Yet another adaptive learning management system based on Felder and Silverman's learning styles and Mashup

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This study designs and implements an adaptive learning management system based on Felder and Silverman's Learning Style Model and the Mashup technology. In this system, Felder and Silverman's Learning Style model is used to assess students' learning styles, in order to provide adaptive learning to leverage learners' learning preferences. Additionally, this learning system also allows learners to use a Mashup search engine to search for related supplementary learning materials for better learning outcomes. An experiment is conducted to evaluate the effectiveness of the developed adaptive learning management system. A questionnaire is also circulated to collect data for qualitative and quantitative analysis of the usability of the developed system. The results show that the system significantly improves learning outcomes and the usability is also well-accepted by the participants.

Keywords: learning style, adaptive learning, Mashup, programming language

INTRODUCTION

Adaptive learning gives different students the opportunity to follow individual learning paths and to meet their specific learning/training needs and has received considerable attention. Recent developments in advanced Web-based technologies have led scholars to reconsider research into learning style in adaptive systems. Akbulut & Cardak (2012) undertook a content analysis of recent studies of adaptive educational hypermedia (AEH), which addressed learning styles. Seventy studies were selected and subjected to a documentary analysis. The results showed that 41 (58.6%) proposed a framework or model for adaptivity, 12 (17.1%) proposed an

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automatic learning style detection framework and 11 (15.7%) assessed the effectiveness of learning style-based AEH. The majority of studies (81.4%) also focused adaptivity based on learning styles and the most preferred learning style model was Felder–Silverman Learning Style Dimensions, which was utilized in 35 studies (50%).

In terms of an adaptive learning framework, Brusilovsky (2001) devised a method to establish an adaptive learning environment. He claimed that a good system must be a hypermedia system, be equipped with learner modules and be a hypermedia model with adaptive learning functions. Therefore, the adaptive technologies required to construct an adaptive learning system can be divided into two main categories: adaptive presentation and adaptive navigation support. These studies focus on navigation support to provide adaptable personalized learning programs (Zhao & Wan, 2006; Chen, 2008; Chu, Hwang, Huang & Wu, 2007; Chiou, Tseng, Hwang & Heller, 2010). Paramythis & Loidl-Reisinger (2003) noted that a good learning system must be able to monitor users' behaviors, understand their needs and preferences and provide appropriate learning content, based on information about the users.

Mashups have been the subject of much recent attention, as more studies use Web 3.0. The term, mashup, pertains to pop music that combines different types of music to provide a new different type of music (Courtney, 2010). From the definition of Ikeda, Nagamine & Kamada (2008) and Mödritscher, Neumann, Garcia-Barrios & Wild, (2008), mashup is a new concept, rather than a new technology, and an important concept of Web 2.0. Mashup accesses and combines two or more different types of resources to generate a new feature or service from the services provided by network service providers. However, the needs of end-users are not well served, because there is a lack of integration and adaptation in the retrieved content. Therefore, this study uses a mashup approach to combine the resources in related social network platforms to provide better learning materials for adaptive learning.

In this study, an adaptive learning management system was designed for better supporting online courses with adaptive learning feature. The developed system adopts the Felder and Silverman's Learning Style Model for acquiring students' different learning styles and uses Mashup search technique to enrich adaptive learning materials. An experiment was conducted to evaluate the effectiveness of the developed system.

State of the literature

- Akbulut & Cardak (2012) pointed out that the most preferred learning style model was Felder–Silverman learning style dimensions, which was utilized in 35 studies (50%), followed by cognitive styles (17.1%), Kolb (8.6%), VARK (7.1%), Honey and Mumford (5.7%).
- In terms of research related to mashup in the field of E-learning, a search engine was designed to allow learners to search for relevant web content and to display it in a grid layout. But the APIs lack of the integration ability of data.

