Learning strategy feedback system for students using data mining technology

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ABSTRACT: Using data mining technology, we developed a feedback system of learning strategies based on models that were created from data obtained from high school students. Using this system, we evaluated it from three perspectives. Results showed the following. (1) The models were validated because the difference of academic ability estimated from the models was reflected in data obtained from a monitor test. (2) The signal metaphor, representing the achievement levels of learning strategies, was effective because the length of time spent to read explanations of learning strategies differed according to the signal color; the direct road metaphor, representing the order of learning strategies, was understood by nearly half of the students. (3) Some users reported that the system animations were too long, but the overall system evaluation was favorable.

KEY WORDS: Learning strategy, Feedback, Data mining

1. INTRODUCTION

1.1. Objective of Research and its Background

A learning strategy is defined as "an activity or a mental operation intended to raise learning efficiency" (Tatsuno, 1997). An effective mode of learning is an important factor for improving the academic ability of students.

On the other hand, a learner might not necessarily understand what learning strategy is best to use. Considering responses to the question of "Are you a student who does not know how to learn efficiently?", 72.1% of junior high school students and 75.7% of high school students responded with either "very much true" or "maybe true" (BERD, 2005) .

It might not necessarily be true that the learners who responded with "I do not know how to learn in an efficient way" are "not using an efficient mode of learning." If they are given no information to indicate what the best-fitted learning strategy might be, even learners who are actually practicing "an efficient mode of learning" might believe that they do not know "how to learn in an efficient way."

There are therefore two aspects of guidance of learning strategies. First, for learners who already know the right learning strategy and who are practicing it, a person intending to guide those learners should tell them that theirs is a good way, thereby giving them confidence. Secondly, learners who know of no appropriate learning strategy can be provided with information about proper learning strategies to facilitate their acquisition and practice of a more effective mode of learning.

What would be the best possible mode of guidance to a proper learning strategy? One method might be that used normally for cognitive counseling: giving guidance about learning while meeting with the learner face-to-face while diagnosing the learner in terms of their motivation for learning, comprehension level, and structure of recognition to help the learner acquire an appropriate learning strategy and improve their learning skills independently (Ichikawa, 1995). In other countries, such as in the U.S.A., some questionnaires used to diagnose learning strategies used by learners have been developed such as the Learning and Study Strategies Inventory (LASSI) by Weinstein et al. (1988), and Motivated Strategies for Learning Questionnaire (MSLQ) by Pintrich and DeGroot (1990). They were developed to assist teachers in giving correct guidance to students about learning strategies based on the diagnoses they supported. Other universities are providing training programs on learning strategies based on those diagnoses.

It is true that we can expect high performance from such methods of learning, as described above, because those methods do present a plan and course by which teachers can become involved. However, in current circumstances, in which many learners just do not know how to "learn in an efficient way," using some kind of information system, for example, would present another efficient means of guidance. To date, however, no development of such system to discern the most appropriate learning strategy and to give a feedback directly to the learner has been reported in the relevant literature.

Through this study, we devote ourselves to developing a system that can ascertain whether a learner's currently used learning strategy is appropriate. Based on that inference, feedback can be given to guide the learner to better modes of learning in the future.

The system's performance criterion, however is not improvement of the learner's academic ability. The improvement of academic ability is something that might be influenced by such complex factors as the learning environment, how many hours are used for learning activities, what learning strategy is actually used, and so on.

1.2 Design Requirements

The system is designed to give feedback to the learner of "appropriate" learning strategies. To do so, we must be able to ascertain that it is truly appropriate.

Many studies of learning strategies pose questions that require responses to be made on a Likert scale and examine the structures of learning strategies using factor analysis. The MSLQ introduced above is a method derived from such studies (Duncan and McKeachie, 2005).

On the other hand, because factor analysis uses a mode of multivariate analysis with no criterion variables engaged, it would not be able to inform us of the most appropriate learning strategy, although it can certainly tell us the structure of learning strategy based on results of the analysis. To determine the propriety of the learning strategy, criterion variables must be used.

A learning strategy is defined as "an activity or a mental operation intended to raise learning efficiency (Tatsuno, 1997)." The learners we are supporting are currently at the high school education stage. They are constantly evaluated for their study performance according to numerous examinations taken at schools and also through the entrance examinations they take to move on to the next higher level of education. Considering those facts, we decided to use the scores of those academic ability examinations they took as a criterion variable to judge whether the learning strategy used is appropriate or not.

Additionally, learning strategies can be abstracted automatically if examined in a structured manner using a factor analysis. Such a study can give us a lot of information which is psychologically important, but even with it, the learner would not be able to be given the correct information related to a practical level of learning strategy to which the learner can agree and which can be understand without difficulty.

