行政院國家科學委員會專題研究計畫　成果報告

子計劃二：『個人化學習資訊蒐集、分析與推薦模組』之研究(3/3)

計畫類別：整合型計畫
計畫編號：NSC92-2520-S-216-001-
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智慧型個人化網路學習、測驗與診斷服務平台之研究 - 子計畫二：『個人化學習資訊蒐集、分析與推薦模組』之研究(3/3)

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智慧型個人化網路學習、測驗與診斷服務平台之研究 - 子計畫二：『個人化學習資訊蒐集、分析與推薦模組』之研究(3/3)

A Personalization Engine for a Network-based Learning Environment

計畫編號：NSC-92-2520-S-216-001

執行期間： 92年 8月 1日至 93年 7 月 31日

計畫主持人：曾秋蓉

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Abstract

With the rapid growth of computer and network technologies, the development of on-line computer-assisted learning systems has become an important and challenging issue. In this project, we focus on the influence of multiple sources of personalization information, such as individual differences and learning styles, on the performance of learning science courses, from which a platform for helping teachers in developing adaptive subject materials for science courses is proposed. To determine the initial learning styles of the students, the Keefe questionnaire is employed in our approach. To precisely reflect the actual learning style and talent of each student, the interactions and learning results of each student are analyzed when adjusting the subject materials. An experiment was conducted to evaluate the performance of our approach, by employing one-way ANOVA and t-test to analyze the test results on three groups of students using different adaptive learning approaches. The analysis results show the novel approach is helpful in improving learning performance and is worthy of further study.

Keywords: computer-assisted learning, adaptive learning, learning style, distance education, science education

1. Introduction

With the recent rapid advances in computer and network technologies, educational researchers have developed methods, tools and environments for computer-assisted learning. When used for educational purposes, hypermedia systems are particularly suitable for providing a higher degree of control, such that training or learning performance can be enhanced immensely by identifying the personal characteristics of students and adapting subject contents and presentation to better suit their needs. In additions, a hypermedia system can offer more than predefined learning paths by selecting different nodes in different orders, thus individual students produce a multitude of paths through the subject materials [1][20][28].

Several researches have already addressed the importance of adaptive learning, either in traditional instruction or in computer-assisted instruction. In studying the effect of adaptive learning in science courses, most CAI researches often focus on the determination of difficulty levels, learning paths and learning styles of subject material, whilst the interactions between personalization information, learning styles and adapting subject material are seldom taken into consideration.

In this project, a Multi-Source Adaptive Learning (MSAL) system is proposed. MSAL can assist instructors to construct adaptive subject materials for science courses, by taking personalization information and learning styles into consideration. To evaluate the performance of our approach, an experiment was conducted by employing one-way ANOVA and t-test to analyze the test results on three groups of students using different adaptive learning approaches. The analysis results show that the novel approach is helpful in improving learning performance in science courses, and is worthy of further study.

2. Relevant Work

When considering individual differences in adaptive learning, not only the cognitive levels but also the learning styles of students have to be considered. In the following subsections, various relevant studies addressing adaptive learning and learning styles are given.

2.1 Adaptive learning

Snow and Farr suggested that sound learning theories are incomplete or unrealistic if they do not include a whole person view, integrating both cognitive and affective aspects [26], which implies that no educational program can be successful without due attention to the personal learning needs of individual students. A single approach to instruction whether traditional or innovative, simply fails to do the job [10]. Russell suggested that educators should identify and acknowledge learning differences and make maximum use of the available technology to serve them accordingly [25].

In 1965, an Individually Guided Education (IGE) program was proposed for organizing and delivering educational experiences from teams that studied on how people learn and how to personalize instruction process. In 1994, the Comprehensive Application of Behavior Analysis to Schooling (CABAS) program was proposed [14]. CABAS schools are self-correcting and self-sustaining, and incorporate the science of teaching into every aspect of schooling. The Fred S. Keller School located in Yonkers, New York, is one of the schools participating in the program. The School functions as a cybernetic system of education in which the individualized instruction of each student influences the behavior of the entire education community.

Brusilovsky suggested using adaptive hypermedia to support individual learning [3]. The idea of adaptive hypermedia is to adapt the course content for a particular learner based on the profile or records of the learner. According to Brusilovsky's approach, the adaptive hypermedia system should satisfy three criteria: (1) it should be a Hypermedia or hypermedia system, (2) it should have a user model, and (3) it should be able to adapt the hypermedia using the user model [3].

Paolucci addressed the importance of individualization in hypermedia that any strategy should be adaptive and personalized [23]. To insure personalization, adaptive hypermedia systems should be capable of diagnosing and identifying each student’s misconceptions. Based on the conception, Lo et al. developed a Hypermedia-based English Learning system for Prepositions (HELP), which provides non-native speakers of English learning diagnosis and remedial instruction according to their assessment results [18].

To provide effective adaptive learning on computer networks, it is important to understanding the on-line learning behaviors of students. In 1998, an on-line learning behavior diagnosis system was proposed [6]. Several parameters were defined and recorded to describe the on-line behaviors of students, such as idle time, response time, effective learning time, ineffective learning time, and login time. Based on those parameters, the system can detect several learning attitudes of students, such as “concentration”, “willingness” and “patience”, and hence the course contents can be adapted to meet individual requirements.

