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Acceptance of personalized e-learning systems: a case study of concept-effect relationship approach on science, technology, and mathematics courses

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Abstract Current scholars to propose testing and diagnosing conceptual learning problem approaches with personalized e-learning systems designed for providing proper guidance to individual students are growing. The benefits of personalized e-learning systems have also been discussed in various previous studies. Students' perceptions of the personalized e-learning environment with drawing perspectives on the technology acceptance model still need to be examined to reveal findings from various cohorts. Therefore, a conceptual technology acceptance model was employed to investigate students' perceived ease of use, usefulness, attitude, and behavioral intention to use the personalized e-learning systems based on the concept-effect relationship approach in this study. Using a validated questionnaire, the stepwise multiple regression technique was applied to 1175 sample data collected from primary school, secondary school, and university settings in Thailand. The results showed that perceived ease of use and usefulness affects students' attitudes toward and behavioral intention to use the personalized e-learning system. This study highlights that the concept-effect relationship approach could detect causes of learning failure and provide learning paths corresponding to students' conceptual learning problems. It led to students' perceived usefulness of learning guidance generated by the personalized e-learning systems based on the concept-effect relationship approach. The findings from this study will be discussed to further

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implementation by concerning proper learning strategy to facilitate the students' learning in the personalized e-learning systems based on the concept-effect relationship approach.

Keywords Personalization · E-learning · Technology-enhanced learning · Intention · TAM

Introduction

Teaching and learning strategy are viewed as the set of activities to allow students to practice and get direct experience for performance. From this point of view, the proper strategy can be considered to help students gain knowledge. Meanwhile, scholars have been concerned about teaching Science, Technology, and Mathematics (STM) because they are fundamental knowledge for related subjects and each other. For example, the inquiry-based learning approach is grounded by constructivist learning theory and provides a student-centered learning environment by engaging students in the authentic conception of scientific phenomena (Krajcik & Blumenfeld, 2006; Kubicek, 2005; Kuhn et al., 2000). That is to say, students are encouraged to learn and gain conceptual knowledge of science through authentic investigation activities emphasizing posing questions, gathering and analyzing data, and constructing evidence-based arguments. Similarly, the learning cycle models (i.e., 3E learning cycle model, 5E learning cycle model) are an inquiry-based approach that involves a series of teaching strategies. These models promised to encourage students to use their prior knowledge or experience to learn something new or understand something in greater depth. These models are intended to help students progress from concrete to abstract thinking about content based on Piaget's intellectual development theory. A key aspect of the learning cycle approach is its ability to engage students in meaningful inquiries to improve their inquiry skills and help them construct tenable concepts. Likewise, mathematics is generally seen as complicated content since those are consisted of many variables and symbolics. With this perspective, understanding the circumstance behind those expressions is the way to acknowledge the whole concept of mathematics. Bruner's (1965) model was adapted to be a concrete–pictorial–abstract (CPA) approach to deliver knowledge in the form of instrumental activity for enabling students to manipulate it (Chang et al., 2017; Leong et al., 2015). It also has been used to support the students to construct an understanding through doing that activity and reinforces them to generate or summarize conceptual understanding from the image. However, most of them still hold conceptual understanding failures when applying the STM disciplines to real-world phenomena. It might be because they had no complete understanding of the STM conceptions when participating in the common learning materials or learning environment. It is widely acknowledged that individuals have different preferences and need to learn something new. Therefore, scholars suggested that properly preparing instruction for individuals could support educational goals (Russell, 1997). In other words, if the individual students received more preferred and more efficient instruction and effective learning strategies in STM education, they might remedy incomplete conceptual understanding for applying it to real-world phenomena.

Generally, the STM classrooms consist of a large number of students as well as there are varieties of students' characteristics in one classroom. Managing the STM classrooms concerning individual differences and personalized instruction is not easy. On the other hand, with the rapid growth of computing technology, a personalized e-learning environment has been becoming to cope with such issues (Akbulut & Cardak, 2012; Chen et al., 2016; Chookaew et al., 2014; Klašnja-Milićević et al., 2011; Komalawardhana & Panjaburee, 2018; Komalawardhana et al., 2021; Schmid & Petko, 2019). Therefore, the STM classrooms could provide more effective instruction using personalized e-learning systems in which STM conceptions and students' preferences are key features. Scholars suggested that the personalized technology-enhanced learning environment could improve individual instructions for improving individuals' learning performance (Chen, 2008, 2011). Students also reflected that personalized e-learning systems could support them in setting the learning process based on their strategies and following the pace of the class. Moreover, in receiving feedback, they are more enthusiastic about improving their abilities regarding their plans. It indicates that the learning environment was more favorable and challenging (Vidergor & Ben-Amram, 2020). On the other hand, personalized e-learning effort to design remedial instruction provided adaptive lessons based on individual conditions. The students are thus willing to complete the remedial task and outperform the improvement on their learning outcome (Chen & Wu, 2020). In recent years, researchers have demonstrated that technology-enhanced learning could enhance teaching and learning in formal and informal classroom settings (Pham et al., 2012; Smith et al., 2009). At this time, there is an excellent demand for mathematics, science, and technology teaching and instructional supports for those subject areas. The development of adaptive learning systems, intelligent tutoring systems, and other formats of educational technology in mathematics, science, and technology is critically important and has led to much research being carried out in the area of computers in education. Recent information and communication technology, particularly Internet access, appear to offer exciting possibilities for an alternative learning culture and to overcome distance barriers to learning in this century. Technology-enhanced learning is a new pedagogical domain that enables students to use information and communication technologies to support learning, facilitate the construction of knowledge, and improve the way of learning of a person (Porta et al., 2012; Steffens, 2008). Another feature of technology-enhanced learning is testing and diagnosing systems embedded in the learning environment to detect students' learning information in response to the personalized e-learning environment.

