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Guideline for the Development of Personalized Technology-enhanced Learning in Science, Technology, and Mathematics Education

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Abstract: With a rapidly changing world, science, technology, and mathematics (STM) hold the key to achieve a certain level of development. Technology in education is, therefore, a key ingredient to enhance learning as it helps produce creative and lifelong learning individual students. Recent progress in computer and communication technology has encouraged the researchers to demonstrate the pivotal influences of technological personalized learning environments on student learning performance improvement. Many researchers have been investigating the development of such learning environment by basing upon the concept-effect relationship model on student learning performance improvement. Such learning environment has been demonstrated to be useful for helping teachers to diagnose learning problems for individual students according to test answers, and to provide personalized remedial learning guidance for improving students' learning performance. However, each student has different preferences and needs, which are very important factors, affecting on STM learning ability. Moreover, individualizing the learning experience for each student is an important goal for educational systems. It is very crucial to provide the different styles of learners with different learning environments that are more preferred and more efficient to them. Therefore, this paper proposes a guideline for the development of personalized technology-enhanced learning where the student's conceptual learning problems and preferences are diagnosed, and then user interfaces are customized in an adaptive manner to accommodate such learning problems and preferences, in order to emphasize on promoting STM education.

Keywords: STM education, e-learning, adaptive learning, technology-enhanced learning, concept-effect relationship model

1. Introduction

In STM education community, most educators are concerned about applying teaching and learning theories/strategies/approaches to enhance students learning ability. For example, inquiry-based learning approach, which is promised to improve STM teaching by engaging students in authentic investigations emphasizing on posing questions, gathering and analyzing data, and constructing evidence-based arguments, has been applied to achieving a more realistic conception of scientific endeavor as well as providing a more student-centered and motivating environment (Kuhn, Black, Keselman, & Kaplan, 2000; Kubicek, 2005; Krajcik & Blumenfeld, 2006). A learning cycle approach basing on the concept of inquiry-based learning approach is most widely used in promoting the students' understanding in the idea of chemistry education, biological education, physics education, life science course, and computer science education (Allard & Barman, 1994; Ates, 2005; Dibley & Parish, 2007; Kaynar, Tekkaya, & Cakiroglu, 2009; Liu, Peng, Wu, & Lin, 2009). This approach could enable an opportunity for students to reveal their prior knowledge exist in two ways such as they make predictions before exploring, and generate hypotheses to explain new phenomena. From these studies, the researchers reported that students still often displayed learning difficulties in understanding and hold failures status of conceptual understanding for real world phenomena. Although learning activities based on the effective teaching and learning approach, in reality, each student has different preferences and needs. These mentions are very important factors affecting on STM learning ability and individualizing the learning experience for each student is an important goal for educational systems (Snow & Farr, 1987; Russell, 1997). Therefore thinking about learner difference and personalized learning information and providing the different styles of learners with different learning environments during applying teaching and learning theories/strategies/approaches in STM are more preferred and more efficient to them, it might overcome learning difficulties in understanding and hold failures status of conceptual understanding for real world phenomena.

In past decade, the rapid advance of computers and communication technologies has promoted the utilization of technological applications in STM educations. The technology in STM education serves as a key ingredient to enhance learning as it helps produce creative and lifelong learning for individual students and promotes personalized learning as well. However, managing STM classroom with a large number of students is very difficult when concerning about the learner difference and personalized learning information. Personalized or adaptive online-based learning, thus, has been becoming to overcome that issue in technology-enhanced learning and teaching (Smith & Smith, 2004; Sun, Lin, & Yu, 2008; Yang, & Tsai, 2008; Akbulut & Cardak, 2012; Chookaew, Panjaburee, Wanichsan, & Laosinchai, 2013). To realize personalized technology-enhanced learning, STM-concept status and learning style are two of the key components. The personalized technology-enhanced learning environment is referred to enable individual students to improve their own learning performance (Chen, 2008; Chen, 2011). Consequently, many researchers have developed personalized technology-enhanced learning environment based on several approaches, models, and algorithms including Bayesian cybernetics, fuzzy rules, genetic algorithms, clustering techniques and concept-effect relationship model (Bai & Chen, 2008a; Cheng, Lin, Chen, & Heh, 2005; Kaburlasos, Marinagi, & Tsoukalas, 2008; Panjaburee, Hwang, Triampo, & Shih, 2010).

