Enhancing Learning Attitudes and Performance of Students in Physics with a Mastery Learning Mechanism-based Personalized Learning Support System

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***Abstract*—Most existing personalized learning support systems facilitate students' learning by providing learning suggestions or learning content to individual students based on their background or profiles. It is difficult to adapt learning activities to respond to students' ongoing learning performances and status, leading to the limitation in enhancing online personal learning performance and learning attitudes. To address this issue, a mastery learning mechanism was proposed to monitor individual students ongoing learning situations; moreover, students' conceptual learning problems, learning styles and current understanding status were considered for providing effective personalized learning activities. An online personalized learning support system was developed basing on the novel mastery learning mechanism. The experimental results show that the students who learned with our proposed system had better learning attitudes toward the learning activities, better understanding and higher perception of the usefulness of the learning system, and better learning performance of Simple Electricity on Physics course than those who learned with the conventional system.**

Keywords- personal learning environment; interactive learning; mastery learning; multi-source personalization; technology-enhanced science learning

I. Background and Rationale

In the past decade, online personal learning support system has become significant for individual students. It can provide learning activities suitable for individual students over the Internet [1]. By accessing to the Internet, students can take advantage of this personalized learning as for either primary learning environment for actual classroom replacement or supplementary learning environment for supplementing classroom learning. It has been studied and found to be effective method to improve students' learning performance [2], [3].

Recent studies have developed such learning system more effective for individual students by including their personalization information, e.g. gender, age, learning problem background and learning style [4], [5]. In 2003, Hwang proposed a model to diagnose students' learning problems and provide learning suggestion accordingly [6]. This model has been widely used in various areas including Mathematics, natural science and electronics [7], [8]. In addition to that, recent studies have also considered students' learning styles and provide learning materials fitting with their learning styles, and have been studied in many subjects including physics, biology, computer science and language learning [9], [10]. It was found that those who learned with such systems had not only better learning performance, but also learning attitude and learning motivation [11].

However, such existing learning systems still have a major limitation in adapting learning activities during the learning process. This happens because they are not able to monitor the ongoing learning situation after learning suggestion is provided with given learning materials, consequently the rest of learning activities are not based on the actual learning progress. During learning process, diagnostic assessment was an effective approach for providing feedback and reflection to students to construct their own knowledge as well as constructivist learning theory [12]. Some researchers have pointed out that if the instruction provided during learning has been corrected properly to students, this would result in learning improvement [13]. As a result, this finally might lead to limited learning success in online personal learning.

To tackle with such flaws, we need to analyze students' ongoing learning status in order to adapt the rest of learning activities accordingly in time. Mastery learning method was proposed as an effective approach to continuously monitor students' ongoing learning status and the instruction prior to the end of learning can be adjusted [14]. Owing to its benefit, mastery learning approach has been adopted in many studies on online adaptive learning systems and found to be successful in better learning performance [15], [16]. Moreover, it could be challenging if the adapted learning activities provided to students not only based on the actual learning status, but also formatted to fit with their learning

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styles and suggested according to their learning problems background.

In this study, we proposed a novel mechanism, mastery learning with order-multiple choice technique, to monitor ongoing understanding for analyzing the difficulty level of understanding in order to adapt and provide the learning activities accordingly. We embedded the proposed mechanism in a personalized learning support system named a mastery learning mechanism-based personalized learning support system. To examine the effectiveness of the system, an experiment was conducted with high-school students in Simple Electricity content on Physics course.

The originality of this study would enhance the understanding of the development of online personalized learning support system and also enhance the online personalized learning support success of the students learning in physics.

II. Development of Mastery Learning Approach based Online Multi-Source Personalized Adaptive Learning System

A. Oveall Learning System Structure

The system was developed in online web-based learning platform by PHP programming language, MySQL database and Bootstrap HTML5 framework. There were 3 key modules in the system architecture: 1) Learning diagnostics module, 2) Learning style diagnostics module, and 3) our proposing mastery learning mechanism module.