Based on these results, we would not analyze the learning strategy in a structured fashion, but rather analyze it in relation to academic ability using each item of the questionnaire related to the learning strategy as an independent variable. After doing so, it is possible to give good feedback related to the learning strategy that is practical and easy for the learner to understand, and which is highly associated with the learner's academic ability.

As a feedback system, we use a regression binary decision tree analysis (regression tree analysis), which is one method of data mining. The regression tree analysis provides a way to divide the collection of objective variables into two classifications sequentially based on the specific values of the several criterion variables. It has the unique characteristic that the criterion variables and their values are determined such that the variance of the variables is much smaller after binary division than the variance before the collection was divided.

Looking at one collection after being divided, we can extract and know the conditions used during the course of division using the rule of If-and-Then types of clauses. In other words, using regression tree analysis, we can discern a rule that shows how to reach the node with a high mean value knowing what variable to divide at what value in what sequence in the dividing process.

This point is considerably important when we consider the feedback of the learning strategy. That way we can show in a practical sense the learning strategy that the learner of high academic ability is using as well as to what extent they use the learning strategy. Moreover, we can tell how a learner's academic grade could be improved by showing, for example, what learning strategy to begin with, and in what order to proceed in recommending others.

Another mode of analysis that is currently available in addition to the regression tree analysis is multiple regression analysis. A multiple regression analysis can combine academic ability with its most commonly associated learning strategies to produce a model, but the resultant model would not include the information of the order in which the learning strategies could be recommended.

Furthermore, regression tree analysis, which is a nonlinear model, can express a more flexible model than multiple regression analysis, which subsumes a linear relation among the variables. A regression tree analysis can create a more detailed model considering other variables in addition to learning strategies if sufficient data become available for analyses.

However, it is noteworthy that it would be useless if we provided a learner directly with the model created using a regression tree analysis. We would need to use some other expression to help the learner understand the feedback in a more intuitive fashion when we provide it from such a model as created using a regression tree analysis.

First, we would need to present the learner with information of whether the correct learning strategy for that person was obtained or not. That information can be created based on criterion values given at every branch node of the decision tree, which is automatically induced from regression tree analysis.

Another fact is that the decision tree produced from the regression tree analysis can be divided sequentially starting from the root node (Fig. 1). When leading a learner to the one node among the non-divisible ones that is of the highest academic grade—the node that it is presumed to be the best-fitted of all nodes—we would need to guide the learner to start with that node to explain the learning strategy of that branch first, with other explanations offered for other strategies sequentially. In the regression tree, because it is branched sequentially from the top downward, as portrayed in Fig. 1, if the learner went over the second to the fourth strategies successfully out of the five, for example, the learner would not be able to reach the final and best-fitted node unless the first strategy had already been mastered.

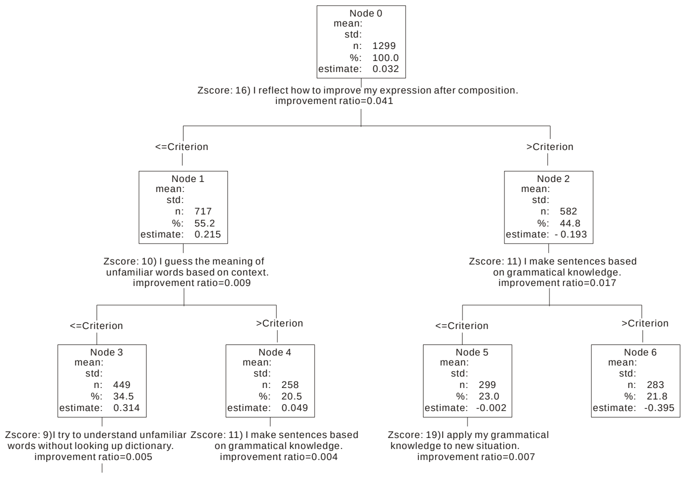

Figure 1 Example of regression tree analysis

Based on the facts and observations described above, the system would be required to accomplish the following three tasks.

1) It can judge whether or not the learner's strategy is appropriate based on the decision tree produced by regression tree analysis using the academic ability as a criterion variable.

2) It can show, readily and comprehensibly, whether the learner's strategy is appropriate or not (or whether the proper learning strategy has been accomplished or not).

3) It can show, readily and comprehensibly, which learning strategy a learner should begin with most efficiently.

Based on these three requirements, we designed and developed a web-based feedback system: the Learning Navigator.

2. INTRODUCTION TO THE SYSTEM

The Learning Navigator is a web-based system that can infer whether the currently used learning strategies by the learner, which are entered into the system on the web, are truly appropriate. It can also return feedback of the results to learners using a readily comprehensible metaphor.