It can be seen that, with the popularization of the World Wide Web, the use of hypermedia in learning has attracted the attentions of many researchers from the fields of computers and education. Therefore, it is worth studying how to effectively develop adaptive learning systems on the World Wide Web environment [19].

2.2 Learning Style

Learning style is a concept that followed the research from a cognitive perspective starting in the 1960's. Numerous writers have addressed the concept of learning styles and the various ways they are measured [2] [9][16].

Keefe [12] described learning style as both a student characteristic and an instructional strategy. As a student characteristic, learning style is an indicator of how a student learns and likes to learn. As an instructional strategy, it informs the cognition, context and content of learning. Learning style is a consistent way of functioning that reflects the underlying causes of learning behavior [10].

Learning problems frequently are not related to the difficulty of the subject matter but are associated with the type and level of cognitive process required to learn the material [11]. Gregorc and Ward claimed that if educators want to successfully address the needs of the individual they must understand what “individual” means and adjust their teaching styles to meet the learning styles of students [5].

Talmadge and Shearer have proved the existence of learning styles. Their study shows that the characteristics of the content of a learning experience are a critical factor affecting relationships that exist between student characteristics and instructional methods [27]. Reiff indicated that learning styles influence how students learn, how instructors teach, and how they interact [24]. Keefe asserts that perceptual style is a matter of student choice, but that preference develops from infancy in a subconscious way [10].

The knowledge to the features of student preferences is helpful for developing more flexible learning environments. For example, students with the visual-audiolearning style have greater recall of concepts that are presented visually [1]. All students can benefit from a responsive learning environment and from the enhancement of their learning skills [12]. Using one teaching style or learning style exclusively is usually not conducive enough to a successful educational program [1]. Additionally, research has shown that there is little relationship between overall college achievements and learning style [28], yet they indicated the possible relationships between learning style and performance in specific subject areas. For example, there is evidence that individual cognitive learning styles are related to programming ability in novice programmers [2][20]; moreover, Larkin-Hein showed the critical role that a learning style approach could play in terms of physics and engineering education [17].

The Learning Style Profile (LSP) provides educators with a well validated and easy-to-use instrument for diagnosing the characteristics of an individual's learning style. It also provides an overview of the tendencies and preferences of the individual student [12]. Several studies have reported that students learn in different ways, depending upon many personal factors and everyone has a distinct learning style [21][22].

There have been several models for defining and measuring learning styles proposed, such as the following: Kolb’s experiential learning [16], Dunn’s PEPS (Productivity Environmental Preference Survey)[4], and James Keefe’s four-fold framework [10]. The James Keefe four-fold framework aids in the classification of various learning style conceptualizations. This framework categorizes learning style instruments as measures of cognitive, affective or physiological styles, or as comprehensive instruments designed to measure several types of learning styles. It measures the strength of twenty-four skills across independent scales as follows:

- Cognitive Styles

Cognitive styles of learning include those aspects of the brain, which perceive meaning and interact with the world, and are often used to predict student achievement on standardized tests. Students who are aware of their cognitive strengths can use them to assist in weak areas. The following table shows the cognitive learning styles.

Cognitive learning style	**Functions of the cognitive learning style**
Analytical skill	Identifying simple figures hidden in a complex field; use the critical element of a problem in a different way
Spatial skill	Identify geometric shapes and rotate objects in the imagination; to recognize and construct objects in mental space
Discrimination skill	Visualize the important elements of a task; to focus attention on required detail and avoid distractions
Categorization skill	Use reasonable vs. vague criteria for classifying information; to form accurate, complete and organized categories of information
Sequential processing	Process information sequentially or verbally; to readily

skill	derive meaning from information presented in a step-by-step, linear fashion
Simultaneous processing skill	Grasp visuospatial relationships; to sense an overall pattern from the relationships among the component parts
Memory skill	Retain distinct vs. vague images in repeated tasks; to detect and remember subtle changes in information

- Affective Styles

Affective styles of learning are a by-product of personality, cultural environment, parental and peer pressure and school influence. The following table shows the affective learning styles.

Affective learning style	**Functions of the affective learning style**
Persistence orientation	Willingness to work at a task until completion
Textrisk orientation	Willingness to express opinions, speak out
Grouping preference	Preference for whole class, large group, small group or dyadic grouping
Verbal-Spatial preference	Preference for textor nontextactivities
Manipulative preference	Preference for "hands-on" activities