In the first module named learning problem diagnostics, it was implemented based on Concept-Effect Relationship (CER) model [6]. In CER model, a relationship among learning concepts was firstly associated as conceptual diagram, a conceptual test was then pre-loaded with a number of test items; each was given a weight number to relevant learning concepts behind and stored in Test-Item Relationship Table (TIRT) database. The test was used to collect students' prior understanding. Together with TIRT, Error Ratio (ER) for each concept, number of items answered incorrectly divided by number of all items associated with the concept, was calculated. Any concept with ER>= 0.5 was diagnosed learning problem; moreover, learning suggestion was provided accordingly as learning paths by mapping with conceptual diagram, as shown in Fig. 1(a). Currently, this information was stored in the database to be used with the mechanism later. Students may receive learning suggestion paths differently based on their initial diagnosed learning problems.

In the second module, learning style diagnostics, we analyzed students' learning style with Index of Learning Styles (ILS) on active/reflective and visual/verbal dimensions, which have been widely accepted for online learning systems [17]. The appropriate learning material layout for each dimension in this system could be either hands-on video layout for verbal or active learners or simulation layout for visual or reflective learners. Based on diagnosed learning style, as shown in Fig. 1(b), students then received initial learning material presentation layout which was also stored in the database to be used with the mechanism later.

B. Mastery Learning Mechanism

After the students completed with first two modules, the students were asked to follow each learning concept recommended as learning path suggestion and were triggering by the third module (the proposing mastery learning mechanism). This module was mainly in charge of monitoring their ongoing understanding in order to adapt learning activities accordingly together with current learning problems status and learning material layout status stored in databases. The detailed procedure was presented in Fig. 2.

Starting learning with the initial material presentation layout, each student was analyzed for understanding level on this particular learning concept as shown in Fig. 3(a). Followed by checking their current ongoing understanding as shown in Fig. 3(b), he/she was prompted with 3 consecutive Order-Multiple Choice (OMC) items randomly to avoid students guessing the correct answers. Note that each OMC item was prepared by teacher while its individual choice was assigned with understanding level ranging from 1 to 3. Choices answered on each OMC item were analyzed and calculated for current understanding level. If the calculated understanding level met the requirement of 3, the mechanism considered pass for this learning concept, indicating that the student was ready to learn next recommended learning concept(s); otherwise, the mechanism would consider another learning style for this student and adapt the learning material presentation layout accordingly for learning activities, and also consider difficult level according to current understanding level of each student. Students were then prompted with feedback based on current understanding level to hint their misunderstanding, followed by the learning activities. At this point of mechanism, their ongoing learning understanding could be enhanced and ensured to pass this particular failed learning concept as diagnosed with learning problems. After learning, students took another round(s) of understanding checking and repeat the previous steps. The mechanism continuously synchronized the learning status in with database enabling students could pause and resume their learning anytime.

III. Experiment and Results

In order to examine the effectiveness of the developed system, an experiment was conducted with 126 high-school rosters. 73 students learned with the developed system, called Experimental Group (EG); while another 53 students learned with conventional online personal learning system, called Control Group (CG).

(a) Learning path suggestion based on diagnosed learning problems

(b) Learning style presentation with initial learning material layout recommendation

Figure 1. Example screenshots of student's multi-source personalization analysis results

Both systems were implemented with the same learning activities and objectives of high-school Simple Electricity content on Physics course. Both groups of students have had online learning experience. All of them had 60 minutes in total to learn the content on the assigned learning system by following the given instruction and were found that at least 3 need-to-be-learned concepts were diagnosed.

A. Attitude toward The Personalized Learning Activities

After learning was completed, all students in both groups took the same 5-point Likert scale questionnaire for 10 minutes, which included 5 items on Adaptive Learning Activity (ALA) dimension, 6 items on Content Understanding (CTU) dimension, and 6 items on Usefulness (USN) dimension. The questionnaire items were intended to assess the attitude on key features of online adaptive learning system [18], [19]. The revised questionnaire was piloted and obtained accepted reliability with Cronbach's alpha of 0.76.