Scholars have proposed methods involving cognitive status diagnosis when constructing a personalized e-learning environment for promoting students' conceptual learning individually in the past decade. Among the previous methods, such as Bayesian cybernetics, fuzzy rules, genetic algorithms, clustering techniques, and concept-effect relationship model (Bai & Chen, 2008a; Cheng et al., 2005; Hwang, 2003; Hwang et al., 2012; Kaburlasos et al., 2008; Wanichsan et al., 2012), the concept-effect relationship model has been widely recognized to diagnose students' conceptual learning problems and provide corresponding conceptual learning suggestions for individual students in natural science, mathematics, and health education (Bai & Chen, 2008a, 2008b; Chen, 2008; Chen & Bai, 2009; Chu et al., 2006; Günel & Aşlıyan, 2010; Hwang, 2003; Hwang et al., 2013; Panjaburee et al., 2010). The concept-effect relationship model has been recognized as a hierarchical-ordered model of concepts that is more properly used with a specific concept ranging from basic to advanced learning modules. Such that many studies have examined the effectiveness of the personalized e-learning systems based on the concept-effect relationship model regarding learning achievement and perceptions about the systems (e.g., Chookaew et al., 2014; Li et al., 2019; Srisawasdi & Panjaburee, 2014). However, the potential impact grounded by the technology acceptance model as perceived usefulness, ease of use, attitude, and intention to use personalized e-learning systems based on the concept-effect relationship model in the various cohorts is less investigated. In other words, examining perception impact with personalized e-learning systems based on the concept-effect relationship model is a novelty in the current study.

Concerning personalized e-learning systems, it is recognized that generating a personalized learning path and providing related learning materials are two key elements in the instructional design of such a personalized e-learning system (Komalawardhana et al., 2021). That is to say, the well-designed personalized learning environment could shape individuals with a customized path (Essalmi et al., 2010). Likewise, the remedial materials related to a student's difficulties could support his/her learning achievement (Lin et al., 2013) and provide multiple representations and experiences in abstract concepts to each student (Chen & Wu, 2020). However, examining the impacts of the two elements on students' perceptions in the technology acceptance model has been uninvestigated by applying the concept-effect relationship model. That is to say, understanding students' perceptions toward personalized e-learning systems are an issue for improving personalized e-learning usage in this study. Therefore, the investigation is based on personalized e-learning in the various cohorts and validated Technology Acceptance Model (TAM).

Literature review

Personalized e-learning systems

A personalized e-learning environment could be provided individual or adaptive presentation layouts, learning contents, learning materials, learning approaches, and learning support systems. Regarding "personalized learning" and "adaptive learning" definitions, e-learning systems are essentially used to accommodate the diverse individual characteristics and preferences with adapting to the ongoing progress of a learner's ability to perform learning tasks whenever and wherever by individual paces thoroughly. Mario et al. (2015) suggested that adaptive learning could enhance university students' learning performance and complete the SQL database course task faster than conventional learning. Hwang et al. (2012) reported that a personalized learning approach characteristic of role-playing game based included game components (e.g., incentives, immediate feedback and rewards, and game design techniques) for elementary students in a natural science course could not only be used to promote learning motivation but also to improve learning achievements. This approach can promote a subject into an online non-game scenario to increase students' motivation, enjoyment, and performance. Moreover, Xie et al. (2019) found that personalized data sources, including students' preferences, learning achievements, profiles, and learning logs, are the main parameters for personalized learning support systems. González-Castro et al. (2021) proposed an adaptive learning module for JavaPAL based on the item response theory (IRT) to recommend video fragments extracted from the MOOC when students fail questions. Komalawardhana et al. (2021) reported that the personalized conceptual learning and mastery learning approach could promote students' learning perceptions and achievement in general science courses for elementary students. However, there is no single e-learning system that fits all. This issue considers more suitable features to help students acquire knowledge along the personalized learning path. Scholars have suggested a practical approach for developing personalized e-learning systems that might facilitate students to predefined personalization strategies. Afterward, the system could allow teachers to combine proper parameters (i.e., information seeking a task, level of knowledge, learning goal, media preference, language preference, learning style, participation balance, progress on a charge, waiting for feedback, motivation level, navigation preference, cognitive traits) to define personalized learning according to the target of the course (Essalmi et al., 2010).

Therefore, providing proper e-learning instruction and approach that combines individual learners' characteristics (e.g., learning concept, learning style, gender, age) with educational goals has become an important and challenging issue. Each student receives a personal learning path in this learning environment and participates in an online learning system; this has been called a personalized e-learning system.

Concept-effect relationship model and its applications in STM education

Numerous computer-assisted testing and diagnosing system researchers have referred to the concept-effect relationship (CER) model as a potential theoretical basis for developing an individual learning diagnosis system. The diagnostic system based on the CER model is geared to a mechanism of causal relationships among concepts that need to be learned in a particular order, which is considered a prerequisite to understanding the target concept (Panjaburee et al., 2010). Hwang (2003) originally proposed the relationship between new and previously learned concepts and their effect on other concepts to be a key strategy for diagnosing causes of learning failure, students' conceptual learning status, and learning progression. This model offers an overall cognition of the subject contents in a hierarchical order of concepts; that is, a concept may have multiple prerequisite concepts affecting the efficient performance of related complex and higher-level concepts. At the same time, a given concept can also be a prerequisite concept of multiple concepts. According to this hierarchical order, it is easy to trace the causes of learning failure through the concepts. However, an additional procedure is required to analyze student conceptual learning status to identify poorly learned, medium-learned, and well-learned concepts for individual students, such as applying Fuzzy membership functions (Hwang, 2003). Therefore, scholars have suggested a five-step procedure for implementing the CER model. Firstly, multiple domain experts create and construct the CER for the particular learning unit covering all concepts to be learned (Hwang et al., 2013). They also work together for setting conceptual tests and weighting the degree of test item and related concepts by multiple domain experts (Panjaburee et al., 2010). The incorrect answer rate for each student in each concept will be calculated to detect a cause of learning failure. Accordingly, learning paths will be defined by starting from failure concept affecting other related concepts. Lastly, feedback and related learning material will be provided to individual students (Hwang, 2003; Hwang et al., 2008).