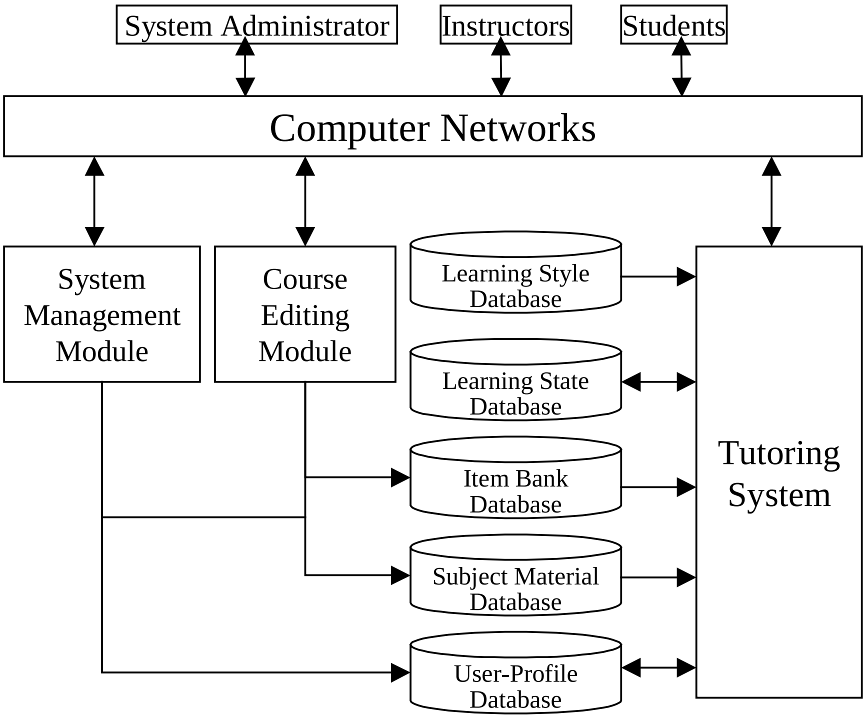
- Physiological Styles

Physiological styles include perceptual modes and environmental factors that affect response to information as a visual, auditory, or emotive response. The following table shows the Physiological learning styles.

Physiological learning style	**Functions of the physiological learning style**
Perceptual response	Initial reaction to information is visual, auditory or emotive
Study time preference	Preference for study time in early morning, late morning, afternoon or evening
Posture preference	Preference for formal or informal study arrangements
Mobility preference	Preference for moving about and taking breaks vs. working until finished
Sound preference	Preference for quiet study vs. background sound
Lighting preference	Preference for brighter or dimmer study areas
Temperature preference	Preference for studying in a cooler or warmer environment

3. Implementation of MSAL

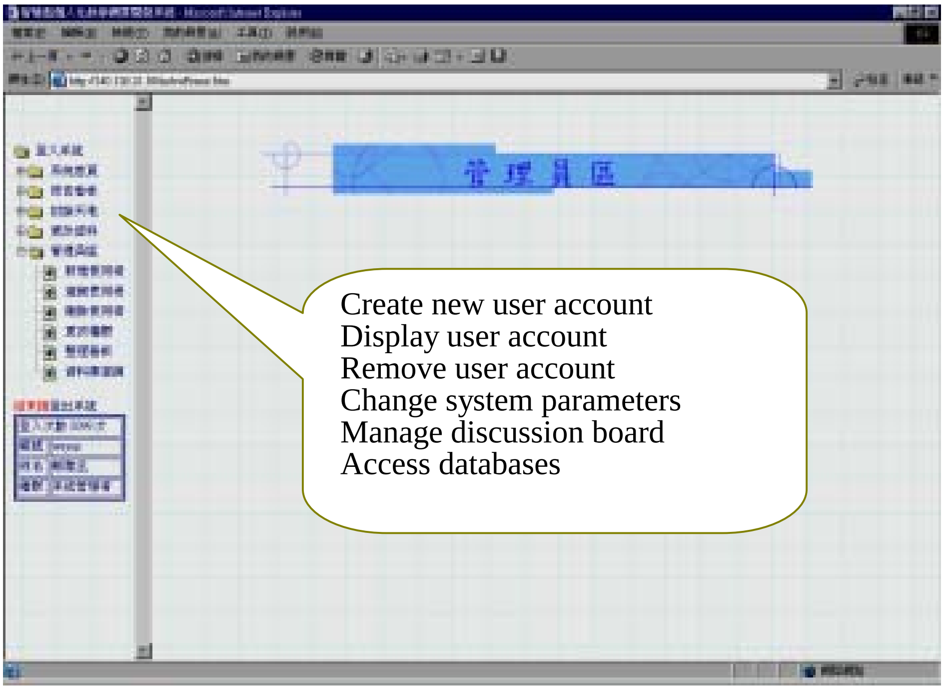
MSAL consists of eight modules: Course Editing Module, Tutoring System, System Management Module, User-Profile Database, Subject Material Database, Item Bank, Learning State Database and Learning Style Database (as shown in the following figure).



