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Moderating effects of gender differences on the relationships between perceived learning support, intention to use, and learning performance in a personalized e-learning

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Abstract Current endeavors to integrate students' personal characteristics with e-learning environments designed for the delivery of content to individual students are growing. However, few studies have been conducted to investigate how gender differences moderate the relationships between students' perceived personalized learning support and learning performance, and between the intention to use a system and the users' learning performance. Drawing together perspectives from the literature on developing effective e-learning systems, technology acceptance, and gender differences, this research proposes a conceptual model to examine the influences of the relationships among students' attitudes, acceptance, gender differences, and learning performance. Moreover, a personalized learning system was developed by taking learners' to-be-enhanced concepts and learning preferences into account. An experiment was conducted with four classes of Thai high-school students studying the same topic of simple electricity to examining the proposed conceptual model as well as evaluate the performance of the personalized learning system. The Partial Least Square technique was employed to analyze data collected from school settings in Thailand. The path coefficient results showed that the perceived usefulness of the mastery learning support and intention to use had direct effects on the students' learning performance in the personalized e-learning environment, and that gender moderated the relationship between perceived usefulness of conceptual learning suggestions and learning performance, and between intention to use and learning performance. These findings suggest that there are direct attitudinal and gender moderating factors affecting learning performance in personalized e-learning environments.

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Introduction

With the growing advancement of computers and communication technologies, e-learning is increasingly being used by schools as a significant approach for improving students' learning performance. E-learning works over the Internet and offers cost-effectiveness, time and place-free availability, and delivery efficiency (Klett 2010). Furthermore, it has been successfully implemented for promoting learning in various fields including science, mathematics, social science, and languages (Chookaew et al. 2014; Wang 2014; Wongwatkit et al. 2015; Yang et al. 2015a, b)(Klašnja-Milićević, Vesin, Ivanović, & Budimac, 2011; Lin et al., 2013). With its successful use, researchers have suggested that the essential components in developing effective e-learning should include navigation, engaging learning, feedback, guided direction, fluidity, dynamic experience, learner-centeredness, and personalized learning support (Koohang and Paliszkiewicz 2013; Toven-Lindsey et al. 2015). Moreover, Garrison (2011) suggested that e-learning environments should provide adaptable educational contexts with meaningful and worthwhile learning activities to promote better learning success. Accordingly, the alignment of e-learning with personalized learning support and performance requirements has been recognized as a critical success factor in e-learning effectiveness (Chookaew et al. 2015; Wang and Wu 2011). However, researchers have reported several limitations of the existing learning support systems (Liu et al. 2008; Schiefele and Csikszentmihalyi 1995; Xie et al. 2019). First, students might not know whether they have sufficient understanding of current contents to proceed to the next learning stage. Second, the learning tasks and guidance provided by the learning systems are usually not based on students' learning status. Third, the feedback from the learning systems is non-informative.

To tackle these flaws, it is necessary to consider the ongoing learning status of each student while learning in personal characteristic-based e-learning. Among the various ongoing learning status approaches, mastery learning is an effective approach (Stiggins 2006). With this approach, the contents of the learning topic are broken down, while each learning step is examined to meet the required understanding level before going further (Lin et al. 2008). The system can elaborate on insufficient understanding by providing learning activities and feedback adapted to the ongoing learning status of individual students (Martinez and Martinez 1999). Therefore, e-learning environments integrating personalized learning support features adopting the mastery learning approach would be a worthwhile development in effective personalized e-learning environments to enhance learning performance for individual students.

In recent years, researchers have revealed that positive learning attitudes toward e-learning environments with personalized learning support could lead to successful learning performance (Ali et al. 2018; Hwang and Chang 2011; Shih and Gamon 2001; Sung et al. 2013). Bachari et al. (2011) stated that once students are satisfied with a learning environment that is suitable for their preferences and adapted to their actual learning situation, they may feel that the environment is useful for improving their learning performance. Moreover, researchers have revealed that students with the intention to use an e-learning system show improved learning performance (Lee 2010; Teo et al. 2009). That is, there are two direct attitudinal factors (perceived personalized learning support and intention to use) which affect learning performance in personalized e-learning environments.

In addition, researchers have suggested that human factors (e.g., age, social status, and gender) play a critical role in one's learning experience (Borun et al. 2010; Tarhini et al. 2014). Research related to e-learning environments has indicated that there are gender differences found in students' learning performance, which may be influential (Tarhini et al. 2014; Yang and Chen 2010). The barrier to successful design and implementation of e-learning initiatives is the lack of consideration of students' perceived personalized learning support and intention to use moderated by gender differences in personalized e-learning environments. In other words, how gender differences affect the way in which students perceive personalized learning support and their intention to use e-learning systems requires further investigation.

Certainly, perceived effectiveness of e-learning environments, in terms of individual and social learning support, is related to the adoption of e-learning in school environments (Cho et al. 2009; Liu et al. 2010). However, few studies have been conducted to analyze the impact of perceived personalized learning support and intention to use on students' learning performance in a personalized e-learning environment, not to mention the issue of how gender differences moderate this impact.

Based on the aforementioned issues, the first step of the current work is to prove that the personalized e-learning environment used in our experiment is at least as effective as traditional instruction at school settings by concerning knowledge acquisition. Next, we focus on the main research question of this study, which is "Are there moderating effects of gender differences on learning performance regarding the personalized e-learning environment?" The rest of the paper is structured as follows: in the next section, the literature review and the research model and hypotheses of this study are outlined; the method including examination of personalized e-learning environment used in our experiment, instrumentation, and conceptual validation of main research is then presented followed by results and discussions of the main research.

Literature review

Personalized learning or personal characteristic-based online learning can be referred to as analyzing learning background and learning preferences to provide individual learning activities (Walonoski and Heffernan 2006; Xie et al. 2019). Personal characteristics include learning performance, cognitive style, learning preference, and poorly/well-learned concepts (Chen 2010; Hwang et al. 2012; Klašnja-Milićević et al. 2011). Personal characteristic-based online learning has been widely used by schools to drive the teaching and learning process to enable students to receive appropriate instruction according to their preferences, resulting in better learning performance. In recent years, researchers have revealed successful attempts to integrate personal characteristic-based approaches into e-learning environments to improve students' learning performance in various educational areas, such as mathematics (Lin et al. 2013; Yang et al.

2015a, b), natural science (Chiang et al. 2014; Srisawasdi et al. 2012; Wu et al. 2008), health courses (Bossers et al. 2014; DeBate et al. 2014; Lee and Lee 2015; Zhang et al. 2015), computer science courses (Chookaew et al. 2014; Latham et al. 2014; Yang et al. 2015a, b), language learning (Latham et al. 2014; Wongwatkit et al. 2015), medical courses (Lewis et al. 2014; Trukhacheva et al. 2011), and physical education (Huang et al. 2011). Moreover, researchers have suggested that online personalized learning environments are an effective approach to promoting students' achievement, attitudes, and motivations (Chookaew et al. 2014; Elgamal et al. 2011; Wang and Huang 2011).

On the other hand, researchers have pointed out that the existing systems only provide learning guidance corresponding to students' individual characteristic information without feedback during learning activities (Liu et al. 2008). That is, some of the learning activities might not be adjusted to meet students' learning reality (Rodrigues and Oliveira 2014), which might affect their learning performance (Chen 2009, 2011; Hwang et al. 2012). This shows that analyzing students' status (e.g., their understanding of the learning content) during the learning process needs to be taken into account.

Mastery learning method provides good guidance for students to engage in self-paced learning based on their learning progression (Guskey 2010). Students make corrections in their learning to meet the criteria set throughout their learning experiences by acquiring a foundation of appropriate knowledge for mastering the relevant concepts (Achufusi and Mgbemena 2012; Amiruddin et al. 2015). During the mastery learning process, students are asked to repeatedly practice via assessment. They also receive remedial instruction and feedback for improving their learning status (Martinez and Martinez 1999; Staiger 1997). Researchers have indicated that the mastery learning approach can benefit students in terms of their learning performance, and is applicable to various subjects, including science and mathematics (Furo 2014; Ozden 2008; Wambugu and Changeiywo 2008).

The literature discussed above provides useful perspectives and a basis for designing effective personalized e-learning environments; that is, the personalized e-learning environment employs personal characteristics and adopts the mastery learning approach as the pedagogical structure. This learning environment detects conceptual learning problems and provides a learning recommendation path for individual students, as well as formatting the learning material presentation based on individual learning preferences. Learning preference can be defined as the individuals prefer particular material to present the content or information (Mayer & Massa, 2003). The individuals have the different ways to process the information, to learn content, and to solve the problem. In other words, they have their own way to deal with information and experience for acquiring knowledge (Brock & Cameron, 1999). In addition to that, the mastery learning method helps to examine students' ongoing understanding level.