In the recent years, several researchers have applied concept-effect relationship model to develop technological personalized learning environment (Bai & Chen, 2008a, 2008b; Chen, 2008; Chen & Bai, 2009; Chu, Hwang, Tseng, & Hwang, 2006; Günel & Aşlıyan, 2010; Hwang, 2003; Hwang, Panjaburee, Shih, & Triampo, 2013; Panjaburee et al., 2010). Successful uses of this model not only demonstrated the benefits of applying it for coping with learning diagnosis problems but also enhanced learning performance in several areas including natural science, mathematics, and health education. In this paper, therefore, we propose a guideline for the development of personalized technology-enhanced learning. This guideline will take into account two aspects about the conceptual status, which presents the learning status of each concept of each student in the course content, needs to be diagnosed by the testing and diagnosing process within a personalized technology-enhanced learning system. Moreover, learning style of each student is needed to be identified for adapting user interfaces within a personalized technology-enhanced learning system, in order to emphasize on promoting STM education.

2. Characteristics of Concept-Effect Relationship Model

In 2003, Hwang firstly proposed the concept of concept-effect relationship (CER) as a concept-map oriented approach as the researchers/ practitioners/ teachers/ experts need to define the prerequisite relationships among concepts to be learned in hierarchical order based on curriculum or teaching experience before the course begin (Hwang, 2003). The CER is appropriated for the subject containing the explicit concept relationships. Panjaburee et al. in 2010 showed an example of CER construction on topic “Division of Positive Number” is shown in Figure 1.

In Figure 1., consider two concepts, Ci and Cj, concept “C2 Addition of Positive Integer” is a prerequisite for the efficient performance of the more complex and higher-level concepts “C3 Subtraction of Positive Integer” and “C4 Multiple of Positive Integer”. Clearly, a concept may have multiple prerequisite concepts, and a given concept can also be a prerequisite concept of multiple concepts. Therefore, if a student fails in C5, it may be caused of incompletely learn in C3 and C4.

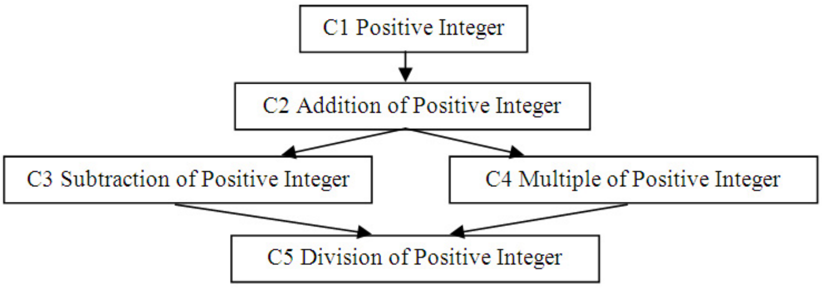

Figure 1. Illustrate example of CER construction on topic "Division of Positive Number"

Following the construction of CER the main problem is how to diagnose student conceptual learning problems. Obviously, previous research used the CER to diagnose student conceptual learning problems in five steps (Hwang, 2003; Hwang et al., 2008): (1) Constructing the CER for the subject unit. (2) Presetting the weight values between test item and related concepts. (3) Calculating the incorrect answer rate for each student in each concept. (4) Defining a concept which affects the learning of other related concepts. (5) Providing feedback and corresponding learning material to each student. These five steps of the use of CER are called the CER model in diagnosing student conceptual learning problem in technological personalized learning environment.

3. A conceptual framework for adaptive learning with conceptual status

As a learner learning difficulties, conceptual status is an indicator of how well a learner learns and needs to be improved. If educators want to successfully address the needs of the individual they must understand how well a learner learns and adjust the difficulty level of subject material to meet the conceptual status of each learner. Within an adaptive learning system, the testing and diagnostic process widely used to diagnose conceptual status of each leaner. To acquire the personalized information about conceptual status of each concept in the course content, usually, several researchers in the area of technology-enhanced learning and teaching have applied the concept of a Fuzzy membership function (Hwang, 2003; Chu, Hwang, Tseng, & Hwang, 2006; Bai & Chen, 2008; Panjaburee, Hwang, Triampo, Shih, 2010; Srisawasdi, Srikasee, & Panjaburee, 2012; Panjaburee, Triampo, Hwang, Chuedoung, & Triampo, 2013). Before starting this testing and diagnosing process, the teachers need to develop the test items which cover all concepts that student need to learn in the course content and determine the intensity of association concepts for each test item. Normally, the intensity values range from 0 to 5, with 0 indicating no relationship and 1-5 representing the intensity of the relationship, with 5 the most intense (as shown in Table 1).

