all" to 7 "agree strongly." The scores for the item (g) and (h) were reverse-coded. The reverse-coded items were recoded to adjust to the other items.

Table 1. The question items in the e-learning course adaptability questionnaire

Item	Mean
(a) The content of this e-learning course is more understandable than regular class contents.	4.03
(b) The style of learning of this e-learning course is easier to learn than regular classes.	4.27
(c) The pace of this e-learning course is more suitable than regular classes.	4.30
(d) This e-learning course is more satisfying than regular classes.	3.91
(e) This e-learning course is more effective than regular classes.	3.82
(f) This e-learning course is more interesting than regular classes.	4.74
(g) This e-learning course makes me more tired than regular classes. (recoded)	4.26
(h) This e-learning course makes me more nervous than regular classes.(recoded)	5.14
(i) This e-learning course brings me more endeavor than regular classes.	3.67
(j) This e-learning course brings me more motivation than regular classes.	4.16

3.3 Developing the Multiple Regression Model

In this section, we discuss the way to estimate the course adaptability based on the learning preference scores obtained at the beginning of the course. The course adaptability score (the mean of all the ten items in the Table 1) is calculated using the multiple regression model with learning preferences as independent variables. In order to estimate the adaptability to the e-learning course i, a multiple regression model was developed by using several independent variables extracted from the 33 items in the learning preference questionnaire administered at the beginning of the course i. The way to develop the model is described below:

(Step 1) Calculate correlation coefficients between results from each of the items in the learning preference questionnaire and the adaptability score to the course i.

(Step 2) List the items in a descending order based on their correlation coefficients and select the top eight.

(Step 3) Based on the correlation matrix of the above eight items, select the item pair that shows the highest correlation coefficient. Then, drop the one which has the lower correlation coefficient with the course adaptability score.

(Step 4) Create the multiple regression model for the course adaptability using the remaining items described above.

(Step 5) Analyze the existence of multicollinearity among the items selected and drop the item that is suspected to have a high multicollinearity.
(Step 6) Drop the item which has the high p-value.

The remaining items are eventually used to develop the multiple regression model for the course adaptability.

4 Estimation of the Course Adaptability

For the course A that had the largest number of registered students in the spring semester of 2009 and 2010, using the steps described above, the course adaptability is estimated based on the learning preference scores that were measured at the beginning of each course (18 responses to each of the 33 items).

The correlation coefficient of the selected items from the learning preferences measure for the course adaptability score was shown in Table 2 (Step 1 and 2).

Next, the correlation matrix of the eight selected items that have the higher correlation coefficients is created and is shown in Table 3. Regarding q28 and q15 as well as q30 and q15 that are correlated highly (as underlined in Table 3), q15, which has a lower correlation with the course adaptability, is dropped (Step 3).

The partial regression coefficients and p-values in the multiple regression model for the adaptability to the course A are shown in Table 4 (Step 4). Concerning x(q10) and x(q28), their partial regression coefficients are minus and show the possibility of multicollinearity. Therefore, these two items are also dropped (Step 5).

Then another multiple regression analysis for the adaptability to the course A is conducted using the remaining five items. Finally, the two items with relatively high p-values (q21 and q19) are dropped and the model below is created (Step 6).

$$y_a=0.245x(q11)+0.168x(q30)+0.246x(q8)+1.401 \quad (R^2=0.559) \qquad \textbf{(1)}$$

The correlation coefficient between the course adaptability score calculated using the above model (y_a) and the course adaptability score measured at the end of the course is 0.748 that shows a high correlation between the two. Fig. 2 shows the correlation between the calculated scores of the course adaptability and measured ones.

Based on these results, the adaptability score to the course A can be estimated by applying the responses for q11, q30, and q8 to the multiple regression model described above **(1)**. Furthermore, as the adaptability scores to the course A have positive correlations with all the three items (i.e., q11, q30 and q8), it can be expected that increasing those learning preferences will raise the adaptability to the course A.