The researchers developed a testing and diagnostic system based on the usefulness of the CER model for an effective learning environment in many educational levels and subject areas. For example, Chu et al. (2006) presented a CER-based learning diagnosis to provide students with personalized learning suggestions by analyzing their test results and test item-related concepts to develop a testing and diagnosis system in an Internet working environment. The experimental results on a nutrition course demonstrated the feasibility of this approach in enhancing students' learning performance. Jong et al. (2007) developed a learning behavior diagnosis system for a university computer course and yielded positive experimental results for both learning status and learning achievement. In the meantime, Tseng et al. (2007) employed this model to provide helpful learning guidance for individual students in the physics course of a junior high school level. Hwang et al. (2008) reported the effectiveness of this model in improving students' learning achievements in a mathematics course of an elementary school. Hwang et al. (2013) also evaluated the effectiveness of the e-learning system based on the CER model on mathematics courses. It was found that the proposed system could help secondary school students improve their learning achievement in the computations and applications of quadratic equations topic. These findings were similar to Wongwatkit et al.'s (2017), showing that the CER model's learning diagnosis system could enhance primary school students to learn the circle area in a mathematics course. Moreover, the CER model could support the personalized e-learning systems to improve knowledge acquiring about basic computer programming for higher education (Chookaew et al., 2015; Wanichsan et al., 2021). These studies showed that the applications of the CER model had been applied widely to successfully detect students' learning problems and provide learning paths for individual students in various areas, including Natural Science, Mathematics, Physics, Electronic Engineering, and Health courses. They had studied with students at various levels, including elementary school, high school, and higher education levels. The previous studies were only concerned about learning achievement and attitudes toward the personalized e-learning systems. However, it is less understanding how the key elements of the CER model impact students' intention to use the personalized e-learning systems. Therefore, the scholars have suggested that investigation about students' perceptions of e-learning usage is worth to be studied to form the effectiveness of a technology-enhanced learning environment (Damnjanovic et al., 2015; Elbasuony et al., 2018; Komalawardhana et al., 2021).

Acceptance of technology/technology acceptance model

Technology Appetence Model (TAM) was the analysis tool to study the acceptance of technology from user behavior (Davis, 1989). That is to say, beliefs are defined as the individual's estimated probability that performing a given behavior will result in a given consequence (Teo et al., 2008). Perceived usefulness is a variable directly influencing intention to use. Understandably, a user who has a positive attitude on using any system could then show the intention to use behavior that matches the first relation. In the case of perceived usefulness, a user who focuses more on cognitive settings like getting better performance from using the system no matter what they hold a positive or negative attitude could then form behavioral intention to use it.

Many researchers have widely studied TAM in several fields, including learning that primarily focuses on influence intention factors. Cheung and Vogel (2013) applied TAM to explain the factors that influence the acceptance of Google Application for collaborative learning. Similarity to Abdullah and Ward (2016), gathering the commonly used external factors of TAM in the context of e-learning adoption and the identified effects of these factors on students' perceptions of e-learning. Moreover, TAM could support general information about the technology that the user has been developed. In specific fields, further information is needed. Therefore, technology development can be guided in the right direction (Mathieson, 1991). Komalawardhana and Panjaburee (2018) showed that the inquiry-based learning into digital game approach by investigating gender and learning style differences in perceptions, such as perceived ease of use, perceived usefulness, attitudes toward digital game use, and behavioral intention to use digital games could decrease the gap between gender (male and female) and learning style (visual and verbal) learners' perceptions. Fink (2003) reported that an online-course design is the most important factor of students' learning effectiveness. Therefore, instructors must adopt the proper pedagogical strategy and technology when designing an online learning course. From another perspective, a good interface design helps users resolve technical problems that may arise when using a system (Metros & Hedberg, 2002). The interface design will not facilitate better learning outcomes if it is not comprehensive or meets users' needs (Wang & Yang, 2005). In gender difference and age, the studies showed that the gender difference effort of perceived usefulness on intention to use is more outstanding for men than women (Sun & Zhang, 2006) and more outstanding for younger people than old ones. Another human factor, learning style, influences perceptions of ease of use, usefulness, and usage behavior of e-learning (Lu, 2012). Furthermore, previous studies found the mixed result of gender and learning style differences in perception and acceptance of technology, such as online games and mobile learning; however, various cohorts have been less studied (Komalawardhana & Panjaburee, 2018; Komalawardhana et al., 2021).

Research model and hypotheses setting

Based on the gap mentioned above in the literature on personalized e-learning systems with the applications of the concept-effect relationship model, fewer studies are attended to intention to use such systems. Moreover, the adoption of e-learning following the TAM has been used to frame this current investigation on the personalized e-learning systems based on the key elements of the concept-effect relationship applications. Therefore, this study proposed a conceptual model as presented in Fig. 1.

In this study, the learning suggestions provided by the personalized e-learning system were determined by applying the concept-effect relationship model. Answers from individual students are used to calculate the ratio of incorrect answers in each concept concerning the degree of test item and related concepts for detecting cause(s) of learning failure. When the cause of the learning problem is defined, the learning status of each concept, such as poorly learned, medium-learned, and well-learned concepts, is provided. The hierarchical order of the current concept and its prerequisite concepts is also used to generate critical learning paths for individuals. On the other hand, features include conceptual and learning preference tests, types of learning material, and interactive learning activities focused on how the students perceive their ease of use in the personalized e-learning system. The screenshot showing key elements of the personalized e-learning system based on the concept-effect relationship model is presented in Fig. 2.