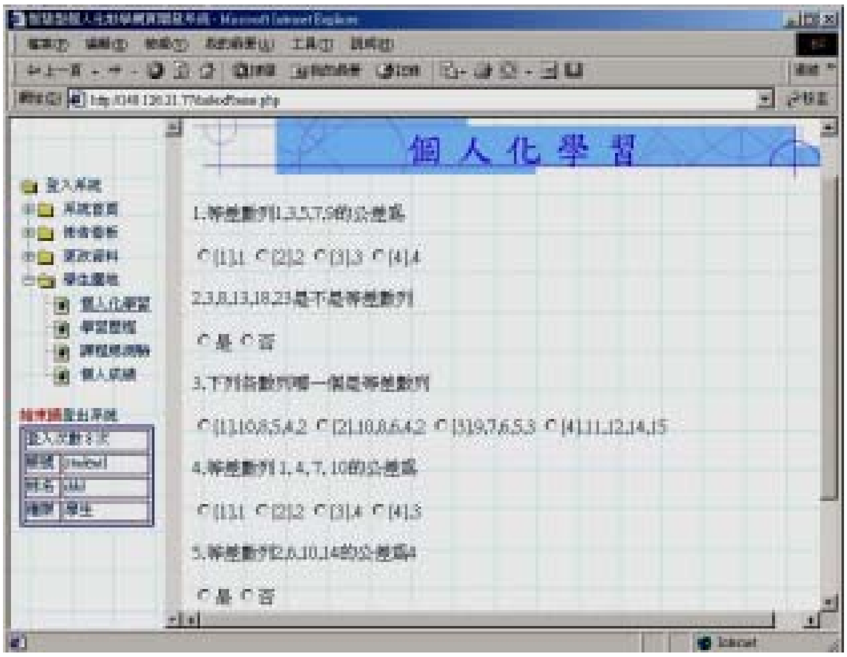
Course Editing Module enables the instructors to access the subject material database and the item bank. Tutoring System Module offers adaptive tutoring and test for the students based on each student’s learning style, ability and learning efficiency. The functions of Tutoring System Module include on-line tutoring, on-line discussions, profile modification, and self-assessment. System Management Module enables the system administrator to access the subject material database, the user-profile database and the item bank. The system administrator can also perform several system maintenance operations via this module, such as user account manipulation and discussion board management.

MSAL is implemented with PHP and MySQL on the Linux environment. The subject materials in MSAL consist of three difficulty levels and two presentation styles; that is, six versions of subject materials have been implemented to achieve the adaptive tutoring feature.

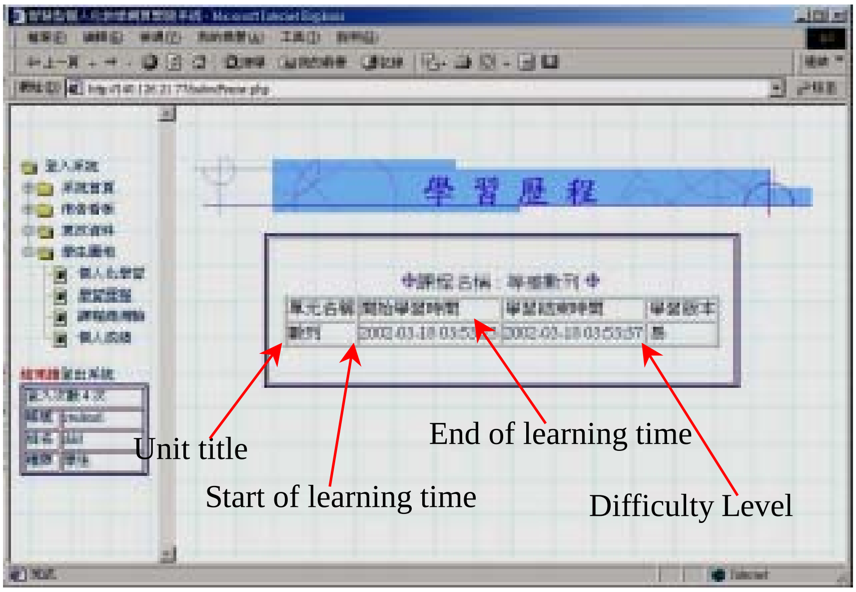
The following figure shows the administrator interface.



During the learning process, MSAL will record a student's study portfolio including Unit Learning Time, Idle Time, Response time, Unit Test Score, Unit Learning Efficiency, Absorbed, and Difficulty level. For each subject unit, a test is performed to decide the learning status of current unit and the feasible level of next unit for the student based on the student's score and learning efficiency. The following figure shows the post-test interface.



All of the learning status and test results are recorded by MSAL. The following figure depicts the Learning-Portfolio interface.



4. Multi-Source Adaptive Learning Approach

During the learning process, MSAL records student characteristics, which can be used to determine individual learning style and subject materials for each student. In the following subsections, the parameters for describing student characteristics and the algorithms for determining the difficulty levels of subject materials for individual students are presented.