The system comprises the following components. 1) A web page provides the learner with some learning strategies. It makes inquiries about how much the learner is using it. 2) A logic portion (hereinafter, a strategy engine) is set on the server side to judge how much each strategy that the learner follows is appropriate based on the information available from the questions posed as described above. 3) Another logic part (hereinafter, a visualizer) on the client side gives feedback of judgment results in an easily visualized fashion. 4) A database stores information produced from each engine, providing it interchangeably to the learner.

2.1. Questionnaires

The questions designed to assess the propriety of each learning strategy were chosen among the references to studies made in the past related to the learning strategy. Reports of studies were undertaken by Kubo (1999) and Oxford (1990) with respect to English language learning. Ichihara and Arai (2005), National Institute for Educational Policy Research (2004), and others examined mathematics learning. In addition, Inuzuka (2002) and Ichihara and Arai (2005) and others investigated Japanese language learning. Relevant questions were produced in reference to the reports of those studies. We limited the number of questions to 20 for each of the learning subjects described above to avoid unnecessary burdens on the user. The response to every question related to learning strategies was expected to be given with one of the seven levels of response on a Likert scale: “1 Very much so” – “7 Not likely at all”.

The questions were presented to each learner for each subject on web pages.

2.2. Strategy Engine

The strategy engine is the part of the system that infers whether the learning strategy that is used by the learner is appropriate.

During development of the strategy engine, we defined the appropriate learning strategy as that which a learner of a high academic ability level was using. Academic ability here is inferred based on the score of a specific achievement test. For this study, we used results of achievement diagnostic tests that were developed for each of the subjects by Benesse Corp. Based on those results, we used the score that every individual student obtained, which was calculated using the simultaneous estimation method inside the test-taking group based on Item Response Theory.

We then created an inference algorithm according to the following process.

First, we made a survey to assess the learner’s academic ability level and learning strategies. The survey was conducted for as many as 1300 third year high school students who had experience of taking the center examination in 2005; it was conducted during March 18 – March 21, 2006. Additionally, it was made by asking as many as 100 questions placed on the questionnaire sheet related to the achievement tests of English, Japanese, and Mathematics, the learning strategies examined in section 2.1 above, and other learning-related perspectives.

Based on the survey results, we produced a regression tree analysis using the typical method of creating a regression binary tree, the Classification And Regression Tree (CART). The analysis was made in the following sequence. First, we subtracted the mean value of the seven levels of question points on the learning strategy survey made to the 1300 students from each of the seven level points answered by the learner for each of the learning subjects. We then divided the subtracted results by the standard deviation to create a normalized value (hereinafter, the normalized strategy evaluation value) defining it as an explanatory variable, and also defining the score of the achievement test taken by each learner for each learning subject as an objective variable. Finally, we created a binary tree for each learning subject that was 4–5 levels deep. Each binary tree is divided into binary branches at every node, depending on whether the normalized strategy evaluation value there for each specific learning strategy was greater than or less than the criterion value. For that purpose, we used the SPSS Classification Trees for regression tree analysis.

Then, starting from the end node of each binary tree made for each of the learning subjects, we chose, using the analysis of variance, 1 or 2 nodes for which the mean value of the objective variable was considerably high.

As a practical matter, during the following test conducted (5% level) using the Tukey method, the node that was classified into the homogeneous subgroup of having the highest mean value, and which did not belong to the other homogeneous subgroup, was chosen as the best fitted node.

In cases where we devise more than one fitted node, we selected one as the best-fitted node for the learner while processing the following sequence. First, we obtained the seven levels of evaluation points to the learning strategy for every learning subject based on those evaluation points entered on the Web screen. For the selection, we also considered the learner for whom the learning strategy was diagnosed. We normalized the data using the mean value and the standard deviation of the point values of all 1300 third-year high school students for whom the survey for learning strategies had been conducted. We then calculated the normalized learning strategy evaluation value. We then looked at the branch nodes in the tree structure for the learner starting from the root node downward for every possible fitted node. Calculating the cumulative value to the absolute value of the differences between the branch node value and the normalized learning strategy evaluation value that does not satisfy branching, we selected the node with the smallest cumulative value as the best-fitted node for the learner. In other words, we selected the node that the learner can be expected to reach with the least effort.

Consequently, the best-fitted node group that is set to be returned to the learner as feedback is the combination of the information of those 4–5 strategies that go through from the top root node of the decision tree down to reach the best-fitted node, and of the branch point value for each node passed during that process.

The strategy engine compares the normalized learning strategy evaluation value of the learning strategy for every learning subject against the branch point values of the best-fitted node group set. For that reason, it can produce a quantitative inference and determine how the learner can reach the best-fitted node in the most efficient manner in terms of which strategy to take or not to take on the way. It then passes that information to the Visualizer.