Contribution of this paper to the literature

- Felder and Silverman's Learning Style model is used to assess students' learning styles, in order to provide adaptive learning to leverage learners' learning preferences.
- To achieve the availability and value of big data existed in the social websites. That is, the proposed learning system implement provided a Mashup search engine to search and integrate for related supplementary learning materials from social websites for better learning outcomes.
- To provide an important reference for authors to design an efficient tool retrieving and integrating data from social websites.

LITERATURE REVIEW

Learning style

As stated in introduction, Akbulut & Cardak (2012) pointed out that the most preferred learning style model was Felder–Silverman learning style dimensions, which was utilized in 35 studies (50%), followed by cognitive styles (17.1%), Kolb

(8.6%), VARK (7.1%), Honey and Mumford (5.7%). Various names were given to developed adaptive systems which provided learning materials to match with learning profiles of learners. For example, Shaw (2012) used Kolb's learning style to determine a learner's learning type: 'Diverger' 'Assimilator', 'Converger', and 'Accommodator'. Mampadi, Chen, Ghinea & Chen (2011) developed an adaptive hypermedia learning system tailored to students' cognitive styles, with an emphasis on Pask's Holist–Serialist dimension. Shukr, Zainab & Rana (2013) used Learning Style Questionnaire (LSQ) to assess and categorize the learners into Honey and Mumford classification of learning styles.

The learning style model of Felder & Silverman (1988) divides students' learning styles into four dimensions, each of which has two learning styles. The four dimensions are Process (Active, Reflective), Input (Visual, Verbal), Perception (Sensitive, Intuitive) and Understanding (Sequential, Global). In the application of Felder and Silverman's learning style model, the Felder and Silverman model was selected by Franzoni-Velazquez, Cervantes-Perez & Assar (2012) as the base of their study because it has been successfully implemented in previous works. In this study, the authors pointed out that the teacher should be allowed to determine the most appropriate teaching strategy and course material. A recommendable approach consists in clustering students with similar learning styles and using the appropriate teaching strategy and material for each of the groups. Usually, the teacher is not able to implement such an approach, for example due to course time constraints, unavailability of the appropriate resources, etc. In the experiment, one of outcomes suggests that learning styles of today's learners facilitate them to experience emerging and varying technologies while their learning preferences are not limited to a particular tool.

Ultanir, Ultanir & Temel (2012) translated the Felder-Silverman learning styles instrument into Turkish, to study the reliability and validity of the instrument at Mersin University. The differences between learning styles were examined, according to students' fields of science. The findings show that Mersin University students were sequential, sensory and active learners. Yao, Zheng, Wu & Li (2011) constructed a campus digital learning hub platform that supports many types of learning styles, such as formal learning, informal learning, or ubiquitous learning. Since the target of the platform is facing students of all major and all level in university, there are large quantities of learning resources need to be stored. On storage system selection, the authors concern to make use of existing storage system firstly to seamless joint with digital library and database server. In the conclusion, the authors pointed out that cooperation with other campus platforms and data seamless joint are also difficulties. So does the cooperation among resources storage points.

Adaptive learning

Many adaptive learning systems that use different learning strategies have been proposed. Ozyurt, et al. (2012) designed a personalized adaptive and intelligent web-based tutoring system, based on learning style and an expert system named UZWEBMAT was evaluated for its effect on 10th grade students' studying a unit about probability. A more complete adaptive learning system was presented by Jiang, Qian, Zhou & Fan. (2009), which provides learners with a path and a map for adaptive learning knowledge items, as well as the learning preferences for users. Jovanovic, et al. (2009) proposed an ontology-based online adaptive data-sharing mechanism, through which users share learning resources based on the correlations between learners' attributes and an ontological tree structure. A study by Takano & Li (2011) found that an adaptive learning system in which 3D dynamic graphics are used to help learners understand the content of a book, can also increase users'

interest in learning. Matar (2011) also proposed an Adaptive Learning Object Repository Structure that enables students from different universities to use the adaptive learning systems of other schools.