Research model and hypotheses

Based on the literature review, this study proposes a conceptual model as presented in Fig. 1. In the following sub-sections, the rationale for each variable is explained in depth and the hypotheses are formulated.

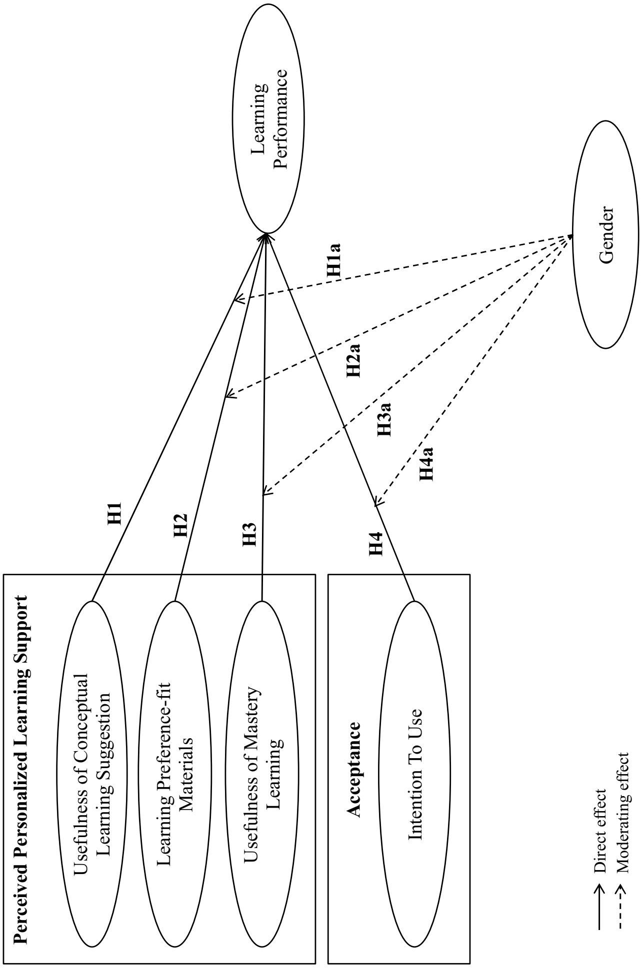

Fig. 1 Hypothesized conceptual model

Students' perceived usefulness of conceptual learning suggestions

Researchers have suggested that one of the key features of personalized e-learning systems is the ability to diagnose conceptual learning problems in order to provide subsequent learning guidance (Casamayor et al. 2009; Hwang et al. 2011, 2008; Hwang et al. 2013a, b; Wu et al. 2012a, b). For example, Wu et al. (2012a, b) proposed a computer-based concept map-oriented learning approach for evaluating students' concept map construction and providing corresponding feedback for each student. It was found that this approach could help promote students' learning achievement and attitudes. Wu et al. (2012a, b) proposed four adaptive testing algorithms based on the ordering theory to shorten the testing time and precisely diagnose students' knowledge status. Their results indicated that the system integrating the proposed algorithms revealed the best performance among other approaches, implying that students could be benefited more by participating in the learning activities that met their needs better. Hwang et al. (2013a, b.) proposed a group decision approach for enhancing the concept map-oriented model to diagnose students' conceptual learning problems by domain experts. It showed that students gained better learning achievement using this approach. Kim and Lee (2013) developed a web-based intelligent instruction system for mathematical computation to diagnose students' comprehension status and provide individualized information regarding the cause of the error. This procedure was performed by recording students' behaviors and analyzing their responses. Tsai, Ouyang, and Chang (2015) proposed a diagnostic mechanism to identify English reading comprehension errors by applying the association rule, a data mining technique for mining students' reading errors. With the diagnostic results, the teacher could develop appropriate learning materials that could economically facilitate students' learning outcomes.

There was a consensus among these results that providing conceptual learning suggestions in e-learning systems could help students improve their learning performance. This was because the students received the necessary step-wise guidance related to their actual learning background which led to achievement of the learning goal (Horton 2000). This approach contrasts with conventional online-learning systems in which the students make efforts and spend time learning all of the learning activities regardless of their actual learning problems. That is to say, their learning performance in conventional systems is not sufficiently promoted (Wang and Wu 2011).

Therefore, based on the previous literature, providing conceptual learning suggestions is recognized as one of the personalized learning support features influencing students' learning performance in personalized e-learning environments (Merhi 2015). Consequently, a hypothesis of the effect of perceived usefulness of conceptual learning suggestions on learning performance is proposed as follows:

H1 Students' perceived usefulness of conceptual learning suggestions will have a positive effect on their learning performance.

Students' perceived material related to learning preference

In a personalized e-learning support system, another kind of personalization information which is widely integrated into the system is learning preference (Panjaburee and Srisawasdi 2016; Yang et al. 2013). Grasha (2002) defined learning preference as a preferred way of learning of individual students. As their learning preferences may differ, if the system could analyze and understand how individuals learn, this could make their learning easier. A number of studies have shown that integrating learning preference analysis into such systems could make e-learning more personalized (Brady 2013; Popescu 2010; Santo 2006). With the learning preference analysis results, the system could provide learning material formatted according to the students' learning preference information; as a result, this could make students' learning performance better (Bajraktarevic et al. 2003). This perspective has been implemented in various fields of educational context including science, computer science, and mathematics (Chookaew et al. 2014; Hung et al. 2015; Nguyen 2011; Thanyaphongphat and Panjaburee 2019). In the past decade, researchers have widely studied whether learning material related to students' learning preference could improve their learning performance in e-learning systems. They found that the students had better learning performance in the subject matter because when they perceived that such material made their learning easier, they could have better understanding of the learning content (Graf 2007; Halbert et al. 2011; Soflano et al. 2015).

Therefore, based on the previous literature, the formatting of learning material in accordance with the student's learning preference is recognized as one of the personalized learning support features influencing learning performance in personalized e-learning environments (Hwang et al. 2013a, b; Komalawardhana and Panjaburee 2018; Tseng et al. 2008; Yang et al. 2013). Consequently, our hypothesis of the effect of perceived material related to learning preference-fit materials on learning performance is as follows:

H2 Providing learning preference-fit materials to students has a positive effect on their learning performance.

Students' perceived usefulness of the mastery learning approach

In online-learning support systems, most of the time the systems evaluate the students' learning only through summative assessment, mostly using post-tests. The result is that there are some limitations to the students' progress during the learning process and to receiving feedback for improving learning in the subject matter (Liu et al. 2008). To address these limitations, one of the formative assessment strategies called the "mastery learning approach" has been used for checking and monitoring students' ongoing learning progression toward reaching the required learning objectives, as well as for providing learning feedback to individual students. The approach urged the students to be more involved in the supplementary learning activities so that they could complete such activities; that is to say, repeated learning may also be required in this learning process (Lin et al. 2008; Martinez and Martinez 1999).

Incorporating an integrated mastery learning approach into an online-learning support system would have a great effect on the students' learning performance (Lin et al. 2013; Shafie et al. 2010). During the learning activities, the students are evaluated to ensure that they have met the requirements of each learning unit before moving on to the next one. On completion of all learning units, they can be expected to show improvement in their learning performance (Kularbphettong et al. 2015; Wang et al. 2006). In the literature on the applications of the mastery learning approach, the findings suggested that learning would be successful when the mastery learning approach is incorporated into the online personalized learning support system (Achufusi and Mgbemena 2012; Adnan Khan and Masood 2013; Furo 2014; Shafie et al. 2010). Moreover, it was found that the students' perceptions of the mastery learning approach had a direct impact on their learning performance (Guskey 2007). This was because they felt that such a system offered sufficient reliability for their learning, eventually shifting their learning performance (Furo 2014).

Therefore, based on the previous literature, the mastery learning approach is recognized as one of the personalized learning support features that influences students' learning performance in personalized e-learning environments (Furo 2014; Kularbphettong et al. 2015; Lin et al. 2013; Wongwatkit et al. 2017). Consequently, our hypothesis regarding the effect of the perceived usefulness of the mastery learning approach on learning performance is as follows:

H3 Students' perceived usefulness of mastery learning has a positive effect on their learning performance.