Table 1. Illustrative example of intensity values between concept and test item (adapt from Srisawasdi, Srikasee, & Panjaburee, 2012)

Concepts / Test Items	1	2	3	4	5	6	7	8	9
1	2	0	5	0	0	0	0	0	0
2	*1*	*0*	*5*	*0*	*0*	*1*	*0*	*0*	*0*
3	*4*	*4*	*5*	*1*	*1*	*0*	*0*	*0*	*0*
4	4	4	5	2	1	1	0	0	0
5	2	5	5	1	4	1	0	0	0
6	1	5	3	5	5	0	5	0	0
7	*0*	*0*	*1*	*0*	*0*	*0*	*0*	*5*	*0*

Concepts Test Items	1	2	3	4	5	6	7	8	9
8	5	3	2	5	1	2	0	0	0
9	0	1	0	0	0	0	0	0	5
10	5	0	0	0	0	0	0	0	5
Sum	24	22	31	14	12	5	5	5	10
Error	9	8	16	3	2	2	0	5	0
Error Rate	0.38	0.36	0.52	0.21	0.17	0.80	0.00	1.00	0.00

The summary steps in the testing and diagnosing process for diagnosing leaners' conceptual status consist of the following steps:

Step1: Finding concepts related to the test items that a leaner failed to correctly answer, assuming that the leaner failed to correctly answer of test item 2, 3, 4, and 7.

Step2: Calculating the error of each concept by summation of the intensity only failed test item 2, 3, 4, and 7.

Step3: Calculating error rate of each concept by division of error by sum. As indicated in Table 1, the error rate of concept 1 is 9/24 = 0.38, indicating that the leaner failed to answer 38% of the test items related to concept 1.

Step4: Finding the conceptual status of the student by applying the Fuzzy membership function as shown in Figure 2. For example, error rate of concept 6 is 0.80. 0.80 in x-axis will meet the maximum value at HIGH curve in y-axis. It means that the student has high error in this concept, implying that the conceptual status of this concept is poorly-learned. Otherwise, if the student has low error in this concept, implying that the conceptual status of this concept is well-learned. If the student has medium error in this concept, implying that the conceptual status of this concept is partial-learned.

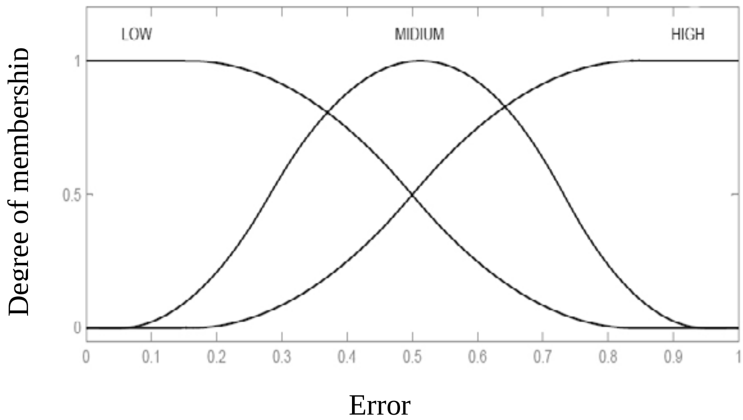

Figure 2. Illustrate Fuzzy membership function

For the benefit of the Fuzzy membership function in judging the conceptual status of each concept for each leaner, we can easy gain the personalized conceptual status within an online-based learning system. Based on this information, the content on online-based learning system could be adapted to fit with each leaner in specific conceptual status (well-, partial-, or poorly-learned).

4. Examples of CER model-based implementation

Regarding it is necessary to establish the degree of association between test item and related concepts in the CER model, Panjaburee et al., in 2010, proposed a multi-expert approach to integrate such degree given by multiple experts/ domain to making high quality degree of association between test item and related concepts. The integrated degree was used to be input in a testing and diagnostic learning problem (TDLP) system which was developed basing upon the concept of CER model. Panjaburee et al. (2010) evaluated the effectiveness of their system on mathematics course for topic “System of Linear Equation” with 113 secondary school students in Thailand. Three teachers with fifteen experienced teaching on the topic were domain experts in this study. The participating students, thus, were divided into 4 groups (i.e., three control groups and one experimental group). Students in control groups were asked to participate in TDLP linked with the degree of association between test item and related concepts given by single expert, while those in experimental group were asked to involve in TDLP linked with the degree of association between test item and related concepts given by multiple experts. All students were asked to log on the online system to take a pre-test. The system analyzed their answers, provided the learning performance level of each concept related to the topic, guided the way to improve their own learning problems, and gave supplementary homework in paper-based format accordingly. We could see that the students in control group 1, 2, and 3 received those personalized information given by domain expert 1, 2, and 3, respectively, and those in experimental group received the information from integrated opinion of these three domain experts. After experiencing corresponding homework, all students took a post-test to compare learning achievement among four groups. This study showed that students in experimental group performed significant better than those in control groups. Finally, Panjaburee et al. mentioned that a multi-expert approach could help students improved learning achievement after experiencing in a TDLP based on the CER model.