This study developed an adaptive learning environment for learning a programming language, using the manner of construction for an adaptive learning environment proposed by Brusilovsky (2001), but excluding the functions of adaptive annotation and adaptive hiding. In order to provide adaptive learning courses, with rich and varied learning materials, a general video, pictures and text related materials are provided, which the learners search in order to retrieve more adaptive learning materials from the web, based on learners' different learning styles, through the use of mashup technology.

Mashup

Mashup is widely used in many fields, such as e-learning, tourism (Wang, Zeng & Tang, 2011) and business (Liu, Liang & Xu, 2011). In terms of research related to mashup in the field of E-learning, Al-Zoube & Khasawneh (2010) presented an adaptive course composition system that mashes up learning content in a web application. In the proposed system, a search engine APIs allows learners to search for relevant web content and to display it in a grid layout. Bader, He, Anjomshoaa & Tjoa (2012) proposed a context-aware enterprise mashup readiness assessment framework to help business managers and decision makers determine their needs and readiness for enterprise mashups. The results show that this strategy can be used to guide enterprises in the decision whether to use enterprise mashups. Jung (2012) proposed a contextual mashup-based collaborative browsing (co-browsing) platform, called ContextGrid, which provides online users with various knowledge sharing services. These studies indicate that relevent learning resources can be obtained by using mashup, so mashups do play a significant role in the development of adaptive learning systems.

THE DEVELOPED ADAPTIVE LEARNING MANAGEMENT SYSTEM

System architecture

This study developed an adaptive mashup learning system based on learning style, in which a three-layered conceptual framework is used as shown in Figure 1.

1. Presentation layer

A Graphical User Interface, GUI, is used for the presentation layer, to allow users to operate the system by moving a mouse pointer or other pointing devices onto Windows, icons, or buttons. Users can learn online by simply logging on to the Website. At present, the system can support Web page surfing and other mobile devices, such as smart phones.

2. Service layer

The service layer includes the following three modules.

(a) Teaching management agent: this agent is responsible for the classification of teaching materials into different categories, based on their attributes. When the type of information that is needed by the learner is known, the adaptive agent calls the agent to determine the most appropriate teaching materials, according to the information about the learner that is provided by the adaptive agent, and reports back to the adaptive agent, so that the adaptive agent can send the course content to the learner.

(b) Adaptive agent: this module provides the learner with adaptive course content, depending on the results of the learning style classification. It is equipped with a learning style radar chart that identifies users' learning preferences, directs learners to interactive mechanisms such as course-
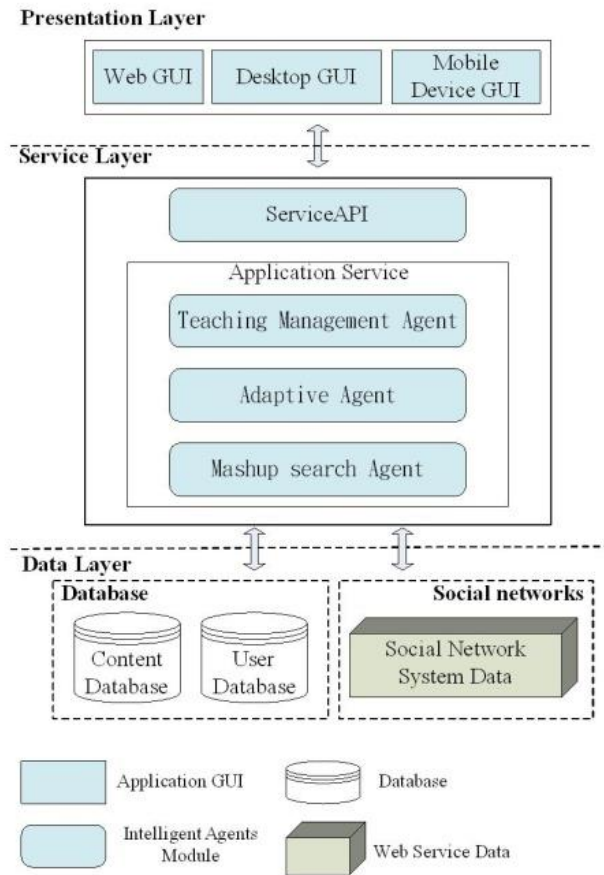
Figure 1. System structure