Students' intention to use the personalized e-learning system

In the past decades, researchers have found that if one has the intention to use technology, there will be a great possibility of one accepting that technology (Cheng et al. 2011). In online-learning support systems, intention to use is one of the key determinants of accepting the use of such emerging technology (Aypay et al. 2012). It is an indicator used to capture how much effort an individual would like to commit to actually using any technology (Ajzen and Fishbein 1980). When students perceive that the system is useful for their learning, they will have a greater intention to use that system for learning success, not only once but many times in the future (Park 2009; Yi and Hwang 2003). This statement is consistent with the ultimate goal of online learning that the more times students get involved in the learning, the greater learning acceptance they will have, and their successful learning performance will definitely increase. This can happen because the online-learning support system could help students learn better in their preferred way such that they have a greater intention to learn through the supports of the system, and their learning performance finally improves (Chen 2011; Joo et al. 2014).

Therefore, based on the previous literature, researchers have identified a direct effect between the intention to use technology and learning performance (Giannakos 2013; Larmuseau et al. 2018; Merhi 2015). Consequently, our hypothesis regarding the effect of intention to use a personalized e-learning system on learning performance is as follows:

H4 Students' intention to use the system has a positive effect on their learning performance.

Moderating effects of gender differences

Although students' perceptions affect their learning performance in e-learning environments, there is another factor that could moderate such relationships, which is the gender difference (Borun et al. 2010). In 2001, Putrevu suggested that biological factors could lead to information processing differences in e-learning systems; more specifically, gender differences are substantial characteristics among students affecting their academic achievement (Huang et al. 2013).

A number of studies have shown that male and female students experience online environments differently in several ways, including performance, motivations, perceptions, study habits, and communication behaviors (Chyung 2007; Komalawardhana and Panjaburee 2018; Price 2006; Rodríguez-Ardura and Meseguer-Artola 2019; Rovai and Baker 2005). For example, Cuadrado-García, Ruiz-Molina, and Montoro-Pons (2010) found that there are differences between male and female students in their use of e-learning and their motivations and satisfactions, while Chyung (2007) found that examination scores of younger male and female students were significantly different. Park, Kim, Cho, and Han (2019) reported the moderating effects of gender differences on technology acceptance and perception to use multimedia technology. Moghavvemi, Paramanathan, Rahin, and Sharabati (2017) also revealed the moderating effects of gender differences on motivations, behavior, intention, and performance to use the e-learning system via Facebook. Meanwhile, Al-Azawei (2019) suggested that the moderating effects of gender difference influenced the relationship of the individuals toward e-learning system. In addition, Rodríguez-Ardura and Meseguer-Artola (2019) found that the gender difference played a significant role in the individuals' interaction effects on e-learning. Female e-learners were more driven by positive emotions, while male e-learners were more driven by functional and analytical factors.

Based on the gender differences literature, it was found that gender differences were considered when studying and developing e-learning environments. By integrating consideration of gender differences with the advantages of personalized learning support, male and female students could differently improve their learning achievement in the personalized e-learning system. Consequently, our hypothesis regarding the moderating effect of gender on the relationship between perceived personalized learning supports and intention to use a personalized e-learning system and learning performance is as follows:

H1a The relationship between perceived usefulness of conceptual learning suggestion and learning performance is moderated by the gender of the students.

H2a The relationship between learning preference-fit materials and learning performance is moderated by the gender of the students.

H3a The relationship between the perceived usefulness of mastery learning and learning performance is moderated by the gender of the students.

H4a The relationship between intention to use the system and the students' learning performance is moderated by the gender of the students.

Method

Personalized e-learning environment design and effectiveness examination

A personalized e-learning environment was developed for this study. There are two main functions for managing learning activities in this environment: the testing and diagnosing function, and the monitoring learning function. In the testing and diagnosing function, the personalized e-learning system asks students to take an online conceptual pretest. After submitting their answers, the system diagnoses individual students' conceptual learning problems. The system provides conceptual learning suggestions corresponding to a series of failed concepts as recommended learning paths based on the concept map-oriented model (Panjaburee et al. 2010).

Moreover, the system asks the students to complete learning preference questionnaire. After submitting their answers, the system identifies each individual student's learning preference, and then uses this learning preference information to format the learning material presentation for individual students. After completing the conceptual test and learning preference questionnaire, the monitoring learning function can work based on the concept of the mastery learning approach. This means that, through the sequence of the learning units with material related to their personal learning preference, each student's understanding level in each learning unit will be detected by the conceptual understanding questions. The system will check if they meet the required level, meaning that the student is ready to learn the next concepts in the provided learning sequence. On the other hand, the student will receive additional learning activities corresponding to their monitored understanding level. The activities include learning material presentation corresponding to their own learning preference, which can be either hands-on activities for verbal and active learners or computer simulation for visual and reflective learners, and feedback information. Figure 2 shows a set of screenshots from the personalized e-learning environment.

The first part of this experiment began with the two groups of students to learn the Simple Electricity topic on a Physics course. The school has five classes for 15–18-year-old students ($M = 16.12$, $SD = 2.72$), who are in the tenth grade in Thailand (a total of 187 students: 78 males and 109 females). The five classes were randomly separated into two groups in this part: three classes for the experimental group and two classes for the control groups. The experimental group (115 students) was engaged the developed personalized e-learning system, while the control group (72 students) was engaged in traditional instruction in usual school setting with teacher's support. Moreover, in each group was further divided into high-, medium-, and low-achieving levels by performing K-mean clustering technique. Using a one-way

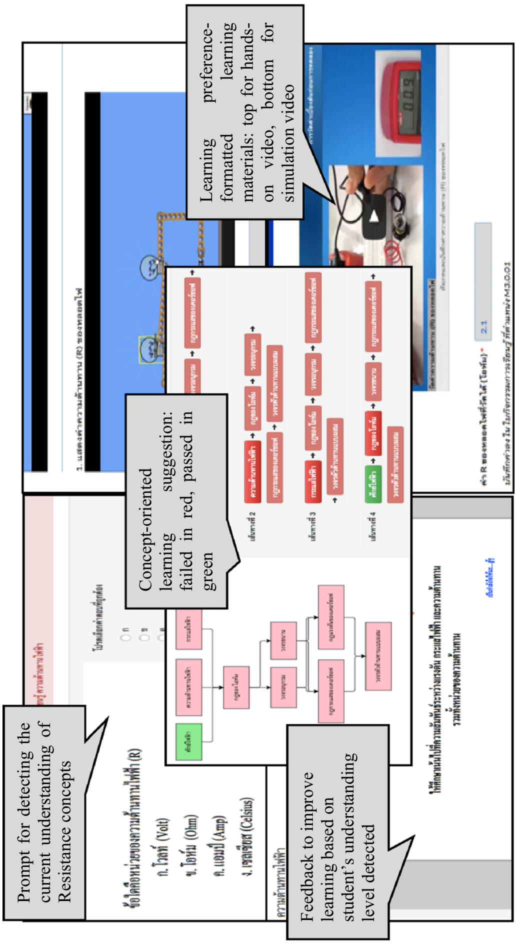

Fig. 2 Screenshots of the system on the "Resistance" learning activity

Table 1 Between-group posttest results of different levels of learning achievement (One-way ANCOVA)

Achieving level	Group	N	Mean	SD	Adjusted mean	Standard error	F	p
High	Experimental	25	8.0800	1.03763	8.082	0.195	0.075	0.786
	Control	18	8.1667	0.85749	8.164	0.230		
Medium	Experimental	71	6.9155	1.70501	6.897	0.179	0.001	0.978
	Control	33	6.8485	0.87039	6.888	0.265		
Low	Experimental	16	6.2500	0.85635	6.253	0.203	16.116	0.001*
	Control	6	4.6667	0.51640	4.658	0.336		

Covariate: Pretest

*$p < 0.05$

ANCOVA test of the two groups, experimental group ($M = 7.0804$, SE = 0.126) and control group ($M = 7.0351$, SE = 0.177), the results showed no significant difference $F(1,166) = 0.103$, $p > 0.05$. As a consequence, there was no difference between the developed personalized e-learning system and the traditional instruction in their overall performance of the test. Interestingly, the developed personalized e-learning system was more beneficial to low-achieving students compared with students using the conventional e-learning system, as shown in Table 1.

The results regarding personalized e-learning system led us to examine the main research question raised in this study. Therefore, the main part of this study conducted a survey to collect and analyze the experimental group's (115 students with 49 males and 66 females) perceptions on the personalized e-learning environment.