Similarly, regarding CER serves as a tool for tracing conceptual learning problems, Hwang et al., in 2013, proposed a group decision approach to integrate CER from multiple experts/ domain to making high quality CER. The integrated CER was used to be input in a testing and diagnostic system which was developed basing upon the concept of CER model. Hwang et al. (2013) evaluated the effectiveness of their system on mathematics course for topic “Computations and Applications of Quadratic Equations” with 104 secondary school students in Taiwan. Three teachers with four experienced teaching on the topic were domain experts in this study. The participating students, thus, were divided into 4 groups (i.e., three control groups and one experimental group). Students in control groups were asked to participate in a testing and diagnostic system linked with the CER given by single expert, while those in experimental group were asked to involve in a testing and diagnostic system linked with the CER given by multiple experts. After taking a pre-test, the students in three control groups received learning suggestions based on the CER given by domain expert 1, 2, and 3, respectively, while those in experimental group received learning guidance followed by the CER from integrated opinion of three experts. The system then provided supplementary material related with personalized conceptual learning suggestions. After finishing learning activities, all students took a post-test. The post-test results showed that there was significant different score between the low-achieved students in experimental group and those in three control groups. Hwang et al. concluded that a group decision of multiple experts could help students improved learning achievement after experiencing in a personalized learning material based on the CER model.

However, it is not enough to address the leaner differences issue with only one aspect. Because each leaner might have his/her learning style, therefore, another aspect, learning style, is needed to be identified for adapting user interfaces within a personalized technology-enhanced learning system.

5. A conceptual framework for adaptive learning with learning style

Over the past decade, several researchers have defined learning style and addressed the concept of learning styles and the various ways they are measured (Keefe, 1979; Cavaiani, 1989). Learning style refers to the different ways that each learner uses to perceive, process, and conceptualize information. As a learner characteristic, learning style is an indicator of how a learner learns and likes to learn. Moreover, if educators want to successfully address the needs of the individual they must aware how learner likes to learn and adjust their teaching styles to meet the learning styles of each student. As we know identifying and accommodating diverse learning styles is a hard task in any classroom environment (Gilbert & Han, 1999). In the recent years, several researchers in the area of technology-enhanced learning and teaching have developed online-based learning system by concerning about the learning style (Smith & Smith, 2004; Sun, Lin, & Yu, 2008; Tseng, Chu, Hwang, & Tsai, 2008; Yang, & Tsai, 2008; Zacharis, 2011; Akbulut & Cardak, 2012; Chookaew, , Panjaburee , Wanichsan, & Laosinchai, 2013). The system could help educators identify and adjust learning environment by accommodating diverse learning styles. And also the learners could improve learning ability because they participate in learning environment that they prefer.

In personalized technology-enhanced learning environment, there are various information sources and various ways of presenting learning content. Felder & Soloman's (1988) Index of Learning Style (ILS) questionnaire might be the most suitable model for an adaptive personalized technology-enhanced learning system. Especially, the visual/verbal dimension plays an important role in determining how a learner receives and processes information. If the students are visual student, the personalized technology-enhanced learning system assumes that they could remember best by seeing. Thus, the system will present the learning material as pictures, animations, and demonstrations for them. For those who are verbal ability, the system assumes that they could gain understanding of material by hearing; therefore, the system will generate the learning material as text, spoken explanations, and exercises to be completed with their friends.

6. Guideline for the Development of Personalized Technology-enhanced Learning in Science, Technology, and Mathematics Education

Due to attention to the personal learning needs of individual students, the educational system can be successful (Russell, 1997). Moreover, educators should use the technology to serve students differences. As the conceptual frameworks above, when developing personalized technology-enhanced learning system, we could not pay attention to single personalized information of student such as conceptual status (including well-, partial-, or poorly-learned) or learning style, while the integration of two sources of personalized information are ignored. If we develop personalized technology-enhanced learning system based only on conceptual status, the students might not participate in learning environment that they prefer. Otherwise, if we develop personalized technology-enhanced learning system based only on learning style, the students could not learn in subject material with difficulty level does not fit with their own performance level. So, it could not use the maximum proficiency of technology to serve students differences. If we can integration those two sources of personalized information for personalized technology-enhanced learning system, it would be benefit for teachers and students in order to promote thinking and could become innovative part of existing model of inquiry-based STM learning by the way of using computer-based instructional technologies. Because, without face-to-face communication in any classroom, teachers could gain student personalized information for preparing any subject material to fit with each student. In the same time, students could participate in subject material with difficulty level corresponding with their own conceptual status and also in user interface of personalized technology-enhanced learning adjusted for the way they like to learn.