related interactive discussion boards, learning forums, or blogs, and allows learners to quickly understand the courses' pre-class guidance and after-class quizzes. The supplementary information that is identified by the Mashup search engine is presented in an adaptive manner and the teaching content for the adaptive courses is also displayed using a knowledge map.

(c) Mashup search agent: this agent uses the Mashup search engine to find additional information, based on the adaptive sorting results provided by the other two agents, so that learners can gain a better understanding of the course content in accordance with their interests. The web service database then records all of the links to the adaptive supplementary information, for future review by the learner.

3. Data layer

The data layer contains the following three databases.

(a) Content database: This database stores basic teaching materials and adaptive teaching materials, including images, texts, pictures, or multimedia.

(b) User database: This database stores users' logging information, such as users' personal information, to verify whether the user has the right to view the course content. It also maintains records related to learners' test processes, discussion boards opened by each user, or forums.

(c) Web Service database: This database stores links to adaptive supplementary information that is identified by the Mashup search engine.

Adaptive learning strategy

This section explains the adaptive learning strategy corresponding to the different learning styles. When a learner first logs in, the system asks him/her to

complete an Index of Learning Styles (ILS) questionnaire containing 44 items and is arranged by Felder and Silverman to ascertain the user's learning style.

Using these descriptions of learning styles, learners can clearly understand their learning characteristics. The system then records learners' learning styles and the adaptive agent guides them to appropriate Web pages for adaptive learning, according to the learning strategy, as shown in Table 1.

Adaptive learning process

Figure 2 shows the adaptive learning process. The system determines users' learning styles according to their questionnaire results, which allows learners to understand their own learning preferences. The system then provides appropriate teaching content, based on learners' preferences, to help them achieve better learning outcomes. Users can also use a Mashup search to find more supplementary information.

Design of learning materials

The learning materials contain the following Visual BASIC topics: Data, Selection Control, Iteration Control, Arrays and Set, Procedure and Function, Event-Driven

Table 1. The learning strategy of different learning style

| Learning aspect	Learning style	Learning strategy (tools/teaching materials)
Process	Active	Internet forum Related VB websites
	Reflective	Wiki, Weblog
Input	Visual	Class video files, Pictures and Tables
	Verbal	Class audio files
Perception	Sensing	Examples, Cases studies
	Intuitive	Calss video files, Examples
Understanding	Sequential	Providing linear guide and related problems for a specific subject.
	Global	Knowledge Map
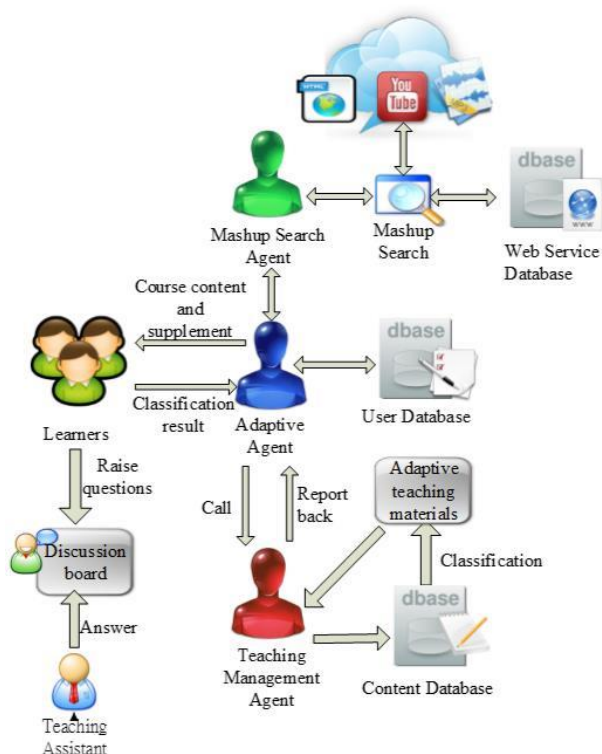
Figure 2. Adaptive learning process

Programming Design, Graphic and Multimedia, Menu Design, File Design and Database Programming Design. Each topic contains the following types of content: multimedia, webpage and videos, as shown in Figure 3.