The following are the hypotheses of this study:

H1 Perception of learning suggestion usefulness will be influenced by the ease of personalized e-learning usage.

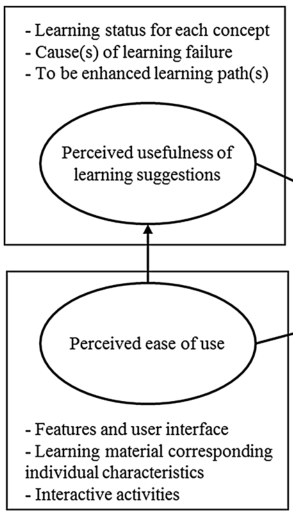

Fig. 1 Conceptual model of research

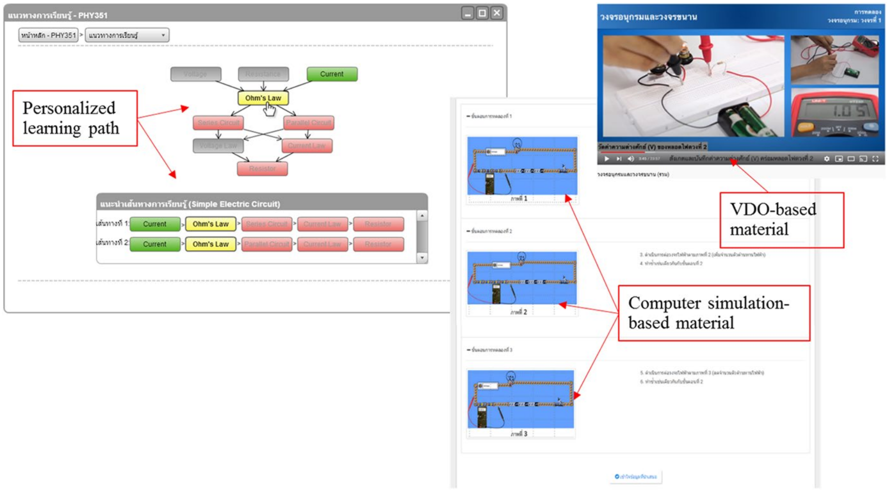

Fig. 2 Screenshots of the personalized e-learning system based on the concept-effect relationship model

H2 Attitude about the personalized e-learning system based on the concept-effect relationship model will be influenced by the perception of learning suggestion usefulness and ease of use.

H3 Students' behavior intention to use the personalized e-learning system based on the concept-effect relationship model will be affected by their attitude about the system.

Research methodology

Participants

In this study, the personalized e-learning systems based on the concept-effect relationship model were implemented in three cohorts in central Thailand. Participants are 1,175 students, including 431 primary school students, 424 secondary school students, and 320 university students during the first semester of 2020. In September 2020, the primary school students used the personalized e-learning systems based on the concept-effect relationship model as their assisted learning tool to learn a general science course on the force and motion topic. They also received the digital game as learning material while following the learning path generated by the system. At the same time, the secondary school students used the system to support their learning of a physics course on the electric circuit topic and received VDO-based demonstration and computer simulation as learning material in the system. The university students also used the system to learn a computer programming course and received text- and diagram-based presentations as learning material in the system.

This study aims to survey the three cohorts to understand their perceptions about the personalized e-learning system based on the concept-effect relationship model on their learning setting. The technology acceptance questionnaire was administered to the students. After using the personalized e-learning systems based on the concept-effect relationship model for one month, the students were asked to respond to the online questionnaire that included four different dimensions (i.e., perceived usefulness of learning suggestion, perceived ease of use, attitude, and intention to use). Their responses were assured confidentially regarding the ethical principles for human research.

Research measurement

In this study, the data were collected by online questionnaire at the end of learning activities in the personalized e-learning systems. The questionnaire was adopted from Teo's (2009) technology acceptance questionnaire and translated to the Thai language by researchers (Panjaburee & Srisawasdi, 2016). A total of 12 items with a five-point Likert rating scale ranging from 1 "strongly disagree" to 5 "strongly agree" was used to cover four constructs (three items per each dimension), including Perceived Usefulness of Learning Suggestion (PULS), Perceived Ease of Use (PEU), Attitude (ATD), and Intention to Use (ITU). PULS represents that the student beliefs using the personalized e-learning systems based on the concept-effect relationship model would help them improve knowledge of the learning unit. PEU aims to elicit the students' belief that interacting with features and participating in learning activities in the system would be easy and without effort to use. ATD aims to measure the students' positive or negative feelings when participating in the system's learning activities. ITU represents that the student would accept the personalized e-learning systems based on the concept-effect relationship model to further support their learning in the other topics. The items of the research instrument are provided in the Appendix.

Results

Descriptive statistics and internal consistency of reliability

To describe the mean and standard derivation values of questionnaire items used for each construct, the descriptive statistics of the construct for overall and each cohort are presented in Table 1. All means for overall and three cohorts are above a middle-value agreement of 3.00. All students agreed that the personalized e-learning system based on the concept-effect relationship model is useful for their learning and easy to follow learning activities in the system could trigger their positive feelings about learning with the system and assist their learning further.