2.3. Visualizer

Figure 2 All learning strategies and their sequence to pass

Figure 3 Checking the accomplishment level for learning strategy and proceeding down the road

Figure 4 Detailed explanation of the learning strategy

Figure 5 Reviewing all completed learning strategies

The Visualizer is the part of the system that receives from the strategy engine such information as the difference between the branch node value and the best-fitted strategy set or the normalized learning strategy evaluation value for the learner. It then displays that information visually in a readily comprehensible form for the learner. Therefore, we satisfy the requirements given at the design stage of the system development: "2) It can show, readily and comprehensibly, whether the learner's strategy is appropriate or not (or whether the proper learning strategy has been accomplished or not.", and "3) It can show, readily and comprehensibly, which learning strategy a learner would most efficiently begin with."

To satisfy those two design requirements, we used the metaphor of traffic signals and a single road. Actually, "communication using images as visual information is comprehensible universally and internationally." Inclusion of metaphors presents the advantage that "it can show the information, definitively, more efficiency in the recognition stage of a communication process (until the image shown is recognized and is understood – the primary communication stage) than the other communication method using letters, for example, in terms of universality, rapidity, and volume of communication" (Fujisawa, 1975). Based on that concept, we used a metaphor in the system to convey such difficult information as if a language were used, such as the degree to which the learning strategies were achieved, and in what sequence to attempt them. It is useful to give such information in a much more readily comprehensible format. The traffic signal metaphor is used to satisfy design requirement 2; the single road metaphor is used for 3.

We used a traffic signal to show the learner the achievement level for the associated learning strategy on the way to the destination on a single road. The learner is expected to stop at each traffic signal and receive a detailed explanation of the strategy. Therefore, we intended to tell the learner which learning strategy the learner should use and in what sequence in addition to the completion level that the learner has accomplished.

The traffic signal turns to green if the learner's normalized strategy evaluation value for the learning strategy satisfies all conditions to proceed to the next fitted strategy. However, it turns to yellow if the difference between the normalized strategy evaluation value and the value at the branch node is within 1 standard deviation (SD); it turns to red if the difference is greater than 1 SD.

In the following, the strategy engine behavior is described in the sequence in which a learner uses the system.

Responding to the questionnaire, the learner is provided with the screen presented in Fig. 2, on which the learning strategies the learner should review are placed in a line. The learner is given the explanation for each as to how important it is to check and proceed through them sequentially. After pressing the "Let's go" button, the screen moves on to that of Fig. 3; the learner on the bicycle proceeds to the first traffic signal. Then the Fig. 4 screen appears; a detailed explanation is provided of the learning strategy that should be taken first. The explanation is designed to change as the traffic light color changes. The explanation can support all learners at their own accomplishment levels. After reading the explanation and pressing the "OK" button, the learner returns to the screen portrayed as Fig. 3. The learner can then move on to the next strategy. This process will be repeated as many times as there are learning strategies that have been proposed. The Fig. 5 screen appears when each explanation of all the strategies is checked. There, the learner examines all strategies once again to finish the process.

3. OPERATION OF "LEARNING NAVIGATOR"

The resultant "Learning Navigator" was prepared for use on the "Manavision" Web site—a Web service provided by Benesse Corp.—from 10:00 am on Nov. 17, 2006 through midnight of Dec. 26, 2006.

On that Web site, users were able to try to use the "Learning Navigator" after taking an academic ability test. The test was given on the subjects of English, Mathematics, and Japanese; the problems on the test were presented as a PDF file. Every user was expected to download the problems and then enter the answers directly using their Web browsing software. After submitting the answers, the "Learning Navigator" for every associated subject became available.

Along with its trial use with test taking, we requested help from 300 student monitors from among Benesse Corporation's first year high school *Shinken Seminar* members who took the "test of evaluating academic and learning ability" during August–October 2006. For evaluation monitoring, we requested that they respond to the questions after having them use the "Learning Navigator" for the English subject. We chose English because we wanted to give fair treatment to students in both the humanities course and the science course, who are studying different subjects aside from English language.

The response entry to the academic ability test by each evaluation monitor was done based on the entry request table sheet that had been mailed separately to each person in advance. The entry request table was created based on answers made by the evaluation monitors who took the "test of evaluating academic and learning ability". Every monitor responded on the questionnaire sheet, which requested a self-writing type of response. The sheet had been mailed separately to each in advance. They responded after every one of them had used the "Learning Navigator" for the English subject. The question sheets with responses filled out by the evaluation monitors were received by post through Dec. 29, 2006. Details of the questions are described in section 4: "EVALUATION OF "LEARNING NAVIGATOR".