Therefore, in this paper, we propose a guideline to manage personalized technology-enhanced learning system in order to emphasize on promoting STM education as shown in Figure 3. The students will take the on-line conceptual test. When the teachers examined the intensity value of association concepts for each test item and the student submitted his/her answers of the conceptual test sheet, the testing and diagnosing process in a personalized technology-enhanced learning system can work effectively. The personalized technology-enhanced learning system will diagnose his/her conceptual learning status and provide the conceptual status of each concept to each student. The students then take a learning style questionnaire and the student submitted his/her answers of the questionnaire, the personalized technology-enhanced learning system will analyze their own learning style. The student will participate in subject material corresponding with conceptual status (well-, partial-, or poorly-learned) of each concept with the user interface adjusted basing upon their own learning style within the personalized technology-enhanced learning system.

This is our framework in which we take into account two aspects about the conceptual status, which presents the learning status of each concept of each student in the course content, needs to be diagnosed by the testing and diagnosing process within a personalized technology-enhanced learning system. Moreover, learning style of each student is needed to be identified for adapting user interfaces within a personalized technology-enhanced learning system.

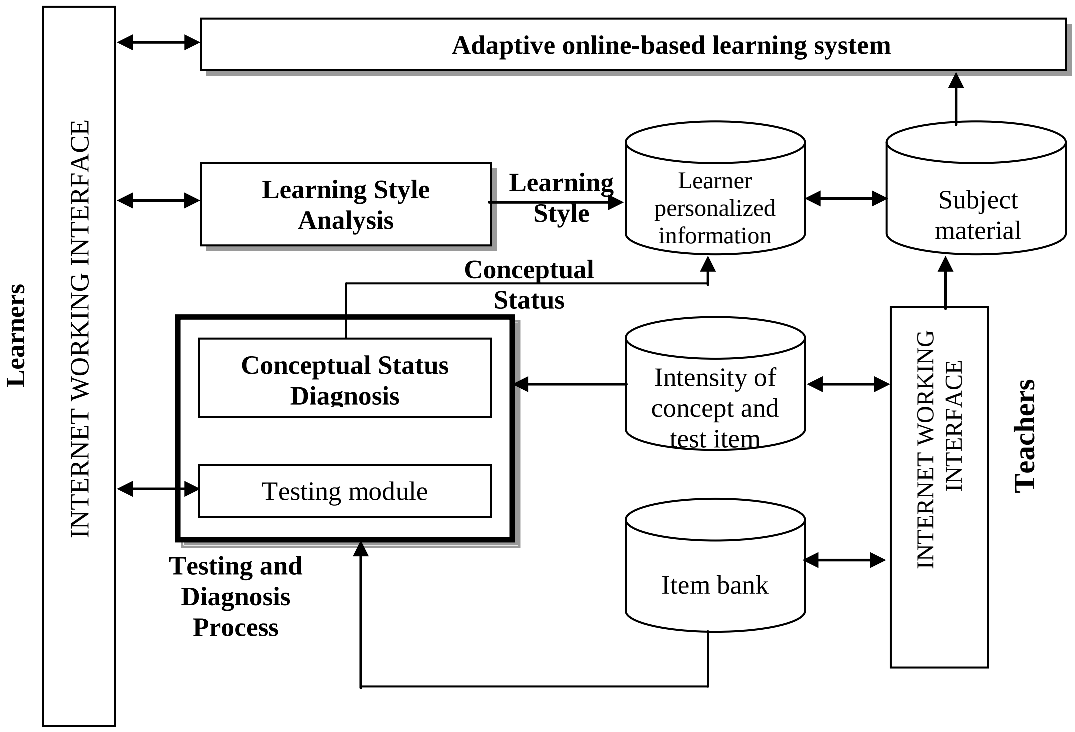

Figure 3. Framework for personalized technology-enhanced learning system

7. Conclusion

To realize personalized technology-enhanced learning system, concept status and learning style are two of the key components. In this paper, a framework for personalized technology-enhanced learning system with integrative diagnosis of conceptual status and learning style is proposed. This framework could be the maximum use of technology to serve learners differences within adaptive online-based learning system. Moreover, it could be served as innovative way of STM education when using computer-based instructional technologies.

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