Moreover, the Cronbach's α values were computed to assess the internal consistency of item reliability. Table 2 shows that the reliability of overall, primary school, secondary school, and university cohorts was highly accepted with the Cronbach's α

Table 1 The descriptive statistics of questionnaire items for the four constructs

Constructs/items	Overall		Primary school student		Secondary school students		University student	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
PULS	3.94	2.86	4.18	3.21	3.52	2.91	3.03	1.60
PULS1	4.02	1.06	4.27	1.21	3.69	1.08	4.13	0.62
PULS2	4.01	1.03	4.21	1.15	3.79	1.08	4.04	0.71
PULS3	3.92	1.05	4.06	1.19	3.61	1.04	4.09	0.74
PEU	3.95	2.37	3.96	3.16	3.82	1.71	3.00	1.82
PEU1	4.09	0.92	4.20	1.18	4.03	0.63	4.03	0.84
PEU2	3.88	1.02	3.93	1.28	3.58	0.75	4.22	0.78
PEU3	3.87	0.97	3.74	1.34	4.02	0.66	3.85	0.65
ATD	3.96	2.80	4.10	3.14	3.66	2.95	3.03	1.75
ATD1	4.01	0.99	4.12	1.20	3.92	0.94	3.98	0.67
ATD2	4.08	0.99	4.15	1.22	3.95	0.88	4.15	0.73
ATD3	3.99	0.95	4.03	1.23	3.85	0.78	4.13	0.67
ITU	3.77	2.86	3.63	3.23	3.67	2.76	3.00	2.22
ITU1	3.83	1.04	3.64	1.23	3.84	0.84	4.08	0.94
ITU2	3.88	1.06	3.57	1.23	3.92	0.94	4.26	0.80
ITU3	3.72	1.05	3.67	1.28	3.73	0.96	3.78	0.82

Table 2 The corrected item-total correlations of item reliability for the four constructs

Constructs/Items	*r*			
	Overall	Primary school student	Secondary school students	University student
PULS				
PULS1	0.73	0.76	0.82	0.58
PULS2	0.76	0.81	0.74	0.68
PULS3	0.73	0.75	0.74	0.63
PEU				
PEU1	0.70	0.73	0.68	0.74
PEU2	0.59	0.66	0.57	0.66
PEU3	0.61	0.70	0.56	0.56
ATD				
ATD1	0.74	0.74	0.84	0.58
ATD2	0.74	0.77	0.76	0.59
ATD3	0.70	0.69	0.72	0.70
ITU				
ITU1	0.69	0.70	0.72	0.73
ITU2	0.70	0.70	0.84	0.66
ITU3	0.69	0.68	0.75	0.70
Cronbach's α value	0.93	0.94	0.94	0.91

values of 0.93, 0.94, 0.94, and 0.91, respectively. The coefficients of items used in the research instrument are also presented in Table 2. The values of overall, primary school, secondary school, and university cohorts ranged from 0.59 to 0.93, 0.66 to 0.94, 0.56 to 0.94, and 0.56 to 0.91, respectively, leading to adequate reliability of the scales for overall and three cohorts in this study.

The Pearson correlation coefficients among the variables are tested and shown in Table 3. All of the variables were significantly correlated with each other for the overall, primary school, secondary school, and university cohorts and that the correlation values were all less than 0.90. These values were given to explore this study's aims and adequate item reliability.

Stepwise multiple regression for the path associated with the variables

To test the hypotheses setting, the stepwise multiple regression was performed and examined the path associated with the variables, such as perceived usefulness of learning suggestion, perceived ease of use, attitude, and intention to use, as shown in Table 4. It was found that a regression analysis for testing H1 to examine the effect of perceived ease of use (independent variable) in terms of features and user interface, learning material corresponding individual characteristics, and interactive activities of the personalized e-learning systems based on the concept-effect relationship model on the perceived usefulness of learning suggestions (dependent variable) in terms of learning status for each concept, cause(s) of learning failure, and enhanced learning path(s) of the system. The overall results revealed that the independent

Table 3 The Pearson correlation analyses among the four variables

Cohorts	Variables	PEU	ATD	ITU
Overall	Perceived usefulness of learning suggestion (PULS)	0.62**	0.74**	0.66**
	Perceived ease of use (PEU)		0.68**	0.64**
	Attitude (ATD)			0.73**
	Intention to use (ITU)			
Primary school	Perceived usefulness of learning suggestion (PULS)	0.77**	0.76**	0.70**
	Perceived ease of use (PEU)		0.79**	0.69**
	Attitude (ATD)			0.71**
	Intention to use (ITU)			
Secondary school	Perceived usefulness of learning suggestion (PULS)	0.68**	0.73**	0.71**
	Perceived ease of use (PEU)		0.66**	0.56**
	Attitude (ATD)			0.89**
	Intention to use (ITU)			
University	Perceived usefulness of learning suggestion (PULS)	0.73**	0.63**	0.69**
	Perceived ease of use (PEU)		0.68**	0.74**
	Attitude (ATD)			0.69**
	Intention to use (ITU)			

**$p < 0.01$

Table 4 The analysis of stepwise multiple regression for the three cohorts

Cohorts	Hypotheses	Variables		β	R^2	p
		Dependent	Independent			
Overall	H1	Perceived usefulness of learning suggestion	Perceived ease of use	0.62	0.388	0.000*
	H2	Attitude	Perceived usefulness of learning suggestion	0.52	0.554	0.000*
			Perceived ease of use	0.36	0.632	0.000*
	H3	Intention to use	Attitude	0.73	0.549	0.000*
Primary School	H1	Perceived usefulness of learning suggestion	Perceived ease of use	0.77	0.593	0.000*
	H2	Attitude	Perceived usefulness of learning suggestion	0.51	0.622	0.000*
			Perceived ease of use	0.37	0.677	0.000*
	H3	Intention to use	Attitude	0.71	0.508	0.000*
Secondary School	H1	Perceived usefulness of learning suggestion	Perceived ease of use	0.15	0.381	0.000*
	H2	Attitude	Perceived usefulness of learning suggestion	0.61	0.536	0.000*
			Perceived ease of use	0.32	0.626	0.000*
	H3	Intention to use	Attitude	0.89	0.783	0.000*
University	H1	Perceived usefulness of learning suggestion	Perceived ease of use	0.73	0.533	0.000*
	H2	Attitude	Perceived usefulness of learning suggestion	0.47	0.459	0.000*
			Perceived ease of use	0.29	0.498	0.000*
	H3	Intention to use	Attitude	0.31	0.558	0.000*