We received the filled-out question sheets from 217 evaluation monitors in all. We excluded the IDs that were associated with any loss found in the log data of the server machine. The log data tell how the "Learning Navigator" is used. In all, the log data of 206 monitoring students were analyzed. Of them, 197 students had no problem with the question sheet data.

The first-year high school students who were members of "Manavision" were also allowed to use the "Learning Navigator" as other general users. The general users were allowed to use it for all three subjects: English, Mathematics and Japanese.

Those general users who used the "Learning Navigator" for all three subjects were requested to answer the questionnaire sheet on the Web regarding the site evaluation. The question sheet included questions related to evaluation to the "Learning Navigator". A description of those questions is given in detail in section 4: "EVALUATION OF "LEARNING NAVIGATOR'"".

We recognized that about 1000 students accessed the Web site as general users during the trial use period. Of them, 600 students used it for all three subjects, 50 had used it for two subjects, and 160 for one subject. We also recognized that 268 general users responded to the question sheet for the site evaluation on the Web. Consequently, 235 students had no problem with data for any question. We were able to analyze those data for this study.

4. EVALUATION OF "LEARNING NAVIGATOR"

4.1 Evaluation Points

For analyses, we used the response data from question sheets returned from the evaluation monitors, the log data on "Learning Navigator" usage, and other response data returned from general users to a question sheet, which was given for general users on the Web.

The "Learning Navigator" was created to use to pass the information to users related to the most fitted learning strategies to follow. We chose the following aspects to consider the "Learning Navigator" for evaluation to satisfy all design requirements described in section 1.2: (1) Appropriateness of the model, (2) Efficiency of the traffic signal metaphor, and (3) Efficiency of the single road metaphor. Furthermore, for use in overall evaluation, we added (4) User opinions for evaluation.

(1) Appropriateness of the model used: To evaluate the satisfaction level for the design requirement 1, we determined the degree to which the model created with the regression binary tree analysis was appropriate: we inferred "whether or not the learner's strategy is appropriate based on the decision tree resulted from the regression tree analysis using academic ability as a criterion variable". If the model were truly an appropriate one, academic ability level differences that the model existing among students would be recognized also for "Learning Navigator" users.

(2) Efficiency of the traffic signal metaphor: To evaluate and know how much we were able to satisfy design requirement 2, we determined whether or not the user fully understood the traffic signal metaphor. In other words it "shows in an easy fashion as to whether the learner's strategy is appropriate or not". If the traffic signal metaphor were truly useful for users, a user who is given a yellow or red light would be expected to read the explanation of learning strategy more carefully than other users who had received given a green light.

(3) Efficiency of the single road metaphor: To evaluate and know how much we were able to satisfy design requirement 3, which is to "show in an easy fashion as to which learning strategy a learner begins with is most efficient" we should determine whether the user fully understands the single road metaphor. If the single road metaphor were a truly useful one, the learner would notice that he or she should begin with the learning strategy of the step where the green light was lit in the first place.

(4) User opinions for evaluation: This is to know how much the user accepted the use of the "Learning Navigator". This evaluation can be made from the response data to the question sheet.

4.2. Consideration of Propriety of Model Usage

To determine the degree to which the model was useful, we used the answers given to the question sheet on the Web related to the learning strategies in addition to the results from the academic ability test that the evaluation monitors took.

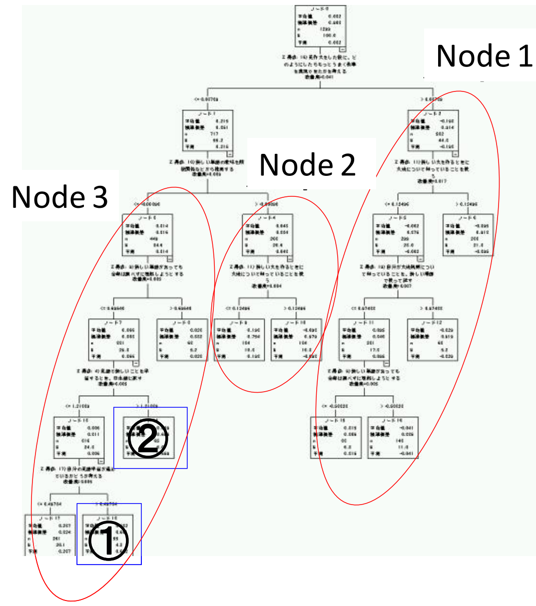

Figure 6 Node classification produced by the model

Figure 8 depicts the model of the English language subject that was examined to determine the degree to which it was useful. In the model, the best-fitted node group sets that were determined using the "2.2 Strategy Engine" were (1) and (2) of Fig. 6.