Then, the adaptability to the course B was also estimated based on 18 responses of the students enrolled in spring semester of2009 and 2010 to the learning preference questionnaire at the beginning of the course as described in 3.3.

$$y_b=0.130x(q22)+0.145x(q26)+0.080x(q33)+2.775 \quad (R^2=0.407) \qquad \textbf{(2)}$$

As a result, the correlation coefficient between the calculated adaptability scores to the course B (y_b) and the actually measured scores was found to be 0.638, showing a relatively strong correlation. Fig. 3 shows the correlation between the calculated scores and the measured scores of the course adaptability.

Based on these results, it has become possible to estimate the adaptability to the course B for a student before taking the course by applying the student's responses to the question times q22, q26 and q33 in the learning preference questionnaire to the multiple regression model described above. In addition, as the positive correlation was found between the responses to the learning preference questionnaire items (i.e., q22, q26, and q33) and the adaptability scores to the course B, it could be said that making the students' learning preferences more positive with respects to the above three items will result in heightening their adaptability to the course B.

The course A and the course B differ in the items in the learning preference questionnaire that contribute to the estimation of the course adaptability. Therefore, it is possible to recommend courses that are suitable for the learning preferences of a particular student as the items on the learning preference questionnaire that contribute to the adaptability differ among different courses. In addition, in the same way the course adaptability for the courses A and B are calculated, the adaptability for each of the remaining courses can be calculated using the multiple regression model and the list of e-learning courses that are suitable for a particular student can be provided before the courses start.

Table 2.Correlation Coefficients Between the Course Adaptability and the Learning Preferences (showing only the eight items with the highest correlation coefficients)

Question items	q11	q30	q8	q21	q10	q28	q15	q19
Correlation coefficients	0.533	0.359	0.344	0.321	0.292	0.219	0.215	0.209

Table 3.Correlation Matrix of the 8 Items

	q11	q30	q8	q21	q10	q28	q15	q19
q11	1.000							
q30	0.548	1.000						
q8	-0.182	-0.414	1.000					
q21	0.124	-0.158	0.435	1.000				
q10	0.374	0.207	0.069	0.269	1.000			
q28	0.345	0.448	0.084	0.494	0.249	1.000		
q15	0.294	<u>0.632</u>	-0.203	0.083	0.251	<u>0.723</u>	1.000	
q19	0.371	0.081	-0.053	0.081	0.099	0.339	0.185	1.000

Table 4.Partial Regression Coefficients and p-Value in the Multiple Regression Model with 7 Independent Variables (*x(q11)* and *x(q30)* indicate each independent variable)

Independent variable	x(q11)	x(q30)	x(q8)	x(q21)	x(q10)	x(q28)	x(q19)	Error
Partial regression coefficient	0.195	0.339	0.255	0.125	-0.06	-0.211	0.104	1.109
P-Value	0.186	0.038	0.021	0.148	0.453	0.106	0.359	0.168

Table 5.Partial Regression Coefficients and p-Value in the Multiple Regression Model with 3 Independent Variables

Independent variable	x(q11)	x(q30)	x(q8)	Error
Partial regression coefficient	0.245	0.168	0.246	1.401
P-Value	0.055	0.149	0.011	0.065

（$R=0.748$，$R^2=0.559$）

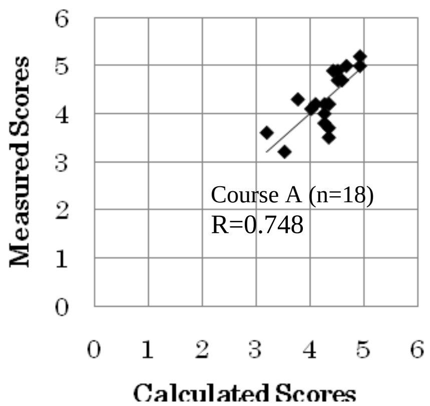

Fig. 2. The Correlation Between the Calculated Scores of the Adaptability to the Course A and the Measured Ones