Instrumentation and conceptual validation

There were five constructs to be measured and modeled in this study. Perceived personalized learning support refers to the learners' perceptions of whether the personalized e-learning environment is helpful to hem in improving their learning performances by providing conceptual learning suggestions and learning preference-fit materials. The measure of Perceived Usefulness of Conceptual Learning Suggestion (PUCLS) refers to the extent to which the personalized e-learning environment is perceived as being helpful for students to receive concept-oriented learning guidance based on their learning problem diagnosis results, which made them more confident to learn in a meaningful way. It consists of three items adopted from the measure proposed by Hwang et al. (2013a).

The measure of Perceived Learning Preference-fit Materials (PLPM) was composed of five items derived from Graf (2007) and Hung et al. (2015). It refers to the extent to which the personalized e-learning environment is perceived to be helpful for students to learn through the learning material formatted by their learning preferences, which made their learning more personalized. Measures of Perceived Usefulness of Mastery Learning (PUML) were based on 5 items derived from Gikandi et al. (2011), Hwang and Chang (2011), and Srisawasdi and Panjaburee (2015), and refer to the extent to which the personalized e-learning environment is perceived to be helpful for students in monitoring their ongoing learning process in order to provide them with suitable learning activities and feedback based on their actual understanding, which could guarantee their readiness for the next learning units. The construct "Intention To Use" (ITU) has been widely investigated in technology acceptance studies, and this study adopted 3 items from Liu et al. (2010) which refer to the extent to which students would commit to using this system in the future and recommending it to their friends. Sixteen items were originally proposed for the four constructs: perceived usefulness of conceptual learning suggestion, perceived learning preference-fit materials, perceived usefulness of mastery learning, and intention to use. These items are assessed using a five-point Likert scale ranging from 1, denoting "Strongly Disagree," to 5, denoting "Strongly Agree."

To validate the four constructs of perceived personalized learning support, this study assessed their reliability and validity. Cronbach's α was assessed for internal consistency and reliability for each individual item in the construct with a lowest accepted value of 0.70 (Cortina 1993; Goffee and Jones 1996). Convergent validity was assessed by examining the factor loadings (λ) of each item, composite reliability (CR), and the average variance extracted (AVE). The factor loadings (λ) of each item were assessed for the strength of the linear correlation between the measuring items and the construct with a lowest accepted value of 0.70 (Hair et al. 2006). CR was assessed for the internal consistency of each construct with a lowest accepted value of 0.70 (Chin et al. 2003). AVE was assessed for the amount of variance that is captured by the construct in relation to the amount of variance due to measurement error with a lowest accepted value of 0.50. Discriminant validity was achieved when the average AVE value of any pair of constructs is larger than the squared correlation between that pair of constructs. The results of the reliability and convergent validity analysis are presented in Table 2, while Table 3 presents the data concerning discriminant validity.

As seen in Table 2, all the Cronbach's α values were higher than 0.7, showing the satisfactory internal consistency reliability of the scales. For convergent validity,

Table 2 Reliability and convergent validity

Construct	Item	Mean	SD	λ	α	CR	AVE
PUCLS	PUCLS1	4.444	0.729	0.918	0.888	0.931	0.818
	PUCLS2	4.486	0.691	0.919			
	PUCLS3	4.416	0.745	0.875			
PLPM	PLPM1	4.470	0.682	0.810	0.790	0.877	0.705
	PLPM2	4.423	0.679	0.872			
	PLPM3	4.423	0.679	0.835			
PUML	PUML1	4.388	0.741	0.803	0.890	0.924	0.753
	PUML2	4.470	0.733	0.894			
	PUML3	4.517	0.700	0.918			
	PUML4	4.494	0.683	0.852			
ITU	ITU1	4.494	0.683	0.907	0.900	0.938	0.834
	ITU2	4.494	0.700	0.939			
	ITU3	4.529	0.682	0.892			

Table 3 Correlation matrix and discriminant validity

Construct	PUCLS	PLPM	PUML	ITU
PUCLS	**0.904**			
PLPM	0.400***	**0.839**		
PUML	0.496***	0.607***	**0.868**	
ITU	0.544***	0.203*	0.320***	**0.913**

Average variances extracted (AVEs) shown on the diagonal

*$p < 0.05$

***$p < 0.01$

all factor loadings were higher than 0.7 and significant, all the four CR values were higher than 0.7, and all the four AVE values were higher than 0.5, showing the satisfactory convergent validity of the scales. Table 3 shows that the four scales had acceptable discriminant validity. Thirteen items of the final instrument are given in the Appendix Table 6.

Moreover, the learning performance (PER) construct was based on 9 multiple-choice conceptual test items designed by an experienced Physics teacher to assess the extent to which students acquired a certain amount of understanding, as learning performance, of the learning topic of 'Simple Electricity' after following the recommended learning activities from the personalized e-learning system. The total score of this test is 9, where the students score 1 point for a correct answer and 0 otherwise. The item difficulty index value ranged between 0.38 and 0.66, while the mean difficulty index of items was 0.52. The item discrimination index of all items was greater than 0.26, implying that the items had good discriminative validity (Doran 1980), whereas the KR-20 of the test was 0.83, indicating acceptable reliability in internal consistency.

Regarding the fact that the data scale of the PER construct differed from that of the other four constructs, the clustering technique was used to cope with this point. Many studies have shown that the k-means clustering technique could be used to distinguish a dataset into different clusters based on similar data, where the results can be easily understood and explained (Huang and Yang 2009; Oyelade et al. 2010; Vaessen et al. 2014). Consequently, the k-means clustering technique was then performed to categorize students' learning performance into three group-based scales with 1 denoting "low-achieving," 2 denoting "medium-achieving," and 3 denoting "high-achieving" (Chen et al. 2014; Chen and Huang 2013; Hung et al. 2015; Hwang and Chang 2011).

Results

In this study, the Partial Least Square (PLS) technique was used to test hypotheses regarding which factors affect learning performance in the developed personalized e-learning environment (Cheung and Vogel 2013). PLS is a type of Structural Equation Modeling (SEM) technique used to confirm the validity of the constructs of a particular instrument and to assess the structural relationships among constructs

Table 4 Model overall fit measurement (APC, ARS, AVIF)

Measure	Value	p
Average path coefficient (APC)	0.161	0.007
Average r-squared (ARS)	0.326	<0.001
Average variance inflation factor (AVIF)	1.958	

under conditions of non-normality and small or medium sample size, and to statistically analyze the posited research hypotheses (Chin 1998). Moreover, PLS is suitable for testing the effects of moderators (Pavlou and El Sawy 2006). Before performing PLS analysis for hypothesis testing, there are some fit indices that should be considered in order to assess the model's goodness-of-fit to test whether the model fits the data (Hair et al. 2010). To assess the model fit, it is recommended that the p values for both the average path coefficient (APC) and the average R-squared (ARS) are lower than 0.05, and the average variance inflation factor (AVIF) is lower than 5 (Faqih and Jaradat 2015). After performing goodness-of-fit analysis, the results showed that the structural model has a good fit to the data, as shown in Table 4; therefore, it is appropriate to perform PLS analysis in this study.

To test the hypotheses in our structural model with PLS, the path coefficients of each path and the R-squared coefficients (R^2) were evaluated for the structural paths by running the model with bootstrapping. Bootstrapping is a non-parametric method to assess the significance level of PLS by generating a certain number of subsamples by randomly choosing a case from the original data set (Chin 1998). In this study, the number of cases used for bootstrapping is equal to the sample size, which is equal to 115 cases, while the number of re-samples used for this study is equal to 1000. After running bootstrapping, the results of the path coefficients and significances are presented in Fig. 3.

Figure 3 shows that there are two direct- and two moderating effects out of 8 hypotheses which were accepted as follows:

H1 PUCLS on PER ($\beta=0.333$, $p=0.325$) was not statistically significant while being statistically moderated by gender with H1a ($\beta=0.167$, $p=0.012$);

H2 PLPM on PER ($\beta=0.040$, $p=0.294$) was not statistically significant while not being statistically moderated by gender with H2a ($\beta=0.095$, $p=0.097$);

H3 PUML on PER ($\beta=0.317$, $p<0.001$) was statistically significant while not being statistically moderated by gender with H3a ($\beta=0.118$, $p=0.055$);

H4 ITU on PER ($\beta=0.389$, $p<0.001$) was statistically significant while being statistically moderated by gender with H4a ($\beta=0.128$, $p=0.042$).