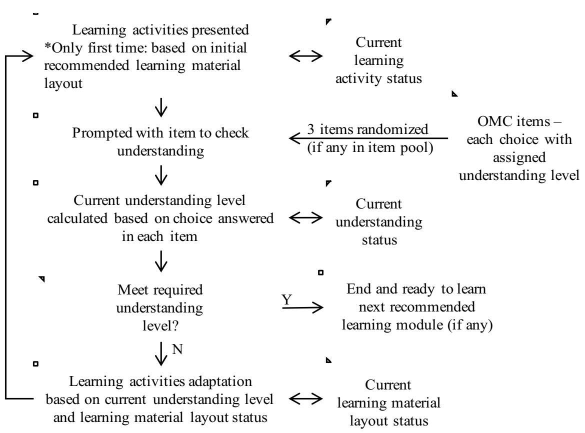


Figure 2. Detailed procedure of mastery learning mechanism with Order-Multiple Choice method

Prior to performing inferential statistic tests, data distribution was examined by Shapiro-Wilk test. It was found that all data sets were not normally distributed ($p < 0.05$). Therefore, we deal with non-parametric test, Mann-Whitney test was appropriate to test the mean differences between 2 groups on each dimension.

As shown in Table 1, it was found that the attitudes on ALA ($Z = 2.34$, $p = 0.02$) and CTU ($Z = 2.46$, $p = 0.01$) dimensions on EG was statistically higher than CG; implying that students found the proposed system is beneficial to them in providing adaptive learning activities which is personalized to their actual understanding; consequently, they perceived that the system could enhance their content understanding.

On the other hand, students did not perceive differently on USN between both systems ($Z = 0.68$, $p = 0.50$); however, the scores on both groups were rated highest satisfaction, indicating that both systems are useful to them.

TABLE I. BETWEEN-GROUP RESULTS OF LEARNING ATTITUDE TOWARD PROPOSED ONLINE LEARNING SYSTEM

Dimension	Group	N	Mean	SD	Z	p
ALA	EG	73	4.70	0.28	2.34	0.02^{*}
	CG	53	4.38	0.64		
CTU	EG	73	4.67	0.30	2.46	0.01^{*}
	CG	53	4.41	0.56		
USN	EG	73	4.72	0.32	0.68	0.50
	CG	53	4.55	0.61		

$^{*}p < 0.05$

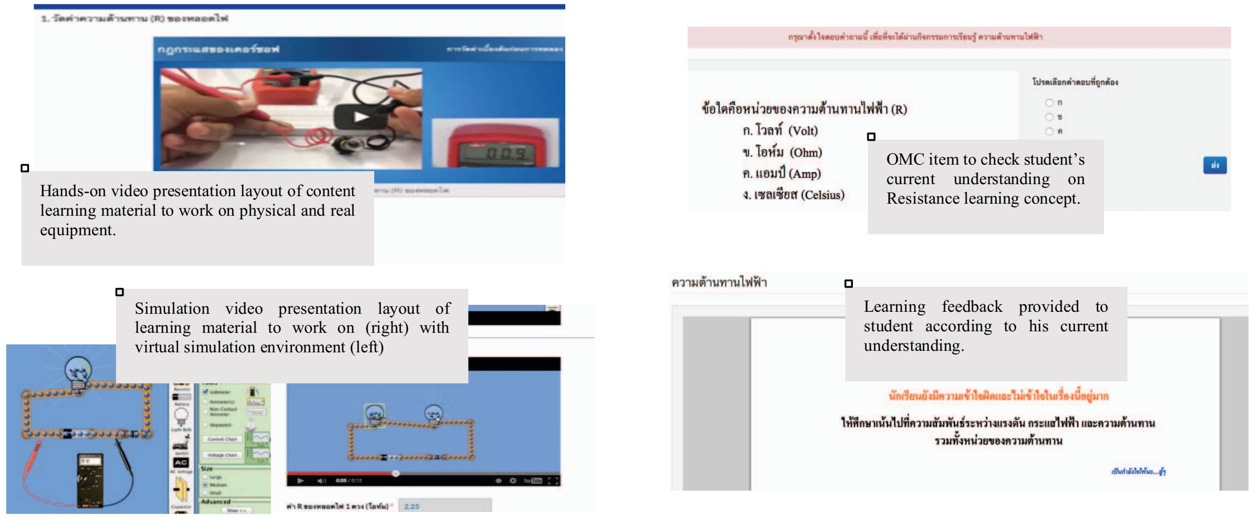
B. Learning Performance on The Proposed Online Learning System