Design of Mashup search engine

The design of Mashup search engine is illustrated in Figure 4 (Chang & Chen, 2011). The concept uses three types of leaning materials: text, graphics and video. The different types of learning materials are searched and retrieved from their corresponding social network platforms, so learners can learn effectively, using social network resources. In conjunction with the Mashup search engine, the three best known search websites, Google Code Search, Flickr and YouTube, are the third-side resources. Because three different types and data sources are provided in an adaptive learning system, when the data is retrieved by the Mashup Module, two problems occur: inconsistent data format and inconsistent tag name and value. To solve these two problems, four functions, a parser, a translator, an integrator and an inference engine, are included in the Mashup Module.

EXPERIMENTAL DESIGN

To evaluate the effectiveness of the developed system, an experiment was conducted with participants from first year college students taking the Visual Basic
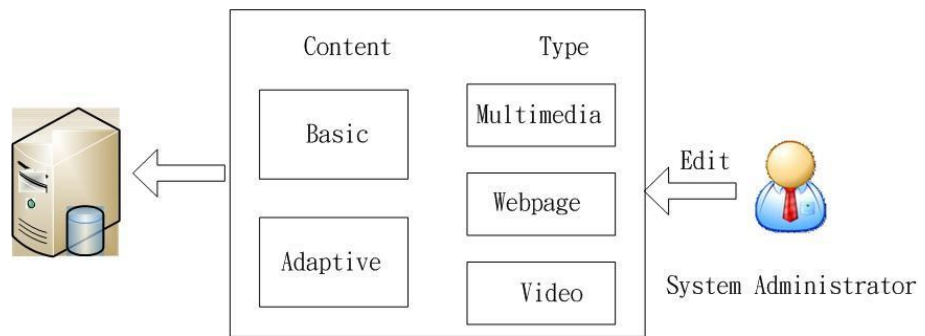

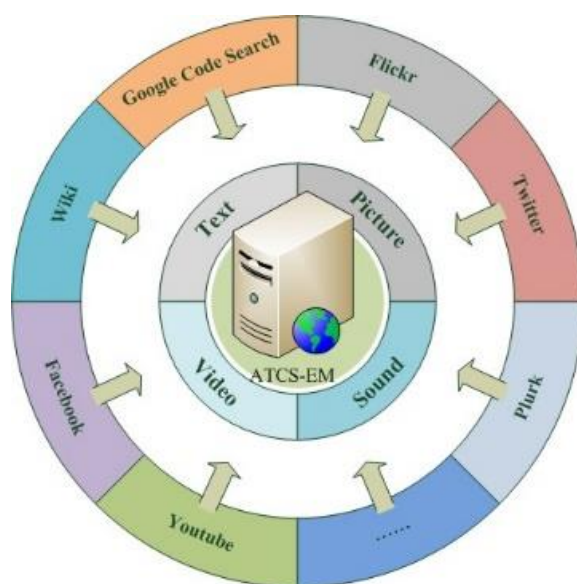**Figure 3.** The contents and types of teaching materials

Figure 4. The contents and types of teaching materials

programming course at the Information Management department of the Southern Taiwan University of Science and Technology. The subjects for this experiment were two classes, each with 58 students. One was experiment group and the other the control group. The experiment lasted 8 weeks. Each week there were three class sessions.