Moreover, Cohen (1988) suggested that the value of the R^2 coefficient refers to the combined effect size of the predictors in the latent variable blocks (constructs), whether or not the effects are indicated by path coefficients, are small, medium, or large with the values of 0.02, 0.15, and 0.35, respectively. In this study, the R^2

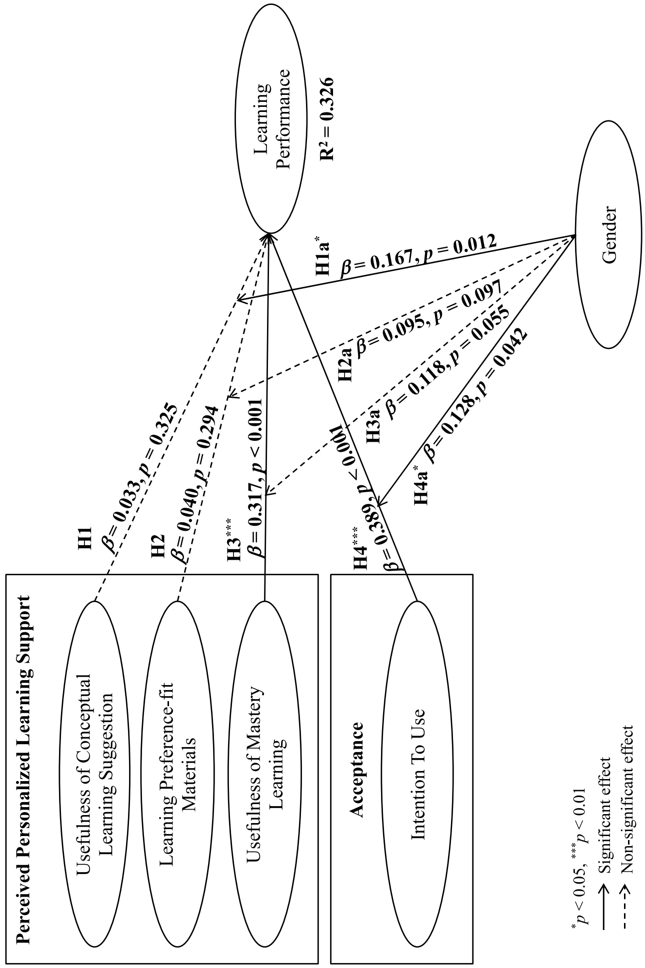

Fig. 3 Path coefficients of hypotheses testing results

coefficient was found to be 0.326, indicating a medium size effect. This means the structural model is considered to be relevant from a practical point of view.

Discussion

In this study, we examined the effectiveness of the developed personalized e-learning system through students' learning performance by comparing with the results from the conventional e-learning system without any personalized learning support. The findings from the validation phase provide some interesting results that only the learning performance of low-achievement students from the developed personalized e-learning system was significantly better than the performance of students learning with the conventional system, indicating that the personalized e-learning environment is found to be beneficial for low-achievement students. This finding synchronizes with the results of Hwang et al. (2013a, b), whose study also found that the developed personalized learning system could help low-achievement students. This was because low-achievement students felt that they had a stronger need to improve their learning than others with extra supports. Therefore, such personalized e-learning environment provided personalized learning supports that could drive their learning to fit their learning background and learning preference; moreover, each of their ongoing learning process was ensured sufficient understanding, leading to a better learning performance.

During the hypotheses testing, we investigated the factors that may affect the learning performance on the personalized e-learning environment. The findings, summarized in Table 5, reveal that perceived usefulness of mastery learning and intention to use had a significant positive influence on learning performance (H3 and H4). With perceived mastery learning support, students directly experienced it during the learning activities as they might get tracked along their learning process,

Table 5 Summary of hypothesis testing results

Hypothesis	Relationship	β	p	Testing result
Direct effects				
H1	PUCLS → PER	0.033	0.325	Rejected
H2	PLPM → PER	0.040	0.294	Rejected
H3	PUML → PER	0.317	< 0.001***	Accepted
H4	ITU → PER	0.389	< 0.001***	Accepted
Moderating effects				
H1a	PUCLS × Gender → PER	0.167	0.012*	Accepted
H2a	PLPM × Gender → PER	0.095	0.097	Rejected
H3a	PUML × Gender → PER	0.118	0.055	Rejected
H4a	ITU × Gender → PER	0.128	0.042*	Accepted

*$p < 0.05$

***$p < 0.01$

and their learning consequences were adapted based on such tracked results. This finding was supported by several studies (Liaw and Huang 2013; Rodrigues and Oliveira 2014). Additionally, the intention to use could determine the success of the students' learning. As the system was designed with personalized learning supports, they felt that it understood their actual learning situation, which led to their intention to pursue the learning activities provided such that they could succeed in their learning. As an attitudinal determinant of intention to use, this result was in line with many other studies (e.g., Chen 2011; Liu et al. 2010).

In addition to investigation of the direct effects on learning performance, gender was included as a moderating factor influencing such direct relationships. The findings reveal that gender differences could moderate the relationship of perceived usefulness of conceptual learning suggestion on learning performance (H1a) and intention to use on learning performance (H4a). The students received learning suggestions provided the personalized e-learning system as conceptual learning guidance. Female and male students could gain knowledge and construct understanding in the different way. That is to say, one may process and interpret information from visual-guided suggestion better than the other one. Therefore, this finding affects their learning performance inevitably. In addition, the different genders could moderate the relationship between the intention to use the system and the learning performance. Both findings would shift a significant concern when developing the online personalized learning system. Specifically, the learning suggestions shall be designed and presented differently, while other factors need to be investigated in order to tackle the effect of intention to use the system (e.g., gender-based learning activities or experiences). These findings are aligned with several studies.

In recent studies of effect, Chyung (2007) showed that different genders perceived the conceptual learning guidance in online-learning systems differently, such that it influences the learning result. Moreover, Tosuntaş et al. (2015) revealed that in online-learning systems, female students tend to show more intention to use the system than male students, which results in better learning performance. However, the hypothesis of gender moderating the effect of perceived material related to learning preference on learning performance was rejected (H2a), which was in agreement with the results of several studies (Yukselturk and Bulut 2009). This could imply that our developed system could be beneficial for all genders in terms of the perceived material related to learning preference, eventually reducing the learning gaps between the different learning preferences of the students.

Conclusions

In this study, a personalized e-learning system was developed by taking students' to-be enhanced concepts and learning preferences into account. An examination was conducted to investigate the value of the personalized e-learning system. In addition, a conceptual model with hypotheses was proposed based on the literature for investigating the factors that could affect the students' learning performance.

The findings from this empirical study serve to offer valuable contributions to the field of online-learning systems with personalized learning support. Importantly, it could support enhancements in developing personalized learning support systems by considering the mastery learning approach to promote students' learning performance. In addition, this research also provides a great contribution to the existing literature. First, this study has contributed to theoretically better understanding the factors of personalized learning features that could influence the learning success in such systems. Second, the findings of the main study revealed that gender difference issue has a particular effect on the learning performance. Therefore, it is necessary to consider this issue when developing a personalized learning environment in order to enable the learning system to be more potent in meeting with specific requirements, learning behavior, and learning experience of females and males. Consequently, the system might provide and present proper learning activities with the inclusion of positive perception and acceptance of the system resulting in a well-learned performance.

However, this study has some limitations. Firstly, the results could not be generalized to other subjects since the participants of this study were limited; also, the nature of other subjects might be different. Secondly, the sampling method used in this study was based on class-based groups of students, and thus freedom of group participation in the experiment was limited. Based on these limitations, therefore, we suggest some guidelines for future studies. There should be more implementation in other subjects to investigate the results that might be affected by the differences in courses. Other human factors, e.g., computer experience, could be considered as moderating effects that could influence the effects on learning performance. Moreover, perceptional effects on learning motivation should also be studied.

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Appendix

See Table 6.