The model assumptions state that the node group that is branched to a different side from the remainder of two best-fitted node groups at the first branch node point downward from the root node of the decision tree, which is shown as node group 1 in Fig. 6: it is of the lowest academic ability level. The next lowest academic ability level is of the node group (node group 2 of Fig. 6), which is branched at the second branch node point to another side from the best-fitted node group set.

It might be true that even node group set 3 of Fig. 6 would produce a difference in the academic ability level. However, because we have only 206 samples to analyze, if further splitting were made down from the node group 3, the number of samples for every subsequent group would become too small to analyze; for instance, the number of samples of node 3 is 45. We checked to see how much the academic ability level difference would be recognized among the three node groups of Fig. 6, which are Node 1, Node 2, and Node 3.

To examine the academic ability level difference among the three node groups, we performed a Kruskal–Wallis test with the three node groups—Node 1, Node 2 and Node 3—each as an independent variable, and with the academic ability as a dependent variable. We look at the mean value (average rank value) of the aligned order positions of the node group because the Kruskal–Wallis test uses the rank of the entire observation values in its test with them aligned from the smallest one first. Thereby, we found that the average rank value was 94.29 for Node 1, 110.27 for Node 2, and 119.76 for Node 3. According to the test results, we recognized a significant difference of the academic ability level among those three node groups ($\chi^2(2)=6.67$, $p<0.05$).

According to the model assumption, the academic ability of Node 3 is the highest, followed by that of Node 2; the worst level is that of Node 1.

The average rank value for each node group did agree with the model assumption; the test shows that there does exist a significant difference at the 5% level. Because only a few evaluation monitors are available now, we admit that this was not a full-scale validation check. However, based on the results we obtained, we can say that the model of the "Learning Navigator" is useful, at least to some extent.

4.3. Consideration of Traffic Signal Metaphor Usage

To validate the degree to which the traffic signal metaphor was useful, we used log data showing how much the evaluation monitors used the "Learning Navigator".

The more carefully the user would read the explanation on the learning strategy provided by the "Learning Navigator", the longer time the learner would stay at that screen for the view. The viewing time length might therefore depend on how elaborately the explanation is described and how easy or difficult it is to comprehend from reading. However, here we had no big difference in the description volume for each traffic signal. For example, the explanation of Step 1 of the English subject includes 149 characters for the green light, 141 characters for the yellow light, and 143 characters for the red light. In addition, the basic explanation for every learning strategy is practically identical for every traffic light color. Therefore, no large difference is apparent in the difficulty level of understanding. Consequently, we used the viewing time that the user spent to read the description to evaluate the usefulness of the traffic signal metaphor. Here we defined the time to view the explanation screen (at each step) to understand the learning strategy as the duration time from when the user clicked on a button to come to the step until the learner clicked another button to proceed to the next step. We calculated the viewing time for each step while examining the log data related to usage.

To look at the possible viewing time difference caused by each traffic light color at the associated step, we made a Kruskal–Wallis test using the traffic signal color at each step as an independent variable, with the viewing time spent at each step as a dependent variable. Table 1 presents test results in terms of the number of students associated with each traffic signal at each step, the mean value of the time spent for every one of the traffic light colors, and the average rank value.

Table 1 Traffic signal color and associated viewing time at each step

	STEP1			STEP2			STEP3		
	No. of users	Avg. time	Avg. rank	No. of users	Avg. time	Avg. rank	No. of users	Avg. time	Avg. rank
Green	92	23.01	93.48	76	14.01	88.05	128	15.05	95.33
Yellow	107	31.93	110.69	105	16.52	112.07	78	17.83	116.91
Red	7	23.57	125.29	25	13.72	114.48	0	—	
x^2	5.10	p<.10		8.14	p<.05		6.37	p<.05	
d.f.	2			2			1		

	STEP4			STEP5		
	No. of users	Avg. time	Avg. rank	No. of users	Avg. time	Avg. rank
Green	189	14.86	101.35	55	10.53	64.38
Yellow	11	14.55	124.41	116	19.68	101.57
Red	6	13.33	132.75	9	18.00	107.39
x^2	3.05	n.s.		20.05	p<.001	
d.f.	2			2		

x^2 value represents results from the Kruskal–Wallis test.

Results of the test show that the significant difference of the viewing time by every traffic signal color was recognized with the 0.1% level at Step 5, 5% level at Step 2 and Step 3, and 10% level at Step 1. However, no significant difference was found at Step 4, as far as the viewing time is concerned.