Experimental procedure

The experimental process comprised the following six phases, as shown in Figure 5. Initially, both groups of students attended normal e-learning sessions. After the mid-period, students in the experimental group engaged in adaptive learning using the developed system, in which an adaptive learning website for Visual Basic programming was used to assist students in their studies. After the experiment, a comparison was made to assess any difference in learning outcomes between the two groups. Students in the experimental group were also asked to complete a questionnaire regarding to their learning experiences. A statistical analysis software was then used to analyze the collected questionnaires to determine whether the goal of this study had been achieved.

Step 1: The motivation and purpose of this study was explained to each group. This phase took 10 minutes for each group.

Step 2: Each group completed the pre-test. This phase took 100 minutes for each group.

Step 3: Learners in the experimental group were taught how to use the system, which took approximately 30 minutes. Each learner first logged into the system and completed a questionnaire to determine the learner's learning style.

For the control group, the basic information for the courses was explained, which took approximately 30 minutes.

Step 4: Learners in the experimental group learned in a traditional manner, which took 8 weeks, with three class sessions each week. The learners also used the proposed system to enhance adaptive learning during the 8 weeks.

Learners in the control group learned in a traditional manner, which took 8 weeks, with three class sessions each week.

Step 5: Each group completed a post-test, which took approximately 100 minutes for each group.

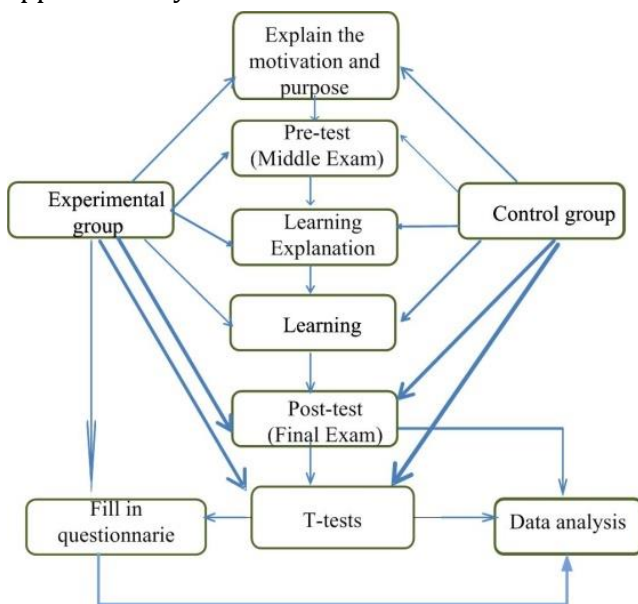Step 6: Learners in the experimental group completed a questionnaire, which took approximately 20 minutes.

Figure 5. Experimental Process

Learners in the control group shared their learning experiences, which took approximately 20 minutes.

Measurement tools

A pre-test and a post-test were used to assess the learning outcomes of the students. The pre-test (midterm exam) comprised 10 true-or-false questions, 2 multiple-choice items and one application, giving a full score of 100. The pre-test verified that the two groups of students had equivalent basic knowledge and abilities to learn the topics, "Operator" and "If statement". The post-test (final exam) comprised 10 true-or-false questions and one application of the use of "For", "Array", "Listbox" and "Combobox", giving a full score of 100. Both the pre-test and the post-test were designed by the teacher who taught Visual Basic programming to both groups of students.

A questionnaire with a five-point Likert scale was also used to measure the effectiveness of the adaptation and the mashup search engine. There were 7 questionnaire items for the "adaptive learning" aspect and 3 questionnaire items for the "mashup search engine" aspect. The Cronbach's alpha values for the two aspects were 0.92 and 0.82, respectively, which demonstrates that the questionnaire is reliable.