*$p < 0.05$

variable was predictor of the dependent variable (F(1, 1,174) = 744.718, p = 0.000, R^2 = 0.623). Similarly, the results of primary school, secondary school, and university cohorts showed that the independent variable was predictor of the dependent variable with F(1, 430) = 624.773, p = 0.000, R^2 = 0.770, F(1, 423) = 71.653, p = 0.000, R^2 = 0.381, and F(1, 319) = 363.040, p = 0.000, R^2 = 0.730, respectively. That is to say, the primary school students revealed that perceived ease of use was the biggest contributor for perceived usefulness of learning suggestions (59.30%) among the three cohorts. To test H2, a stepwise multiple regression was also performed to evaluate the effect of perceived usefulness of learning suggestions and perceived ease of use on attitude. The overall results revealed that the two independent variables were predictor of the dependent variable (F(1, 1,174) = 1006.957, p = 0.000, R^2 = 0.795). Similarly, the results of primary school, secondary school, and university cohorts showed that the two independent variables were predictor of the dependent variable with F(1, 430) = 448.618, p = 0.000, R^2 = 0.823, F(1, 423) = 353.044, p = 0.000, R^2 = 0.791, and F(1, 319) = 157.179, p = 0.000, R^2 = 0.706, respectively. That is to say, the primary school students revealed that perceived ease of use was the biggest contributor for attitude (67.70%) among the three cohorts. Moreover, to test H3, a stepwise multiple regression was performed to evaluate the effect of attitude on intention to use. The overall results revealed that the independent variable was predictor of the dependent variable (F(1, 1,174) = 1377.388, p = 0.000, R^2 = 0.735). Similarly, the results of primary school, secondary school, and university cohorts showed that the independent variable was predictor of the dependent variable with F(1, 430) = 443.337, p = 0.000, R^2 = 0.713, F(1, 423) = 1526.385, p = 0.000, R^2 = 0.885, and F(1, 319) = 143.421, p = 0.000, R^2 = 0.558, respectively. That is to say, the secondary school students revealed that attitude was the biggest contributor for intention to use (78.30%) among the three cohorts.

Discussion

Regarding the descriptive statistical analysis in Table 1, the overall students showed an agreement of perceived usefulness of learning suggestions (M = 3.94), perceived ease of use (M = 3.95), positive attitude (M = 3.96), and intention to use (M = 3.77) the personalized e-learning system based on the concept-effect relationship model. In particular, the primary school students were slightly much-perceived usefulness of learning suggestions (M = 4.19), perceived ease of use (M = 3.96), and positive attitude (M = 4.10) and the secondary school students were slightly much intention to using the personalized e-learning system than other two cohorts. These results deliver a message that the personalized e-learning system based on the concept-effect relationship model is a potential technology-enhanced learning tool for students' cognitive domain. In other words, primary and secondary school levels served as school-based personalized e-learning systems are another potential effect for university settings. Table 2 also reveals that university students only have a middle-level-positive perception of the personalized e-learning system based on the concept-effect relationship model, from perceived usefulness of learning suggestions (M = 3.03) to perceived ease of use (M = 3.00). Although most students perceived that the system is useful in showing conceptual learning status, detecting the cause of learning failure, and providing corresponding learning paths for enhancing learning performance, university students are concerned with system interactivity. While using the personalized e-learning system based on the concept-effect relationship model, university students indicated they needed more communicative features/functions, interactive corresponding learning materials, and systematic learning activities. These results are in line with previous studies. For example, Greenwald et al. (2017) proposed using an immersive virtual reality environment to ease collaborative learning. It provides students to interact with each other within the learning activities. Moreover, the report shows that the perceived level of personalization ignites connectedness with an adult in school or supports cognitive and affective education needs. It generates a positive link to a standardized test score in high school students (McClure et al., 2010). Likewise, an instructional could be integrated real-time techniques that provide close and specific to individual contexts and learning experience, including communication (Xie et al., 2019).

Regarding the hypothesis testing by performing a stepwise multiple regression analysis, Table 4 shows that the perceived ease of use significantly affected students' perceived usefulness of learning suggestions (H1) provided by the personalized e-learning system based on the concept-effect relationship model, remarkably, most effective for the primary school cohort. The result indicated that transforming Science content to a digital game-based platform is more interactive and attractive when they follow the learning path generated by the personalized e-learning system based on the concept-effect relationship model. These results comply with Srisawasdi and Panjaburee (2014) who implemented personalized technological learning based on the concept-effect model to provide personalized guidance to improve their achievement, enhancing their conceptual understanding. Additionally, the best predictor of perceived usefulness of the e-portfolio is perceived ease of use that followed by joy (Abdullah et al., 2016). Moreover, perceived ease of use was the bigger predictor that fostered attitude (H2) toward the personalized e-learning system based on the concept-effect relationship model than the perceived usefulness of learning suggestions. At the same time, the perceived usefulness of learning suggestions was also a significant factor influencing personalized e-learning attitude (H2). Interestingly, the primary school cohort has perceived ease of use as the better predictor that promoted personalized e-learning than secondary school and university cohorts. It indicates that the students enjoyed learning activities as digital games along the learning path, leading to a much more positive attitude about the personalized e-learning system than with VDO-based demonstration and computer simulation or text- and diagram-based presentation. Besides, the different learning styles also indicated the other points of view. For instance, Huang et al. (2012) showed that the application includes ubiquitous technology, and video clips could motivate students to learn on the system. By the way, active students care about the perceived usefulness of the system than passive students who care more about perceived ease of use. As in the remedial calculus course, that attitude toward use significantly affects perceived usefulness and intention to use, indicating that perceived usefulness primarily concerned students' behavioral intention to use through attitude toward use (Chen & Wu, 2020). Table 4 also reveals that personalized e-learning attitude influences more intention to use (H3) for secondary school students than primary school and university students. This result indicates that varied learning materials as VDO-based demonstration and computer simulation as a cognitive tool for presenting learning content in the personalized learning path are crucial for accepting the personalized e-learning system based on the concept-effect relationship model among the three cohorts. The impact of using material based on personalized learning could rely on learner preference, interests, or cultural background, according to the integrating ICT into the remedial course that provides different types of learning resources, for instance, exercises, videos, and instruction software. Therefore, it gives a chance for students to inquire from the source that they prefer. Moreover, students are allowed to attend to their tasks using these materials. This circumstance enables students to construct the concept meaningfully (Chen & Wu, 2020).