Table 6 Questionnaire items

Construct	Item		Source
PUCLS	PUCLS1	The guidelines prior to the learning activities make my learning more interesting	Hwang et al. (2013)
	PUCLS2	The guidelines prior to the learning activities make my learning more enjoyable	
	PUCLS3	The guidelines prior to the learning activities give me more confidence in learning	
PLPM	PLPM1	The learning activities are personalized for me	Graf (2007), Hung et al. (2015)
	PLPM2	The learning activities make my learning more enjoyable	
	PLPM3	The learning activities make my learning more understandable	
PUML	PUML1	The assessment during the learning process makes my learning more interesting	Gikandi et al. (2011), Hwang and Chang (2011) and Srisawasdi and Panjaburee (2015)
	PUML2	The assessment during the learning process makes my learning more enjoyable	
	PUML3	The assessment during the learning process gives me more confidence in learning	
	PUML4	The assessment during the learning process can track my learning continuously	
ITU	ITU1	I will definitely use this system to learn in the future	Liu et al. (2010)
	ITU2	I think I will use this system to learn frequently	
	ITU3	I will recommend this system to my friends	

References

Achufusi, N. N., & Mgbemena, C. O. (2012). The effect of using mastery learning approach on academic achievement of senior secondary school II physics students. *Educational Technology, 51*, 10735–10737.

Adnan Khan, F. M., & Masood, M. (2013). The development and testing of Multimedia-assisted Mastery Learning Courseware with regard to the learning of cellular respiration. *Procedia - Social and Behavioral Sciences, 103*(2013), 999–1005.

Ajzen I, Fishbein M (1980) Understanding attitudes and predicting social behavior (Vol. 278). Prentice Hall, Englewood Cliffs, NY.

Al-Azawei, A. (2019). The Moderating effect of gender differences on learning management systems acceptance: A multi-group analysis. *Italian Journal of Educational Technology, 27*(3), 257–278.

Ali, Z., Gongbing, B., & Mehreen, A. (2018). Understanding and predicting academic performance through cloud computing adoption: A perspective of technology acceptance model. *Journal of Computers in Education, 5*(3), 297–327.

Amiruddin, M. H., Samad, N. A., & Othman, N. (2015). An investigation effects of mastery learning strategy on entrepreneurship knowledge acquisition among aboriginal students. *Procedia - Social and Behavioral Sciences, 204*, 183–190.

Aypay, A., Çelik, H. C., Aypay, A., & Sever, M. (2012). Technology acceptance in education: A study of pre-service teachers in Turkey. *The Turkish Online Journal of Educational Technology, 11*(4), 264–272.

Bachari, E. E., Abelwahed, E. H., & El Adnani, M. (2011). E-Learning personalization based on Dynamic learners' preference. *International Journal of Computer Science and Information Technology, 3*(3), 200–216.

Bajraktarevic, N., Hall, W., & Fullick, P. (2003). Incorporating learning styles in hypermedia environment : Empirical evaluation. In *Proceedings of the Workshop on Adaptive Web-Based System* (pp. 41–52).

Borun, M., Schaller, D. T., Chambers, M. B., & Allison-Bunnell, S. (2010). Implications of learning style, age group, and gender for developing online learning activities. *Visitor Studies, 13*(2), 145–159.

Bossers, A., Phelan, S., Kinsella, E. A., Jenkins, K., Ferguson, K., Moosa, T., et al. (2014). Participants' self-identified learning outcomes in an online preceptor education program for health professionals and students. *The Journal of Practice Teaching and Learning, 1*(1), 79–97.

Brady, C. L. (2013). Understanding learning styles: Providing the optimal learning experience. *International Journal of Childbirth Education, 28*(2), 16–20.

Brock KL, Cameron BJ (1999) Enlivening political science courses with Kolb's learning preference model. PS: Political Science & Politics, 32(2), 251–256.

Casamayor, A., Amandi, A., & Campo, M. (2009). Intelligent assistance for teachers in collaborative e-learning environments. *Computers and Education, 53*(4), 1147–1154.

Chen, C.-M. (2009). Personalized E-learning system with self-regulated learning assisted mechanisms for promoting learning performance. *Expert Systems with Applications, 36*(5), 8816–8829.

Chen, L.-H. (2010). Web-based learning programs: Use by learners with various cognitive styles. *Computers & Education, 54*(4), 1028–1035.

Chen, L. H. (2011). Enhancement of student learning performance using personalized diagnosis and remedial learning system. *Computers and Education, 56*(1), 289–299.

Chen, S. Y., & Huang, P.-R. (2013). The comparisons of the influences of prior knowledge on two game-based learning systems. *Computers & Education, 68*, 177–186.

Chen, C.-H., Hwang, G.-J., & Tsai, C.-H. (2014). A progressive prompting approach to conducting context-aware learning activities for natural science courses. *Interacting with Computers, 26*(4), 348–359.

Cheng, B., Wang, M., Yang, S. J. H., Kinshuk, A., & Peng, J. (2011). Acceptance of competency-based workplace e-learning systems: Effects of individual and peer learning support. *Computers & Education, 57*(1), 1317–1333.

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education, 63*, 160–175.

Chiang, T. H. C., Yang, S. J. H., & Hwang, G.-J. (2014). An Augmented Reality-based Mobile Learning System to Improve Students' Learning Achievements and Motivations in Natural Science Inquiry Activities. *Educational Technology & Society, 17*(4), 352–365.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In *Modern Methods for Business Research* (pp. 295–336).

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research, 14*(2), 189–217.

Cho, V., Cheng, T. C. E., & Lai, W. M. J. (2009). The role of perceived user-interface design in continued usage intention of self-paced e-learning tools. *Computers and Education, 53*(2), 216–227.

Chookaew, S., Panjaburee, P., Wanichsan, D., & Laosinchai, P. (2014). A personalized e-learning environment to promote student's conceptual learning on basic computer programming. *Procedia - Social and Behavioral Sciences, 116*, 815–819.

Chookaew, S., Wanichsan, D., Hwang, G. J., & Panjaburee, P. (2015). Effects of a personalized ubiquitous learning support system on university students' learning performance and attitudes in computer-programming courses. *International Journal of Mobile Learning and Organisation, 9*(3), 240–257.

Chyung, S. Y. (2007). Age and gender differences in online behavior, self-efficacy, and academic performance. *The Quarterly Review of Distance Education, 8*(208), 213–222.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Routledge.

Cortina, J. M. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of Applied Psychology, 78*(1), 98–104.

Cuadrado-García, M., Ruiz-Molina, M.-E., & Montoro-Pons, J. D. (2010). Are there gender differences in e-learning use and assessment? Evidence from an interuniversity online project in Europe. *Procedia - Social and Behavioral Sciences, 2*(2), 367–371.

DeBate, R. D., Severson, H. H., Cragun, D., Bleck, J., Gau, J., Merrell, L., et al. (2014). Randomized trial of two e-learning programs for oral health students on secondary prevention of eating disorders. *Journal of Dental Education, 78*(1), 5–15.

Doran, R. L. (1980). *Basic measurement and evaluation of science instruction.* ERIC.

Elgamal, A. F., Abas, H. A., & Baladoh, E.-S. M. (2011). An interactive e-learning system for improving web programming skills. *Education and Information Technologies, 18*(1), 29–46.

Faqih, K. M. S., & Jaradat, M.-I. R. M. (2015). Assessing the moderating effect of gender differences and individualism-collectivism at individual-level on the adoption of mobile commerce technology: TAM3 perspective. *Journal of Retailing and Consumer Services*, *22*, 37–52.

Furo, P. T. (2014). Effect of mastery learning approach on secondary school students achievement in chemistry in rivers state Nigeria. *Chemistry and Materials Research, 6*(9), 104–110.

Garrison, D. R. (2011). *E-learning in the 21st century: A framework for research and practice*. Taylor & Francis.

Giannakos, M. N. (2013). Enjoy and learn with educational games: Examining factors affecting learning performance. *Computers and Education, 68*(246016), 429–439.

Gikandi, J. W., Morrow, D., & Davis, N. E. (2011). Online formative assessment in higher education: A review of the literature. *Computers and Education, 57*(4), 2333–2351.

Goffee, R., & Jones, G. (1996). What holds the modern company together? *Harvard Business Review, 74*(6), 133–148.

Graf, S. (2007). *Adaptivity in learning management systems focussing on learning styles*. Vienna: Vienna University of Technology.

Grasha, A. F. (2002). *Teaching with style: A practical guide to enhancing learning by understanding teaching and learning styles*. Alliance Publ.

Guskey, T. R. (2007). Closing Achievement Gaps: Revisiting Benjamin S. Bloom's "Learning for Mastery." *Journal of Advanced Academics*, 19(1), 8–31.

Guskey, T. R. (2010). Lessons of Mastery Learning. *Educational Leadership, 68*(2), 52–57.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2006). *Multivariate data analysis* (Vol. 6).

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2010). *Multivariate Data Analysis*. *Prentice Hall.*

Halbert, C., Kriebel, R., Cuzzolino, R., Coughlin, P., & Fresa-Dillon, K. (2011). Self-assessed learning style correlates to use of supplemental learning materials in an online course management system. *Medical Teacher, 33*(4), 331–333.