RESULTS

Adaptive classification for the experimental group

The results of the adaptive classification for the experimental show that 80.65% were primarily active learners in the process aspect, 88.71% were primarily visual learners in the input aspect, 69.31% were sensitive learners in the perception aspect and 62.9% were global learners in the understanding aspect. The results for the process and understanding aspects are a little different to those of Zualkernan, et al. (2006), for which the figures are between 46% to 65% and 29% to 49%, respectively. Zualkernan, et al. used students in the Middle East and America and there are only 58 students in this experimental group in our research. However, a comparison of the learning styles of computer programming students in different countries is of interest.

Learning outcome

An independent-sample t-test was tested to obtain the difference between the two groups in the pre-test. The pre-test results were collected in the mid-term. Table 2 shows the results of the analysis, in which the t-value is .062 and the p-value is .951 (> .05). The results show that there is no significant difference between the two groups and it can be claimed that the two groups have the same level of prior knowledge before the experiment.

The difference between the two groups, in terms of the post-test results of the learning outcomes, an independent-sample t-test was also tested. The post-test results were collected at the end of the semester. Table 3 shows the results of the analysis, in which the t-value is 2.896 and the p-value is .005 (< .05). This shows that the two groups both make significant progress, but the improvement made by the students in the experimental group is much more significant than that for the control group.

Table 2. The difference between the two groups, in terms of the results of the learning effectiveness pre-test Independent-Simples T Test

		Number	Mean	SD	T-value
Experiment group	58	67.52	15.180	.062	
Control group		58	67.34	14.800	

P= 0.951

Table 3. The difference between the two groups, in terms of the results of the learning effectiveness post-test Independent-Simples T Test

	Number	Mean	SD	T-value
Experiment group	58	78.12	10.053	2.896
Control group	58	71.91	12.863	

*P= 0.005, *p < 0.05*

Table 4. The distribution of students in the score interval for post-test

Pre-test Post-test	A	B	C	D	E	Total No.
A	3	3	1	0	0	7
B		5	11	3	2	21
C		1	4	6	4	15
D		1	1	1	11	14
E					1	1
Total No.	3	10	17	10	18	58

Learning style with learning outcome

To better understand how the students in the experimental group with different levels of learning outcomes react to learning style based learning, they are divided into grades A, B, C, D and E, in accordance with the pre-test and post-test scores. The scores between 90 to 100, 80 to 89, 70 to 79, 60 to 69, and below 60 are grades A, B, C, D, and E, respectively. After the classification, the number of students for each grade is shown in Table 4. Each value in the table signifies the number of students with the same corresponding grades of post-test and pre-test. The distribution of students in the score interval for the post-test is illustrated in Table 4. From Table 4, the relationship between learning outcome and learning style is analyzed and the following 4 results are illustrated:

1. For the 3 learners with grade A after the pre-test, their learning styles are all sequential in the understanding aspect. This shows that outstanding learners have a step-by-step approach to the courses and have a considerable understanding of the content in the teaching materials. Therefore, there is not a large difference in their scores for the pre-test and the post-test.

2. For the 10 learners with grade B after the pre-test, 9 learners' learning style is global in the understanding aspect and they acquire a wide range of knowledge. When the learners understand the focus of a chapter, they link other related content in a fast and efficient way.

3. For the learners with grade C, D and E after the pre-test, their sensitivity is relatively weak in the courses and did not immediately discern the focus of the curriculum. Therefore, the learning style model of Felder and Silverman was firstly used to identify their learning preferences and adaptive course content was provided, in accordance with their learning style. The learners then learn in a more relaxed way and achieve greater effectiveness in learning. In addition, it is found that their learning style is active in the Process learning aspect and visual in the Input learning aspect, so their acceptance of group discussion and image learning is relatively high. These learners can use these two learning methods to achieve better learning effectiveness.

4. After the post-test, 55 students' grade increases or does not change and 3 students' which decreases. Overall, the results confirm that this system indeed improves the effectiveness of learners and these results are consistent with previous independent T-test results.