Since the attitude result on CTU was positive, it was interested to confirm this result by conducting another analysis. We utilized students' pretest and posttest data taken during the first experiment.

The pretest and posttest were developed to be parallel in order to examine students' learning performance. Each consists of 12 multiple-choice question items (12 score in total), was designed by experienced teacher who have teaching experience on such topic for years, and was tested and found to be reliable with Cronbach's alpha of 0.83.

To examine learning performance on both systems by avoiding the influence of prior knowledge differences between 2 groups, we employed one-way ANCOVA analysis by having pretest data as covariate [20]. Before conducting one-way ANCOVA, the homogeneity of variance assumption ($F_{(1,124)} = 2.65$, $p = 0.11$) and the homogeneity of regression slopes ($F_{(1,122)} = 2.55$, $p = 0.11$) were tested and found no violation [21].

As shown in Table 2, the result of one-way ANCOVA ($F_{(1,123)} = 4.76$, $p = 0.03$) showed that there was significantly different between the posttest results of EG and CG groups. This indicates that the proposed system driven by mastery learning mechanism could help students improve their learning performance than the conventional one.



(a) Learning materials based on recommended learning material layout (Simulation adopted from University of Colorado Boulder (2015) [22])

(b) Monitoring current understanding

Figure 3. Example screenshots of student's personalized learning activities based on current understanding level

TABLE II. BETWEEN-GROUP POSTTEST RESULTS (ONE-WAY ANCOVA)

Group	N	Mean	SD	Adj. Mean	SE	$F_{(1,123)}$	p
EG	73	7.74	1.13	7.74	0.13	4.76	0.03*
CG	53	7.32	1.07	7.32	0.15		

*$p < 0.05$, Covariate: Pretest

IV. CONCLUSIONS AND DISCUSSION

This study attempts to deal with a limitation in most existing online personal learning support systems, that is, they are not capable of adapting the ongoing learning activities. To cope with this problem, we proposed a mastery learning mechanism to instantly monitor students' understanding of recommended learning concepts, which were diagnosed with learning problems. This mechanism worked during the learning process and provided learning activities according to their current understanding level; moreover, such learning activities were adapted for difficulty level as students were holding and the learning materials were personalized to meet their learning styles. An online personal learning support system was then developed by embedding our proposed mechanism.

Based on the experimental analysis results, it was found that the students who learned with our proposed system had better attitudes toward the adaptive learning activity, content understanding, and usefulness of the developed system; moreover, they have better learning performance of Simple Electricity content on Physics course in comparisons with those who learned with conventional online personalized learning system.

These findings were in an agreement with the studies that students' online learning performance could be enhanced if their learning activities were meaningful and personalized to their actual cognitive understanding; moreover, if students have better learning attitudes towards the learning system, they could have better learning achievement [16], [23]. In addition, this study serves the valuable contribution to the society of online personal learning environment in understanding better mechanism not only to diagnose the learning problems but also to monitor ongoing learning situation and provide personal learning activities accordingly in order to enhance its development and promoting better learning success.

However, the proposed mechanism still has a limitation to be addressed including the ability to monitor students' learning style and motivation after getting additional activities more effectively, while learning activities could be more engaging and enjoyable e.g. game and virtual reality. This could promote better personal learning experience. We would also suggest further studies by implementing such mechanism on other learning platforms as the learning environment is different whereas learning outcome might be different.

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