4.1 Adaptive Learning characteristic parameters

The characteristic parameters recorded by MSAL for determining learning styles of students and difficulty levels of subject materials are listed as follows:

- SLT(Uj): Suggested Learning Time for Unit Uj given by the instructor.
- SQP(Si): Sequential Processing Skill of Student Si. Process information sequentially or verbally; to readily derive meaning from information presented in a step-by-step, linear fashion text environment.
- DS(Si): Discrimination Skill of Student Si. Visualize the important elements of a task, to focus attention on required details and avoid distractions.
- AS(Si): Analytic Skill of Student Si. Identifying simple figures hidden in a complex field, use the critical element of a problem in a different way.
- SS(Si): Spatial Skill of Student Si. Identify geometric shapes and rotate objects in the imagination; to recognize and construct objects in mental space.
- ULT(Si,Uj): Unit Learning Time for Student Si to Unit Uj without taking idle time and test time into consideration.
- AIT(Si,Uj): Acceptable Idle Time for Student Si in learning Unit Uj.
- RST (Si,Uj): Response time when Student Si learns Unit Uj. MSAL will randomly pop-up a window and ask the student to respond.
- UPT(Si,Uj): Unit Post-Test score for Student Si in learning Unit Uj.
- EFU(Si,Uj): Unit Learning Efficiency for Student Si in learning Unit Uj.

EFU(Si,Uj)=SLT(Uj) / ULT(Si,Uj)

- ABS(Si,Uj): Absorbed .The concentration for Student Si in learning Unit Uj.
- CDU(Si,Uj): Course Difficulty level for Student Si in learning Unit Uj. Three versions of the subject materials with different difficulty levels are provided; that is, Primary, Secondary and Advanced levels.
- LST(Si) : Learning Style of Student Si. Two kinds of learning styles, “Verbal” and “Visual”, are taken into consideration.

When students enter MSAL for the first time, they are asked to take a learning style test based on the Keefe’s approach [10]. MSAL then determines CDU and LST based on the SQP, DS, AS and SS values and computes EFU and ABS based on ULT, AIT, RST, and UPT values.

4.2 Analysis of Learning styles

MSAL determines learning style, idle time and concentration degree of a student based on the Keefe learning style test. Four parameters are adopted in the test, including Sequential Processing Skill, Discrimination Skill, Analytic Skill and Spatial Skill.

- **Learning Style（LST）**

If a student obtains a high score in Sequential Processing Skill (SQP), it implies that he learns well on Sequential Frame materials; otherwise, he tends to be suitable for Hypermedia presentation. The corresponding fuzzy rule is:

IF SQP(Si) = High then

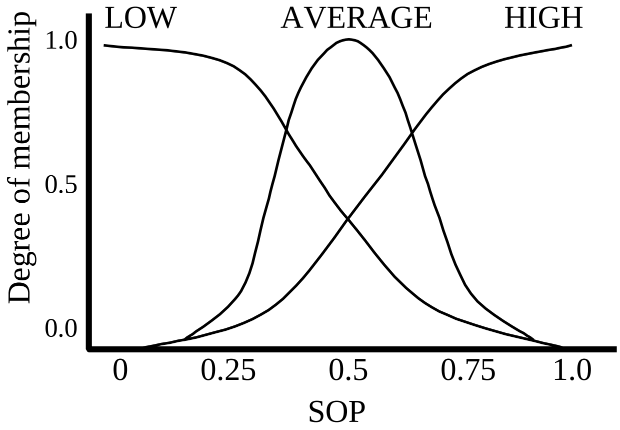
LST(Si) = Sequential Frame

Else

LST(Si) = Hypermedia

End if

For example, assume students A and B get 0.8 and 0.4 for SQP, respectively, student A will be arranged to receive Sequential Frame subject materials, and student B will receive Hypermedia subject materials. The membership functions of subject material style is given in the following figure.



- **Acceptable Idle Time（AIT）**

The initial Ideal Time is five minutes for each student. For students who get higher scores in Discrimination Skill, MSAL assumes that they are willing to take more time to read the course contents, and hence will accept a longer Idle Time during the learning process. Consequently, for the students who obtained lower scores in Discrimination Skill, MSAL assumes that they are not as willing to spend time on reading subject contents, and will accept a shorter Idle Time during the learning process. Therefore, we have the acceptable Idle Time for Student Si to Unit Uj as

AIT(Si,Uj)= 5+5*DS(Si)

Assume that the learning style profile test score in DS for Students S_1 and S_2 are 0.8 and 0.4, respectively. We have AIT (S_1,Uj) = $5 + 5 \times 0.8 = 9$ (minutes) and AIT (S_2,Uj) = $5 + 5 \times 0.4 = 7$ (minutes).

- **Absorbed（ABS）**

The initial Absorbed score for each student is set at 1. MSAL will start to count the time when the student does not perform any action. If the counted time exceeds the limit of Idle

Time, MSAL will pop-up a window and request a response. If the response time is over five seconds, which indicates that the student did not concentrate on browsing the subject contents; therefore, MSAL will decrease the Acceptable Idle Time as well as the Absorbed degree. On the contrary, if the no-action time is very short (less than half of AIT), the Acceptable Idle Time and the Absorbed degree will be increased. The corresponding rules as given as follows:

```
IF the no-action time > AIT (Si,Uj) THEN
   Pop up the response window
   IF RST (Si) > 5 and AIT (Si,Uj) > 10 seconds and ABS (Si,Uj) > 0.1 THEN
         AIT (Si,Uj) = AIT (Si,Uj) – 10 seconds
         ABS (Si,Uj) = ABS (Si,Uj) –0.1
   End IF
ELSE
   IF the no-action time < AIT (Si,Uj)/2 and ABS (Si,Uj) < 1.0 THEN
         AIT (Si,Uj) = AIT (Si,Uj) + 10 seconds
         ABS (Si,Uj) = ABS (Si,Uj) + 0.1
   End IF
END IF
```

4.3 Determination of Difficulty Levels of Subject Materials

MSAL determines difficulty levels of subject materials based on student profile. When a student takes Mathematics course, MSAL will decide the difficulty level based on AS and SS values. When a student takes Science course, MSAL will determine difficulty level based on the student’s AS value. That is, different criteria will be employed in determining the difficulty levels for different courses.