Some users of yellow signal and green signals seemed to have stayed and viewed the page for a notably long period. Therefore, as far as the average view time is concerned, it happened that the average view time for the red signal light was shorter than that of the other colors (Table 1). Consequently, the distribution of viewing time was greatly shifted from the normal distribution. Having said that, however, looking at the average rank values, it is readily apparent that the value of the green light is the lowest of all at all steps, becoming higher with the yellow light and the red light in that order. Results show that, looking at the information of the rank value whose distribution shifting is small and that for which there is not much impact in terms of the value difference, it can be said that the users of the green light tend to view it in a shorter time, although users of the red light viewed it for a longer time. That can be inferred except for Step 4, for which few users were associated with the yellow and red signal lights. Results show that the viewing time difference attributable to the traffic light color was statistically significant. We can conclude that the use of the traffic signal metaphor was functioning efficiently.

4.4. Consideration of Single Road Metaphor Usage

To determine the degree to which the single road metaphor was useful, we requested the evaluation monitors for the response to the question of "What do you think is the first thing to do among the learning methods provided by the [Learning Navigator]?" We asked respondents to write a response in a free-writing format. If the metaphor were useful and well understood, the user would be able to recognize that an efficient mode of learning would be to start with the learning strategy of the step for which a yellow signal or a red signal was shown.

Based on that supposition, we planned to see whether the free-writing response from the monitors agreed or not with the proposed description that they first encountered at the step where a yellow or red signal was lit. The description of the step that was first lit for them as a yellow or red signal was determined based on information available from the usage log data. Of the 197 users whose data were not lost at all in any of the usage log data and on the questions sheet, 190 that were lit with either a yellow or red signal at least once were chosen for analyses.

Whether the proposed description agrees with the free-writing format response was determined by the second author of this paper in addition to a third party person who had not participated in our research study. The decisions made by the two persons agreed 93.7%. They judged that the proposed description and the user's response agreed when, for example, the learning strategy was titled "Let's read English before looking up dictionary", the response was "I will read the entire description of English word by word once before moving on while looking up dictionary".

Based on such a judgment, the agreement on that the proposed description of the step where a yellow or red signal was lit first and the free-writing format response to the questions was reached for the 49.5% of the users thus examined.

Examining the results, we were able to say that the single road metaphor was useful, but that its level was only such that half of the users understood. We admit that room to improve remains for this metaphor comprehension level.

Table 2 User opinions for evaluation

	Eval. Monitors (n=197)					General users (n=235)				
	Mean	Median	S.D.	z		Mean	Median	S.D.	z	
[L. Navi.] operation was not as easy as I thought.	3.49	4.00	1.35	-4.70	p<.01	3.99	4.00	1.20	-9.77	p<.01
[L. Navi.] I thought the animation was too	3.51	4.00	1.06	-5.95	p<.01	2.51	2.00	1.21	-5.57	p<.01
[L. Navi] was just suited for me.	3.49	4.00	0.89	-6.67	p<.01	3.34	3.00	1.01	-4.76	p<.01
[L. Navi] method for study was reliable.	3.93	4.00	0.72	-10.82	p<.01	3.76	4.00	0.89	-9.60	p<.01
The way [L. Navi] tells us was important to	4.07	4.00	0.80	-10.77	p<.01	3.91	4.00	0.88	-10.62	p<.01
I was able to understand how to study.	3.77	4.00	0.92	-8.78	p<.01	3.68	4.00	0.99	-8.43	p<.01
I understood what learning strategy to begin with.	3.56	4.00	0.99	-6.84	p<.01	3.54	4.00	0.98	-7.18	p<.01
I understood what study method was suited for me.	3.68	4.00	0.91	-8.27	p<.01	3.75	4.00	0.93	-9.36	p<.01
I understood what study method I was not	3.90	4.00	0.90	-9.58	p<.01	3.89	4.00	0.91	-10.37	p<.01
I thought I was going to use what [L. Navi] told me.	3.97	4.00	0.86	-10.06	p<.01	3.84	4.00	0.99	-9.58	p<.01
It was fun to use [L. Navi].	3.53	4.00	0.98	-6.62	p<.01	3.75	4.00	1.03	-8.76	p<.01
I thought the way [L. Navi] showed us was good.	3.92	4.00	0.80	-10.28	p<.01	3.86	4.00	0.93	-10.01	p<.01
I want to use [L. Navi] for Mathematics,	4.07	4.00	0.95	-9.93	p<.01	—	—	—	—	—
I want to use [L. Navi] for Japanese language, too.	3.97	4.00	0.97	-9.49	p<.01	—	—	—	—	—

Results of Wilcoxon's signed rank test with "3" as a criterion value for comparison in terms of the z value