Conclusion for promising instructional design of personalized e-learning based on a concept-effect relationship model

Students' characteristics, especially conceptual learning problems, have been recognized by scholars for forcing institutions to establish new ways to improve e-learning system quality (Chatti et al., 2010; El-Bishouty et al., 2010; Panjaburee et al., 2010; Spector, 2013). The personalized e-learning system based on concept-oriented research and practice, as applications of the concept-effect relationship model, has been increasingly used by scholars devoted to the entire e-learning system to enhance learning performance in a particular subject content of students from primary school to university levels. That is to say, most efforts have emphasized system development and implementation for support learning achievement and attitude and less-examined factors influencing usage of the personalized e-learning system based on the concept-effect relationship model. Those factors might impact perceptions and reactions toward this system from all levels of students and contribute to system developers and instructional designers to improve technology-delivered pedagogy. The major findings and contributions of the current study are in line with suggestions from scholars that the perception impacts can serve as a guide for future studies on how to design personalized e-learning systems better to remedy related conceptual learning problems and enhance students' learning experiences (Kabudi et al., 2021). Therefore, based on the case studies of the personalized e-learning system based on the concept-effect relationship model of primary school, secondary school, and university cohorts, this study applied that Technology Acceptance Model's (TAM) Davis (1989) to set a conceptual model for investigating the usefulness of learning suggestions in terms of learning status for each concept, cause(s) of learning failure, and enhanced learning path(s) of the system, ease of use in terms of features and user interface, learning material corresponding individual characteristics and interactive activities, attitude, and intention among the three cohorts, as shown in Fig. 1. The stepwise multiple regression was performed to test the hypotheses setting in this study and shows that various and attractive interfaces of learning materials corresponding to conceptual learning problems will significantly affect the perceived usefulness of learning suggestions provided by the personalized e-learning system based on the concept-effect relationship model. The perceived usefulness of learning suggestions and perceived ease of use will significantly affect students' attitudes, leading to their intention for using the personalized e-learning system based on the concept-effect relationship model. Furthermore, there was a significantly high correlation ($r=0.89$) between secondary school students' intention to participate in the personalized e-learning system based on the concept-effect relationship model and system attitude and a less correlation ($r=0.69$) for university students in this regard. Figure 3 also presents a summary of the significant relationships between the variables.

The above results led this study to propose a personalized e-learning-delivered instructional design in future work, taking more communicative features/functions, interactive corresponding learning materials, and systematic learning activities into account. According to Sadler (1989), formative assessment is used for creating an ongoing process of shaping the students' learning and improving their understandings and competencies. In addition, the use of formative assessment in both primary and higher education is also increasing. The formative assessment aims to enhance knowledge building in informal learning settings and gather valuable data for instructional adjustments through context-aware adaptations. Currently, embedding a formative assessment approach into personalized online-based learning is proposed as a mechanical part to guide the process of teaching and learning. Scholars have been seeking an effective way to integrate the formative assessment into the e-learning environment to adopt e-learning. In this case, the personalized learning system is expected to provide each student with the feeling that the teaching and learning environment are designed specifically to meet his/her expectations and capacities employing formative assessment (Benhamdi et al., 2017; El Faddouli

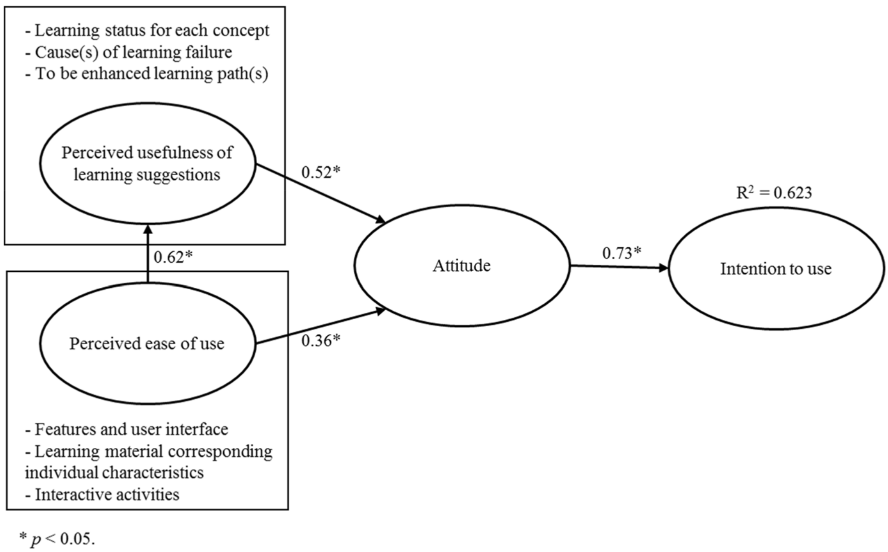

Fig. 3 The summary results of research hypotheses

et al., 2011; Hung et al., 2010; Laksitowening & Hasibuan, 2016; Raman & Nedungadi, 2010; Srivastava & Haider, 2020).