- **Determine the Initial Difficulty Levels**

MSAL will determine the initial difficulty level of subject materials based on the student profile. When a student takes Mathematics course, MSAL will decide the difficulty level based on AS and SS ratings. Higher AS and SS ratings represent an enhanced ability when learning mathematics courses. If the student takes Science courses, MSAL will determine difficulty level based on AS rating. Higher AS rating represents an enhanced ability when learning Science courses. For Technique courses, MSAL will determine difficulty level based on SS rating. Higher SS rating implies an enhanced learning ability for Technique courses. That is, different criteria will be adopted to determine the difficulty levels of different courses. The fuzzy rules are shown as follows:

```
Case Mathematics courses
        IF AS(Si) and SS(Si) = High then
          CDU(Si,Uj) = High
        IF AS(Si) and SS(Si) = Low then
          CDU(Si,Uj) = Low
        IF AS(Si) and SS(Si) is Average
          CDU(Si,Uj) = Average
        Else
          CDU(Si,Uj) = Average
        End if
  Case Science courses
        IF AS(Si) = High then
          CDU(Si,Uj) = High
        IF AS(Si) = Low then
          CDU(Si,Uj) = Low
        IF AS(Si) is Average
          CDU(Si,Uj) = Average
        End if
  Case Technique courses
        IF SS(Si) = High then
          CDU(Si,Uj) = High
        IF SS(Si) = Low then
          CDU(Si,Uj) = Low
        IF SS(Si) is Average
```

CDU(Si,Uj) = Average
End if
Case Else
CDU(Si,Uj) = Average

Assume the learning style profile test indicates that the AS ratings of S_1, S_3 and S_2 are 0.9, 0.8 and 0.2; and the SS ratings of S_1, S_2 and S_3 are 0.8, 0.3 and 0.3, respectively. Based on the fuzzy rules, the difficulty levels of S_1 are "High" for all courses, the difficulty levels of S_2 are "Average" for mathematics courses, "High" for science courses, and "Low" for Technique courses, and the difficulty levels of S_3 are "Low" for all courses.

- **Adapt the Difficulty Levels**

If the post-test score exceeds 60, the student will be allowed to proceed to the next unit. If both the learning efficiency and the post-test score of a student are very high, the difficulty level of next unit will be increased. On the contrary, if the learning efficiency and post-test score are too low, which implies the subject materials may be too difficult for the student, and hence the difficulty level will be decreased. If the learning efficiency and post-test score are within average range, the difficulty level remains the same. The membership functions of passing the user of next difficulty level are given in Figure 6, and the corresponding fuzzy rules are given as follows:

```
IF UPT(Si,Uj) AND EFU(Si,Uj) = High then
IF CDU(Si,Uj) = High then CDU(Si,Uj)
   Remain unchanged
  IF CDU(Si,Uj) = Average then
     CDU(Si,Uj)   = High
  IF CDU(Si,Uj) = Low then
     CDU(Si,Uj) = Average
   End IF
IF UPT(Si,Uj) AND EFU(Si,Uj) = Low then
     IF CDU(Si,Uj) = High then
```

CDU(Si,Uj) = Average

IF CDU(Si,Uj) = Average then

CDU(Si,Uj) = Low

IF CDU(Si,Uj) = Low then

CDU(Si,Uj) Remain unchanged

End IF

Else IF

CDU(Si,Uj+1) Remain Unchanged

End IF

For example, if the learning efficiency and the post-test score of Student S_1 are 1.5 and 90, respectively, the difficulty level will be increased; if the learning efficiency and the post-test score of Student S_2 are 0.5 and 65, the difficulty level will be decreased; if the learning efficiency and the post-test score of Student S_3 are 0.5 and 85, the difficulty level will remain the same.

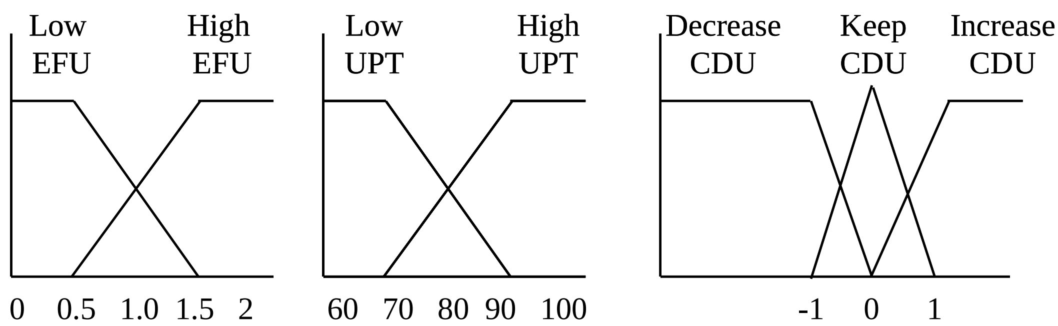


Figure 6: Membership functions to determine the difficulty level for the next phase

5. Experiments and Evaluation

To find out if the web environment with individual learning style and adaptive course contents would be helpful to the learning process, three questions need to be answered:

R1: Will a learning environment with multi-source adaptive subject materials achieve better learning *efficacy* for science courses than a learning environment without adaptive subject materials?