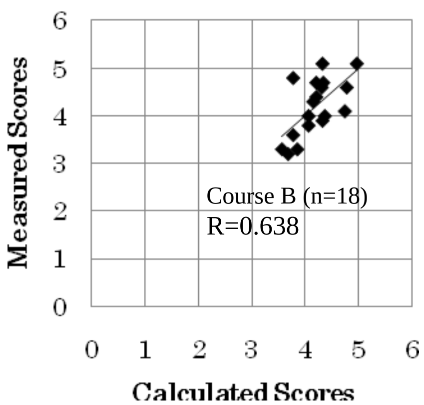

Fig. 3. The Correlation Between the Calculated Scores of the Adaptability to the Course B and the Measured Ones

5 Conclusion

It is desirable that the learning methods, materials, and environments that are suitable to the learner's learning style are designed in order to improve the learning outcome in e-learning. In this study, the multiple regression model for estimating the adaptability to a particular e-learning course based on the student's learning preferences was derived from the past data concerning the relationship between learning preferences and the course adaptability of the students who enrolled in an e-learning course through eHELP. As a result, it was found that the adaptability to a particular course could be estimated based on the student's responses to the learning preferences questionnaire and suggestions for appropriate learning preferences could be made to the student to improve the course adaptability. In addition, it was found to be possible to recommend a list of courses suitable to a particular student based on his/her learning preferences.

At present, we developed the multiple regression model for only two courses because they were the only courses that had 15 or more students. In the future, we would like to develop multiple regression models for as many courses as possible by increasing the student enrolment in each course. In addition, we would like to improve the question items on the learning preference questionnaire in order to estimate the students' course adaptability more accurately. Furthermore, we would like to develop a system within a learning management system (LMS) that automatically provides students with the relevant course information to select e-learning courses appropriate for the students.

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Appendix 1: The Learning Preference Questionnaire

q1) I tend to learn more actively when I study alone than studying with others at one place. (async)
q2) I would rather follow the computer instruction rather than study reading textbooks. (with ICT)
q3) I prefer learning through computers to learning by reading books. (with ICT)
q4) I am familiar with computers. (with ICT)
q5) It is easier for me to take test on a computer than on paper. (with ICT)
q6) I feel less tired when I study independently at my convenience than studying with others at one place. (async)
q7) I study at my own pace and do not care how others study. (async)
q8) I would rather submit my report in an electronic format than in a paper and pencil format. (with ICT)
q9) I understand better when I study at my convenient time rather than learning in class with other people. (async)
q10) I would rather receive answers later from teachers via mail than asking questions in person or through chat. (async)
q11) It is easier for me to take test individually than to take one in a place with others. (async)
q12) I prefer taking notes using a computer than writing on paper. (with ICT)
q13) I understand better when I learn through computers than when I learn by reading books. (with ICT)
q14) I can concentrate better when I study independently at my convenience than studying with others at one place. (async)
q15) I tend to learn more actively using computers than studying in class. (with ICT)
q16) It is easier for me to memorize what is on a computer rather than to review printed materials. (with ICT)
q17) I would rather study alone at the place and time convenient to me than learn in class with other people. (async)
q18) I can be more creative when I think using computers than thinking on paper. (with ICT)
q19) I would rather do group learning through computers than face-to-face. (with ICT)
q20) I can familiarize myself better when I study independently at my convenience than studying with others at one place. (async)
q21) I feel less tired looking at a computer screen than looking at a blackboard or a large screen in a classroom. (with ICT)
q22) When I study through computers, I tend not to care how others study. (with ICT)
q23) I prefer communicating via email to communicating through telephones. (async)
q24) I would rather ask questions using email or bulletin boards than asking teachers in person. (with ICT)
q25) I wan to study at my own pace. (async)
q26) I can be more creative when I study alone than studying with others at one place. (async)
q27) I can be more creative when I think on paper than using computers. (without ICT)
q28) I can concentrate better looking at a computer screen than looking at a blackboard or a large screen in a classroom. (with ICT)
q29) I feel more motivated when I study at my convenience than learning in class with other people. (async)
q30) I feel more motivated when I study using computers than learning from teachers in person. (with ICT)
q31) I can learn better when I study at the time I decide than when I study at the time decided by others. (async)
q32) I wan to study at the same pace with other sudents. (sync)
q33) It is easier for me to communicate through computers or cell phones than to communicate face-to-face. (with ICT)