Statistical analysis

An analysis of the average score and standard deviation is made according to the dimensions and the corresponding items. For standard deviation, the larger the standard deviation, the lesser the users' agreement with the items asked. However, smaller standard deviation indicates that there is greater user agreement with the items asked. In this study, standard deviation is set as 1, in accordance with (Chen, Chiu, Huang & Chang, 2011). That is, if the standard deviation is greater than 1, users agree less with the items asked, but if the standard deviation is less than 1, users are in greater agreement with the items asked.

The results of the analysis of adaptive learning dimension are shown in Table 5, where the total average of the mean and the standard deviation are 3.68 and 0.62, respectively. For question A3, the mean is 3.74, so multimedia learning content aids learning. The results of the analysis of the search engine dimension are shown in Table 6, where the total average of the mean and the standard deviation are 3.81 and 0.664 respectively. For question B1, the mean is 3.87, so the information retrieved by search engine indeed meets the learners' needs.

DISCUSSION AND CONCLUSION

Most learning management systems provide a lot of teaching materials, but ignore the learners' acceptance of the contents. Therefore, In the proposed system, Felder and Silverman's Learning Style Model is used to gain an understanding of students' learning styles to enable them to engage in adaptive learning using their respective learning styles. In addition, learners use the Mashup search engine to search for related supplementary teaching materials to achieve better learning results. The results of the experiment and the analysis show that the developed adaptive mashup learning system substantially improves learners' learning effectiveness. Compared with traditional one-way teaching methods, adaptive learning is more effective in increasing learners' interest in learning and allows them to learn in their own preferred manner. The Mashup search engine also allows users find more useful knowledge for learning.

In the analysis of adaptive learning dimension, the mean for question A1, "Adaptive learning increases your interest in learning", is 3.63, which is the lowest satisfaction level in the dimension. Currently, the learning materials provided by the system are mostly in the form of Web pages, which are easy to understand, but not sufficiently interesting. It is suggested that more attractive and interesting learning

Table 5. Statistical analysis of adaptive learning

No	Question Items	Average	SD
A1	Adaptive learning increases your interest in learning.	3.63	0.623
A2	Adaptive Learning helps you learn more about the course content.	3.67	0.583
A3	Adaptive learning materials with text, video and audio help you learn.	3.74	0.650
A4	Adaptive learning allows you to learn in your favorite way.	3.72	0.564
A5	Adaptive learning is helpful to learning effectiveness.	3.70	0.662
A6	When you finish the adaptive learning courses, you are more familiar with the course content.	3.67	0.583
A7	You agree with the classification result for learning style.	3.65	0.677
Average		3.68	0.620

Table 6. Statistical analysis of the search engine dimension

No	Question Items	Average	SD
B1	The information retrieved by the search engine meets your needs.	3.87	0.616
B2	The information retrieved by the search engine is sufficient.	3.76	0.642
B3	The search engine helps you to find other information that you want	3.81	0.675
Average		3.81	0.644

concepts be incorporated in this type of learning system in the future to make the learning process for computer programming more akin to game-playing and improve students' interest in learning. In the analysis of the mashup search engine dimension, the mean for question B2, "The information retrieved by the search engine is sufficient", is 3.76, which is the lowest satisfaction level in the dimension. Currently, the three most common search websites, Google Code Search, Flickr, and YouTube are the third-side resources, but a more extensive search would be possible if more related third-side websites were added. In the adaptive classification for the experimental group, 80.65% learners are active type in the process aspect, 88.71% learners are visual type in the input aspect, 69.31% learners are sensitive type in the perception aspect and 62.9% learners are global type in the understanding aspect. The number of learners in the experimental group is just 58. In future greater numbers of experiments will give a more accurate distribution of learning styles, so more adaptive learning strategies can be used. In learning style with the learning outcomes aspect, the relationship between learning style and learning outcomes can be used to recommend different learning styles' for different learners. The coherence between the learning concepts and teaching materials must also be improved, as seen by the result of the interview with the students. A domain ontology that presents and reasons the related learning concepts is possible. It is also necessary to monitor learning progress and to remind learners about the improved learning materials.

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