Horton, W. K. (2000). *Designing web-based training: How to teach anyone anything anywhere anytime* (Vol. 1). Wiley New York, NY.

Huang, S.-L., & Yang, C.-W. (2009). Designing a semantic bliki system to support different types of knowledge and adaptive learning. *Computers & Education, 53*(3), 701–712.

Huang, C. H., Chin, S. L., Hsin, L. H., Hung, J. C., & Yu, Y. P. (2011). A Web-based E-learning Platform for physical education. *Journal of Networks, 6*(5), 721–727.

Huang, Y. M., Liang, T. H., & Chiu, C. H. (2013). Gender differences in the reading of e-books: Investigating children's attitudes, reading behaviors and outcomes. *Educational Technology and Society, 16*(4), 97–110.

Hung, Y. H., Chang, R. I., & Lin, C. F. (2015). Hybrid learning style identification and developing adaptive problem-solving learning activities. *Computers in Human Behavior, 55*, 552–561.

Hwang, G.-J., & Chang, H.-F. (2011). A formative assessment-based mobile learning approach to improving the learning attitudes and achievements of students. *Computers & Education, 56*(4), 1023–1031.

Hwang, G.-J., Tseng, J., & Hwang, G.-H. (2008). Diagnosing student learning problems based on historical assessment records. *Innovations in Education and Teaching International, 45*(1), 77–89.

Hwang, G. J., Shi, Y. R., & Chu, H. C. (2011). A concept map approach to developing collaborative Mindtools for context-aware ubiquitous learning. *British Journal of Educational Technology, 42*(5), 778–789.

Hwang, G.-J., Sung, H.-Y., Hung, C.-M., Huang, I., & Tsai, C.-C. (2012). Development of a personalized educational computer game based on students' learning styles. *Educational Technology Research and Development, 60*(4), 623–638.

Hwang, G.-J., Panjaburee, P., Triampo, W., & Shih, B.-Y. (2013a). A group decision approach to developing concept-effect models for diagnosing student learning problems in mathematics. *British Journal of Educational Technology, 44*(3), 453–468.

Hwang, G., Sung, H., Hung, C., & Huang, I. (2013b). A learning style perspective to investigate the necessity of developing adaptive learning systems. *Educational Technology and Society, 16*(2), 188–197.

Joo, Y. J., Lim, K. Y., & Lim, E. (2014). Investigating the structural relationship among perceived innovation attributes, intention to use and actual use of mobile learning in an online university in South Korea. *Australasian Journal of Educational Technology*, 30(4).

Kim, D. G., & Lee, J. (2013). Development of an intelligent instruction system for mathematical computation. *Informatics in Education, 12*(1), 93–106.

Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (2011). E-Learning personalization based on hybrid recommendation strategy and learning style identification. *Computers & Education, 56*(3), 885–899.

Klett, F. (2010). The design of a sustainable competency-based human resources management: A holistic approach. *Knowledge Management & E-Learning: An International Journal (KM&EL), 2*(3), 278–292.

Komalawardhana, N., & Panjaburee, P. (2018). Proposal of personalised mobile game from inquiry-based learning activities perspective: relationships among genders, learning styles, perceptions, and learning interest. *International Journal of Mobile Learning and Organisation, 12*(1), 55–76.

Koohang, A., & Paliszkiewicz, J. (2013). Knowledge construction in e-learning: an empirical validation of an active learning model. *Journal of Computer Information Systems, 53*(3), 109–114.

Kularbphettong, K., Kedsiributt, P., & Roonrakwit, P. (2015). Developing an Adaptive Web-based Intelligent Tutoring System Using Mastery Learning Technique. *Procedia - Social and Behavioral Sciences, 191*, 686–691.

Larmuseau, C., Evens, M., Elen, J., Van Den Noortgate, W., Desmet, P., & Depaepe, F. (2018). The Relationship Between Acceptance, Actual Use of a Virtual Learning Environment and Performance: An Ecological Approach. *Journal of Computers in Education, 5*(1), 95–111.

Latham, A., Crockett, K., & McLean, D. (2014). An adaptation algorithm for an intelligent natural language tutoring system. *Computers and Education, 71*, 97–110.

Lee, M.-C. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation–confirmation model. *Computers & Education, 54*(2), 506–516.

Lee, Y. J., & Lee, D. (2015). Factors Influencing Learning Satisfaction of Migrant Workers in Korea with E-learning-Based Occupational Safety and Health Education. *Safety and Health at Work, 6*(3), 211–217.
Lewis, K. O., Cidon, M. J., Seto, T. L., Chen, H., & Mahan, J. D. (2014). Leveraging e-learning in medical education. *Current Problems in Pediatric and Adolescent Health Care, 44*(6), 150–163.
Liaw, S.-S., & Huang, H.-M. (2013). Perceived satisfaction, perceived usefulness and interactive learning environments as predictors to self-regulation in e-learning environments. *Computers & Education, 60*(1), 14–24.
Lin, H.-T., Liu, E. Z.-F., & Yuan, S.-M. (2008). An Implementation of Web-based Mastery Learning System. *International Journal of Instructional Media, 35*(2), 209–320.
Lin, C. H., Liu, E. Z. F., Chen, Y. L., Liou, P. Y., Chang, M., Wu, C. H., et al. (2013). Game-based remedial instruction in mastery learning for upper-primary school students. *Educational Technology and Society, 16*(2), 271–281.
Liu, C.-L., Wu, S., Chang, M., & Heh, J.-S. (2008). Guiding students to do remedial learning in school campus with learning objects' spatial relations. In *Proceedings - ICCE 2008: 16th International Conference on Computers in Education* (pp. 249–256).
Liu, I.-F., Chen, M. C., Sun, Y. S., Wible, D., & Kuo, C.-H. (2010). Extending the TAM model to explore the factors that affect Intention to Use an Online Learning Community. *Computers and Education, 54*(2), 600–610.
Martinez, J. G. R., & Martinez, N. C. (1999). Teacher effectiveness and learning for mastery. *The Journal of Educational Research, 92*(5), 279–285.
Mayer, R. E., & Massa, L. J. (2003). Three facets of visual and verbal learners: Cognitive ability, cognitive style, and learning preference. *Journal of educational psychology, 95*(4), 833.
Merhi, M. I. (2015). Factors influencing higher education students to adopt podcast: An empirical study. *Computers & Education, 83*, 32–43.
Moghavvemi, S., Paramanathan, T., Rahin, N. M., & Sharabati, M. (2017). Student's perceptions towards using e-learning via Facebook. *Behaviour & Information Technology, 36*(10), 1081–1100.
Nguyen, D. (2011). *College Students Attitudes Toward Learning Process And Outcome Of Online Instruction and Distance Learning Across Learning Styles, 8*(12), 35–43.
Oyelade, O. J., Oladipupo, O. O., & Obagbuwa, I. C. (2010). Application of k means clustering algorithm for prediction of students academic performance. *International Journal of Computer Science and Information Security, 7*(1), 292–295.
Ozden, M. (2008). Improving Science and Technology Education Achievement Using Mastery Learning Model. *World Applied Sciences Journal, 5*(1), 62–67.
Panjaburee, P., & Srisawasdi, N. (2016). An integrated learning styles and scientific investigation-based personalized web approach: a result on conceptual learning achievements and perceptions of high school students. *Journal of Computers in Education, 3*(3), 253–272.
Panjaburee, P., Hwang, G. J., Triampo, W., & Shih, B. Y. (2010). A multi-expert approach for developing testing and diagnostic systems based on the concept effect model. *Computers & Education, 55*(2), 510–540.
Park, S. Y. (2009). An Analysis of the Technology Acceptance Model in Understanding University Students' Behavioral Intention to Use e-Learning. *Educational Technology & Society, 12*(3), 150–162.
Park, C., Kim, D. G., Cho, S., & Han, H. J. (2019). Adoption of multimedia technology for learning and gender difference. *Computers in Human Behavior, 92*, 288–296.
Pavlou, P. A., & El Sawy, O. A. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. *Information Systems Research, 17*(3), 198–227.
Popescu, E. (2010). Adaptation provisioning with respect to learning styles in a Web-based educational system: An experimental study. *Journal of Computer Assisted Learning, 26*(4), 243–257.
Rodrigues, F., & Oliveira, P. (2014). A system for formative assessment and monitoring of students' progress. *Computers and Education, 76*, 30–41.
Rodríguez-Ardura, I., & Meseguer-Artola, A. (2019). Flow experiences in personalised e-learning environments and the role of gender and academic performance. *Interactive Learning Environments*, 1–24.
Rovai, A. P., & Baker, J. D. (2005). Gender differences in online learning: Sense of community, perceived learning, and interpersonal interactions. *The Quarterly Review of Distance Education, 6*(1), 31–44.
Santo, S. A. (2006). Relationships between Learning Styles and Online Learning, *19*(3).