R2: Will a learning environment with single-source adaptive subject materials achieve better learning *efficacy* for science courses than a learning environment without adaptive subject materials?

R3: Will a learning environment with multi-source adaptive subject materials achieve better learning *efficacy* for science courses than a learning environment with single-source adaptive subject materials?

R4: Will a learning environment with multi-source adaptive subject materials achieve better learning *efficiency* for science courses than a learning environment with single-source adaptive subject materials?

5.1 Experiment Design

To evaluate the performance of our approach, an experiment has been conducted. Ninety-one students of Sanyi junior high school in Taiwan, including thirty-seven females and fifty-four males with an average age of 15, participated in the web-based mathematics courses. All of the students were taught by the same teacher, and have been trained to use MSAL system.

Four units of "mathematics" course of junior high school were adopted to develop the experimental subject materials; that is, "Sequence", "Equal Difference Sequence", "Calculate Sequence" and "Sequence Mid Item". Three difficulty levels (Easy, Mid and Hard) and two presentation styles (Hypermedia and Sequential Frame) were considered in developing the course contents; that is, six versions of subject materials were constructed, including "Easy and Hypermedia", "Easy and Sequential Frames", "Mid and Hypermedia", "Mid and Sequential Frames", "Hard and Hypermedia", "Hard and Sequential Frames".

The "Easy", "Mid" and "Hard" versions of subject materials were constructed by considering the detail degree of content descriptions and the concepts to be learned. For "Easy" version, the basic concepts to be learned with very detailed descriptions (including the prerequisite concepts) were given; for “Mid” version, only detailed descriptions of the basic concepts and the most relevant prerequisite concepts (defined by the teacher) were given; for “Hard” version, only the descriptions of the basic concepts and some advanced concepts (defined by the teacher) were given.

In the registration time, the students received the Keefe learning style profile test to exam their SQP values, and were assigned to three learning groups, i.e. Experimental Group1, Control Group 1 and Control Group 2. The following table shows the SQP grades of the members in each group.

SQP grade	Experiment Group1	Control Group 1	Control Group 2
Number of High SQP students	16	17	19
Number of Low SQP students	13	15	11
Total number of students	29	32	30

Consequently, the students in the three research groups were asked to use different web-based learning strategies provided by MSAL. Experimental Group 1 adopted all of the six versions of subject materials, in which the learning environment was adaptive based on each student’s learning ability and learning style; Control Group 1 adopted three versions of subject materials; that is “Easy and Hypermedia”, “Mid and Hypermedia” and “Hard and Hypermedia”; Control Group 2 adopted only one version of subject material; that is, “Mid and Hypermedia”. For Experimental Group 1 and Control Group 1, the learning environment was adaptive based on each student’s learning ability, and difficulty level of a new subject unit was determined based on the test results of the previous unit. For Control Group 2, the test results of a unit were only used to measure the unit progression, and did not change the difficulty level of the next unit.

Note that although part of the students in Control groups 1 and 2 received high SQP values, we assigned Hypermedia presentation materials to all of the students in those two groups to simulate the ordinary web-based learning environments. That is, in ordinary learning environments, without proper arrangement, part of the student might receive subject materials with improper presentation style. The experiment environment designed is shown in the following table.

Group name	Experiment Group1	Control Group 1	Control Group 2
Course	Multi-Source Adaptive course	Single-Source Adaptive course	Non-Adaptive course
Learning Style Test	Yes	Yes	Yes
Pre test	Yes	Yes	Yes
Subject material	Junior high school mathematics chapter 6.1	Junior high school mathematics chapter 6.1	Junior high school mathematics chapter 6.1
Versions of Subject Materials	Six versions (Easy/Mid/Hard and Hypermedia /Sequential Frames)	Three versions (Easy/Mid/Hard and Hypermedia)	One version (Mid and Hypermedia)
Course name	Equal difference Sequence 1	Equal difference Sequence 2	Equal difference Sequence 3
Course unit 1	Sequence	Sequence	Sequence
Course unit 2	Equal difference Sequence	Equal difference Sequence	Equal difference Sequence
Course unit 3	Calculate Sequence	Calculate Sequence	Calculate Sequence
Course unit 4	Sequence mid item	Sequence mid item	Sequence mid item
Post-test	Yes	Yes	Yes

5.2 Analysis of Leaning Efficacy and Efficiency

We aim to analyze the independent and interactive effects of three independent variables (i.e. Multi-Source Adaptive course, Single-Source Adaptive course, and Non-Adaptive course) on one dependent variable (Test score). For the 3 ×1 factorial experimental research designs, one-way ANOVA statistical procedure was employed to analyze all of the experimental results. Three pilot studies were carried out to verify the experiment design and prior to the investigation.