4.5. User Opinions for Evaluation

To obtain sincere opinions from users on the "Learning Navigator", we requested a response to the questionnaire sheet given after they used the "Learning Navigator". From evaluation monitors, we received non-biased subjective evaluations of the "Learning Navigator" for "English language" after they used it. From general users, however, we received evaluations after they used the "Learning Navigator" on all three learning subjects. For each question on the sheet, we requested five levels. To the evaluation monitors, we asked them to give the level point "5" if the response was "very much so" and "1" if it was "unlikely at all". To general users on the other hand, we asked them to give "1" if it was "very much so" and "5" if it was "entirely unlikely". It is noteworthy that the number of the questions passed to the evaluation monitors does not necessarily agree with those passed to the general users. The reason was that we had a little difficulty in supplying exactly the same questions to all users in a practical sense (Table 2 shows the questions given.). Table 2 shows responses from the evaluation monitors and from general users, from whom we have the mean value, the standard deviation and the median, along with results from Wilcoxon's signed rank test in which we used "3" as the standard value for comparison because it is the center value of the level points. We often reversed the questions so that the larger level point values came closer to the favorable side of response to the “Learning Navigator” (most favorable response point is “5”, whereas the most negative one is “1”).

Examining Table 2, we understand that the mean value is greater than 3 and that the median is 4 for responses given by both the evaluation monitors and general users, which tells us that the “Learning Navigator” was evaluated favorably by both the evaluation monitors and the general users.

One point of note, however, was that to the question of “Did you think the animation of the Learning Navigator was too long?”, the response results from general users had a mean value of 2.51, with median 2. From those responses, we understand that we received a negative reaction from general users in relation to the animation duration length. In fact, animation of the “Learning Navigator” includes an opening animation in addition to that described in section 2.3. They might have felt that their animations were too lengthy because we requested an evaluation from general users for all three learning subjects after they reviewed them.

5. CONCLUSION

Based on results of our study, we proposed a feedback system for learning strategies while using a data mining technique followed by the actual development of the system made based on all the data available for it. We also used it in operation with the evaluations given to it. The evaluation to the “Learning Navigator” was made from the following four aspects: (1) Appropriateness of the model used, (2) Efficiency of the traffic signal metaphor, (3) Efficiency of the single road metaphor, and (4) User opinions for evaluation.

As a result of the evaluation, we understood the following. (1) The model produced by the system included the premise that there should be some academic ability level difference among users, which was actually and certainly recognized among the evaluation monitors we had. That finding shows us that the model used was an appropriate one. (2) We recognized also the viewing time spent by the user in viewing the explanatory screen prepared for the learning strategy depended on what color was lit for the associated traffic signal. Results show that the traffic signal metaphor was functioning properly. (3) On the other hand, 49.5% of the evaluation monitors understood the single road metaphor. It is not that such a metaphor did not function at all, but we understand that room for improvement remains. (4) Furthermore, we received from the general users an evaluation that “the animation of the Learning Navigator is too long”, the other opinions from the users were mostly favorable ones.

References

BERD (2005). *First Basic Survey Report on Children’s Life Style and Behavior*; Benesse Corporation, Tokyo.

Duncan, T.G.., & McKeachie, W.J. (2005). The Making of the Motivated Strategies for Learning Questionnaire. *Educational Psychologist*, **40**, 117-128.

Fujisawa H. (1975). *Visual communications*. David Publisher, Tokyo.

Ichihara, M. & Arai, K. (2005). The development of learning strategy scales in math and Japanese: Junior high school students' version. *Tsukuba Psychological Research*, **29**, 99-107.

Ichikawa, S. (1995). *Psychology of education and learning*. Iwanami Shoten, Tokyo.

Inuzuka, M. (2002). The structure of reading strategies for understanding expository text. *Japanese Journal of Educational Psychology*, **50**, 152-162.

National Institute for Educational Policy Research (2004). Knowledge and technique to survive 2: Survey on accomplishment level of learning by OECD students (PISA) *International Survey Results Report of 2003*. Gyosei, Tokyo.

Kubo, N. (1999). Orientation-appraisal model for Japanese university students’ learning of English: Relation among learning motive, cognitive appraisal, learning behavior, and performance. *Japanese Journal of Educational Psychology*, **47**, 511-520.

Oxford, R.L. (1990). *Language learning strategies: What every teacher should know*. Newbury House/Harper & Row Publishers, New York.

Pintrich, R.R., & Degroot, E.V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, **82**, 33-40.

Tatsuno, C. (1997) . *Psychology of learning strategy*. Tosho-Bunka, Tokyo

Weinstein, C.E., Zimmerman, S.A., & Palmer, D.R. (1988). Assessing learning strategies: The design and development of the LASSI. In C.E. Weinstein, E.T. Goetz, & P.A. Alexander (Eds.), *Learning and study strategies: Issues in assessment, instruction, and evaluation.* Academic Press, San Diego, pp. 25-40.