Schiefele, U., & Csikszentmihalyi, M. (1995). Motivation and Ability As Factors in Mathematics Experience and. *Journal for Research in Mathematics Education, 26*(2), 163–181.

Shafie, N., Shahdan, T. N. T., & Liew, M. S. (2010). Mastery Learning Assessment Model (MLAM) in Teaching and Learning Mathematics. *Procedia - Social and Behavioral Sciences, 8*, 294–298.

Shih, C.-C., & Gamon, J. (2001). Web-Based Learning: Relationships Among Student Motivation, Attitude, Learning Styles, And Achievement. *Journal of Agricultural Education, 42*(4), 12–20.

Soflano, M., Connolly, T. M., & Hainey, T. (2015). An Application of Adaptive Games-Based Learning based on Learning Style to Teach SQL. *Computers & Education, 86*, 192–211.

Srisawasdi, N., & Panjaburee, P. (2015). Exploring effectiveness of simulation-based inquiry learning in science with integration of formative assessment. *Journal of Computers in Education, 2*(3), 323–352.

Srisawasdi, N., Srikasee, S., & Panjaburee, P. (2012). Development of a Constructivist Web-based Learning System with Student Personalized Conceptual Profile. In *Proceedings of the 20th International Conference on Computers in Education* (pp. 44–50).

Staiger, J. (1997). Hybrid or Inbred: The Purity Hypothesis and Hollywood Genre History. *Film Criticism, 22*(2), 5–20.

Stiggins, R. (2006). Assessment For Learning: A Key to Motivate and Achievement (Vol. 2). Phi Delta Kappa International.

Sung, H.-Y., Hwang, G.-J., & Hwang, G.-J. (2013). A collaborative game-based learning approach to improving students' learning performance in science courses. *Computers & Education, 63*, 43–51.

Tarhini, A., Hone, K., & Liu, X. (2014). Measuring the moderating effect of gender and age on e-learning acceptance in England: A structural equation modeling approach for an extended technology acceptance model. *Journal of Educational Computing Research, 51*(2), 163–184.

Teo, T., Lee, C. B., Chai, C. S., & Wong, S. L. (2009). Assessing the intention to use technology among pre-service teachers in Singapore and Malaysia: A multigroup invariance analysis of the Technology Acceptance Model (TAM). *Computers & Education, 53*(3), 1000–1009.

Thanyaphongphat, J., & Panjaburee, P. (2019). Effects of a personalised ubiquitous learning support system based on learning style-preferred technology type decision model on university students' SQL learning performance. *International Journal of Mobile Learning and Organisation, 13*(3), 233–254.

Tosuntaş, Ş. B., Karadağ, E., & Orhan, S. (2015). The factors affecting acceptance and use of interactive whiteboard within the scope of FATIH project: A structural equation model based on the Unified Theory of acceptance and use of technology. *Computers & Education, 81*, 169–178.

Toven-Lindsey, B., Rhoads, R. A., & Lozano, J. B. (2015). Virtually unlimited classrooms: Pedagogical practices in massive open online courses. *Internet and Higher Education, 24*, 1–12.

Trukhacheva, N., Tchernysheva, S., & Krjaklina, T. (2011). The impact of E-learning on medical education in Russia. *E-Learning and Digital Media, 8*(1), 31–35.

Tsai, Y.-R., Ouyang, C.-S., & Chang, Y. (2015). Identifying engineering students' english sentence reading comprehension errors applying a data mining technique. *Journal of Educational Computing Research, 54*(1), 62–84.

Tseng, J. C. R., Chu, H.-C., Hwang, G.-J., & Tsai, C.-C. (2008). Development of an adaptive learning system with two sources of personalization information. *Computers and Education, 51*(2), 776–786.

Vaessen, B. E., Prins, F. J., & Jeuring, J. (2014). University students' achievement goals and help-seeking strategies in an intelligent tutoring system. *Computers & Education, 72*, 196–208.

Walonoski, J. a., & Heffernan, N. T. (2006). Detection and analysis of off-task gaming behavior in Intelligent Tutoring Systems. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 4053 LNCS, 382–391.

Wambugu, P. W., & Changeiywo, J. M. (2008). Effects of mastery learning approach on secondary school students' physics achievement. *Eurasia Journal of Mathematics, Science and Technology Education, 4*(3), 293–302.

Wang, H.-C., & Huang, T.-H. (2011). Personalized e-learning environment for bioinformatics. *Interactive Learning Environments, 21*(1), 1–21.

Wang, S.-L., & Wu, C.-Y. (2011). Application of context-aware and personalized recommendation to implement an adaptive ubiquitous learning system. *Expert Systems with Applications, 38*(9), 10831–10838.

Wang, K.-H., Wang, T. H., Wang, W.-L., & Huang, S. C. (2006). Learning styles and formative assessment strategy: Enhancing student achievement in Web-based learning. *Journal of Computer Assisted Learning, 22*(3), 207–217.

Wongwatkit, C., Tekaew, S.-A., Kanjana, S., & Khrutthaka, C. (2015). A Systematic Vocabulary Learning-based Mobile Game Application to Improving English Vocabulary Learning Achievement for

University Admission Examination in Thailand. In *Proceedings of the 23rd International Conference on Computers in Education* (pp. 549–558). Hangzhou, China: Asia-Pacific Society for Computers in Education.

Wongwatkit, C., Srisawasdi, N., Hwang, G., & Panjaburee, P. (2017). Influence of an integrated learning diagnosis and formative assessment-based personalized web learning approach on students learning performances and perceptions. *Interactive Learning Environments, 25*(7), 889–903.

Wu, T. T., Yang, T. C., Hwang, G. J., & Chu, H. N. (2008). Conducting situated learning in a context-aware ubiquitous learning environment. *Proceedings - 5th IEEE International Conference on Wireless, Mobile, and Ubiquitous Technologies in Education, WMUTE 2008*, 82–86.

Wu, H. M., Kuo, B. C., & Yang, J. M. (2012a). Evaluating knowledge structure-based adaptive testing algorithms and system development. *Educational Technology and Society, 15*(2), 73–88.

Wu, P.-H., Hwang, G.-J., Milrad, M., Ke, H.-R., & Huang, Y.-M. (2012b). An innovative concept map approach for improving students' learning performance with an instant feedback mechanism. *British Journal of Educational Technology, 43*(2), 217–232.

Xie, H., Chu, H.-C., Hwang, G.-J., & Wang, C.-C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers & Education, 140*, 103599.

Yang, J. C., & Chen, S. Y. (2010). Effects of gender differences and spatial abilities within a digital pentominoes game. *Computers & Education, 55*(3), 1220–1233.

Yang, T.-C., Hwang, G.-J., Chiang, T. C., & Yang, S. H. (2013). A Multi-dimensional Personalization Approach to Developing Adaptive Learning Systems. In A. Holzinger & G. Pasi (Eds.) (Vol. 7947, pp. 326–333). Berlin: Springer

Yang, K.-H., Lu, B.-C., Chu, H.-C., & Chen, J.-Y. (2015). Developing a Game-Based Learning System with Two-Tier Diagnostic Tool for Math Courses. In *Advanced Applied Informatics (IIAI-AAI), 2015 IIAI 4th International Congress on* (pp. 363–366). IEEE.

Yang, T.-C., Hwang, G.-J., Yang, S. J. H., & Hwang, G.-H. (2015). A two-tier test-based approach to improving students' computer-programming skills in a web-based learning environment. *Journal of Educational Technology & Society, 18*(1), 198–210.

Yi, M. Y., & Hwang, Y. (2003). Predicting the use of web-based information systems: Self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. *International Journal of Human-Computer Studies, 59*(4), 431–449.

Yukselturk, E., & Bulut, S. (2009). Gender differences in self-regulated online learning environment. *Educatiuonal Technology Society, 12*(3), 12–22.

Zhang, Z., Ran, P., Peng, Y., Hu, R., & Yan, W. (2015). Effectiveness of e-learning in public health education: A pilot study. *International Journal of Information and Education Technology, 5*(8), 577.

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