The following table shows the score means and standard deviations of the experimental results for each group. It can be observed that Experimental Group1 had the best average score, and Control Group2 had the lowest average score.

Group	Average score	Number of students	Standard deviation	Mean
Experimental Group 1	73.45	29	24.62	85.00
Control Group 1	70.81	32	15.60	73.00
Control Group 2	61.20	30	21.51	61.00
Total number of students	68.48	91	21.19	72.00

The following table shows the analysis of score variance (ANOVA) for Experimental Group 1 and Control Group 2. Statistically the results show significant difference ($F = 4.151$, $P = 0.046 < 0.5$) of learning efficacy between the learning environment with Multi-Source Adaptive course and the Non-Adaptive learning environment, which implies that the recognition of individual learning styles and difficulty levels is necessary.

	Sum of Squares	D.F.	Mean Squares	F Ratio	F Prob.
Between Groups	2212.163	1	2212.163	4.151	0.046
Within Groups	30379.972	57	532.982		
Total	32592.136	58			

The following table shows the analysis of variance for Control Groups 1 and 2. Statistically the results show significant difference ($F = 4.096$, $P = 0.047 < 0.5$) of learning efficacy between the learning environment with Single-Source Adaptive course and the Non-Adaptive learning environment, which assumes acknowledgement of the difficulty levels of subject materials is necessary.

	Sum of Squares	D.F.	Mean Squares	F Ratio	F Prob.
Between Groups	1430.712	1	1430.712	4.096	0.047
Within Groups	20955.675	60	349.261		
Total	22386.387	61			

The following table shows the analysis of variance for Experimental Group1 and Control Group1. The analysis results ($F = 0.254$, $P = 0.616 > 0.5$) show no significant difference of learning efficacy between the learning environments with Multi-Source Adaptive courses and Single-Source Adaptive course.

	Sum of Squares	D.F.	Mean Squares	F Ratio	F Prob.
Between Groups	105.690	1	105.690	0.254	0.616
Within Groups	24510.047	59	415.425		
Total	24615.738	60			

However, in our experiment environment, there is nearly 47% (fifteen) of the students in Control Group 1 were with the "Low SQP" learning style; that is, those students have received the appropriate Hypermedia subject materials as the ones in Experimental Group 1. Therefore, it might be interesting to focus the learning efficacy analysis on the seventeen "High SQP" students in Control Group 1 with the sixteen "High SQP" students in Experimental Group 1 so that the effects of the single-source and the multi-source adaptive learning environments can be precisely compared.

The following table shows the t-test result of learning efficacy for the "High SQP" students in Experimental Group 1 and Control Group 1. As there are only sixteen "High SQP" students in Experimental Group 1, we use the average score of those sixteen students to simulate the score of the seventeenth student. Based on the analysis result, we have $p = 0.143 > 0.05$, which implies that the difference of learning efficacy between the multi-source adaptive learning environment and the single-source adaptive learning environment is not significant.

	N	Mean	SD	t	p
Experimental Group 1	17	75.24	14.45	3.807	0.143
Control Group 1	17	58.76	10.46		

To more deeply compare the effects of the multi-source and the single-source adaptive learning environments, another comparison on subject material browsing time has been conducted. The following table shows the t-test results of learning efficiency for the "High SQP" students in Experimental Group 1 and Control Group 1. The analysis result ($p = 0.018 < 0.05$) implies that the difference of learning efficiency between the multi-source adaptive learning environment and the single-source adaptive learning environment is significant.

	N	Mean	SD	t	p
Experimental Group 1	17	420.88	97.69		
Control Group 1	17	649.53	146.66	-5.350	0.018

Two observations can be derived from the above analysis results:

(1) Adaptive learning environments (including the multi-source and the single-source environments) can improve the learning *efficacy* of students in comparison with the non-adaptive learning environment.

(2) The multi-source adaptive learning environment can improve the learning *efficiency* of students in comparison with the single-source adaptive learning environment.

To sum up, we conclude that the multi-source adaptive learning environment is helpful to students in improving both learning efficacy and efficiency.

6. Conclusions

In this project, we propose an adaptive learning platform, MSAL, which takes multiple sources of personalization information into consideration, including individual differences and learning styles. MSAL is an intelligent tutoring environment that can assist instructors to develop web-based science courses and provide students with suitable subject materials to improve their learning performance. To evaluate the performance of our approach, an experiment was conducted to compare the performance of the students learning in three different environments. The one-way ANOVA and t-test were employed to analyze the experimental results. The statistical analysis results show that our approach can significantly improve student learning efficacy and efficiency.

Currently, we are trying to employ information techniques to analyze the various learning behavior of students and assemble more personalization parameters, in order to more precisely determine suitable subject materials for individual student.

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