At the same time, the self-regulated learning strategy refers to students' abilities to master learning by their process. Therefore, it includes both cognitive and emotional parts that affect the learning process. It is to say that students master with confidence, diligence, and resourcefulness. In addition, they could be more aware when they know and unknown the fact (Zimmerman, 1990). With this point, students could then display their method or effort to enhance their learning under control and uncontrol situations (Zimmerman, 2015). Self-regulated learning strategies mean the process or action that obtains the skill and information involved. That self-regulated learning is that individual learning and motivating independently. Up to this point, the briefly of self-regulated relies on three aspects: unique self-regulated learning strategies, responsiveness to self-oriented feedback about learning effectiveness, and independent motivational processes (Zimmerman, 1990). Previous studies examined self-regulated learning as an event that happens through learning time, especially when performing a problem-solving activity (Winne, 2015). With this point, students' dynamic (i.e., tracking, collecting, process pattern, analysis) in self-regulated behavior is engaging. Schmid and Petko (2019) supported the idea of using digital technologies for learning and problem-solving. It is, therefore, pointed that using digital technologies like the open learning environment has a positive effect on self-reported skill and self-perceived understanding. As in the case study of Zheng et al. (2019), they used computer-supported collaborative learning to complete STEM tasks which shows an engagement in executing, self-monitoring, and socially sharing.

With the significance of the current findings, this study proposes a conceptual framework for integrating formative assessment and self-regulated learning strategy in the personalized e-learning system based on the concept-effect

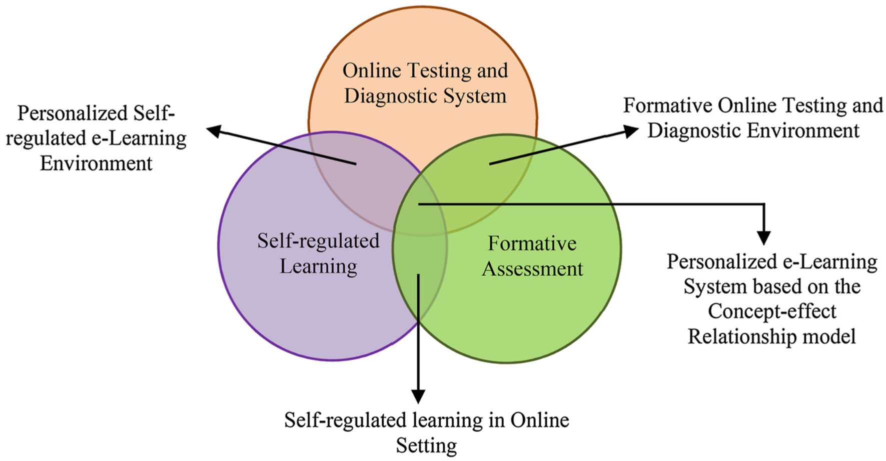

Fig. 4 A conceptual framework for an enhanced personalized e-learning system based on the concept-effect relationship model

relationship model among generalized cohorts. Figure 4 shows the learning environment for a practical personalized e-learning system based on the concept-effect relationship model. This framework could be represented as an arrangement among online testing and diagnostic systems, self-regulated learning, and formative assessment.

This conceptual framework represents three fundamental components: (1) online testing and diagnostic system; (2) self-regulated learning; and (3) formative assessment. This framework also proposes the combination of these three fundamental components, resulting in four additional types of technology-delivered pedagogical design, as follows:

(1) Personalized self-regulated e-learning environment is a state-of-the-art combination of online testing and diagnostic systems and a self-regulated learning strategy. It is used to diagnose learning problems for students according to their test answers by following the applications of the concept-effect relationship model and then supporting individuals' learning with the user interfaces of a self-regulated learning system to attempt to support their learning systematically.
(2) Formative online testing and diagnostic environment are a state-of-the-art combination of online testing and diagnostic system and online formative assessment mechanism for engaging students in rigorous self-assessment of their understanding and then diagnosing their learning problems according to their test answers and provides learning guidance to individuals by following the applications of the concept-effect relationship model
(3) Self-regulated learning in an online setting is a state-of-the-art combination of constructivist web-based learning environment self-regulated learning strategy and online formative assessment mechanism for engaging students in rigorous self-assessment of their understanding and then provide feedback to students on their level of understanding and support them with the user interfaces of self-regulated learning system to attempt to support their learning systematically.
(4) Personalized e-learning system based on the concept-effect relationship model is a state-of-the-art integrative connection among online testing and diagnostic system, self-regulated learning strategy, and formative assessment mechanism for diagnosing learning problems for individual students according to their test answers and provides learning guidance to each student by following the applications of the concept-effect relationship model, and then guides to follow the remedial learning path with the user interfaces of the self-regulated learning system, where installs various media of learning materials. To support their conceptual learning, they continuously engage in rigorous self-assessment of their conceptual understanding and then provide feedback and select particular learning experiences for students based on their understanding of the key concepts associated with each learning activity.

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Appendix

Items of research instrument.

Perceived Usefulness of Learning Suggestion (PULS)

PULS1: This learning system would be helpful for me to identify my knowledge gaps or learning needs.

PULS2: The learning system would be helpful for me to construct knowledge in my learning context

PULS3: Using this learning system would enhance effectiveness in my activity-related learning.

Perceived Ease of Use (PEU)

PEU1: My interaction with this learning system is clear and understandable.

PEU2: I find it easy to get the learning system to do what I want.

PEU3: I find the learning system easy to use.

Attitude (ATD)

ATD1: Learning system make learning activities more enjoyable.

ATD2: I like to follow activities provided by the learning system.

ATD3: I am satisfied with using this learning system as a learning-assisted tool.

Intention to Use (ITU)

ITU1: I will use the learning system to support my learning in the future.

ITU2: I will use the content provided by the learning system to assist my learning.

ITU3: I plan to use the learning system often.

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