An Integrated Theoretical Investigation of Healthcare Students' Perceived Compatibility Using Online Learning Systems on Their Learning Performance

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Abstract

Online learning systems (OLSs) have been widely implemented in higher education settings to facilitate teaching and learning effectiveness. Prior studies have investigated the key success factors of OLSs, and the OLS adoption rate remains one of the essential issues. This study developed a comprehensive theoretical model to understand students' OLS adoption. From an integrated perspective of individuals, environment/technology, and behavior, this study also examined the constructs of compatibility, personal innovativeness, convenience, perceived usefulness, continued intention, and healthcare students' learning performance in OLS use contexts. We found that personal innovativeness, convenience, and perceived usefulness were the key determinants of students' learning performance and adoption of OLSs. Additionally, perceived usefulness was the critical mediator between the influences of personal and environmental factors and students' learning performance.

Keywords: Compatibility, Personal innovativeness, Convenience, Perceived usefulness, Learning performance

1 Introduction

The proportions of the population in Taiwan that have aged 65 and over are among the highest countries and regions globally and are increasing over time. These phenomena have thus created important healthcare issues. Higher education institutions have put significant efforts into promoting and improving healthcare education programs to help handle the healthcare burdens of healthcare institutions caused by population aging. However, the expertise required to be competent healthcare specialists, is difficult to learn through regular learning procedures because it involves developing high-order thinking abilities of healthcare students. The learning processes enabled by digital technologies can provide learners with richer and more up-to-date learning materials than traditional lecture-centered learning activities in classroom settings. Therefore, healthcare education programs in higher education institutions constantly adopt online learning systems (OLSs) to enhance their students' learning effectiveness [1-2].

OLSs make learning more usable and more comfortable, and students can access OLSs via digital technology wherever and whenever they want. OLSs offer diverse forms of learning materials and more opportunities for convenient interactions, making learning more flexible to students; accordingly, they have been widely implemented in higher education institutions. Nowadays, learning technologies are being rapidly developed and applied to various fields, with compatibility and convenience being the critical factors. It can be inferred that information technology and online courses change students' learning styles or strategies and facilitate active learning. Consequently, many universities use OLSs to improve student learning performance have conducted significant modifications in their strategies of delivering online courses because of the high dropout rates of those courses [3-5].

Eliminating technological barriers and increasing new forms of learning are critical factors for effective healthcare education learning [6]. Identifying the key factors and examining their effects is essential for developing an adequate understanding of the design and implementation of OLSs in online learning experiences. When used effectively, OLSs could offer further insight for developers of OLSs into the development of guidelines that enable the design, user-friendly, and delivery of high-quality OLSs. OLSs should include effective online mechanisms for students to obtain specific feedback on learning outcomes or for the instructor to assess students' learning performance [7].

Social cognitive theory (SCT) [8] may be appropriate and has applied in a variety of educational settings, including mass media, private and public institutions, and cloud computing; there have been only a handful of prior studies [9-10] have devoted efforts to

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developing an advanced understanding of online learning in higher education settings based on SCT. Since the causal relationships among personal and environmental factors can significantly shape human behaviors, the adoption of SCT to investigate students' behavioral intentions regarding the use of OLSs enables researchers to develop a holistic understanding of the causes and consequences of adopting OLSs.

Based on the model proposed by SCT, we integrated the theory of planned behavior (TPB) and innovation diffusion theory (IDT) to develop a comprehensive research model that describes the relationships among personal factors (personal innovativeness), environmental/ technological factors (compatibility, convenience, and perceived usefulness), and students' learning performance and continued intention using OLSs in healthcare education settings. The research questions (RQ) of this study are as follows:

RQ1: Do personal innovativeness, compatibility, and convenience positively affect students' perceived usefulness, and in turn, influencing their learning behaviors?

RQ2: Does students' perceived usefulness mediates the relationship between compatibility and learning performance?

2 Research Background and Theoretical Development

Online learning can help students achieve better learning performance than those who learn via the conventional approach in a classroom [11-12]. In the existing literature, various terms have often been used to denote online learning, such as distance learning, m-learning, web-based learning, and e-learning. This study uses the term "online learning system (OLS)" to denote these digital technology-supported learning systems, such as e-learning systems, web-based learning systems, and learning management systems, avoiding confusion. OLSs can provide students with a plentiful amount of critical learning materials and convenient accessed to other sources of learning materials, such as professional online databases/ networks, that are organized in various formats and are accessible at anytime and can facilitate effective communication among the students to enable the development of their professional competence. Enhancing students' competence in applying their professional cognitive reasoning and critical-thinking skills to practical problems promptly are among the top priorities of adopting online teaching and learning in higher education [13-14].

SCT essentially involves comprehending various individual behaviors from three perspectives: person, behavior, and environment. To be specific, SCT argues that individual behaviors tend to be shaped and moderated either by environmental/contextual factors or by the self-perceptions of the individuals involved [15-16]. Additionally, SCT explains human behaviors in terms of reciprocal interaction, in which behavior, personal/cognitive factors, and environmental factors operate as interacting determinants [15, 17]. Based on SCT, personal behaviors are influenced and shaped by the variations of personal/cognitive factors and the conditions of the associated social environments/ networks [15].

In previous studies, various theories and constructs have been proposed to explore students' adoption of OLSs from the students' perspectives in education settings [9]. These theories include the technology acceptance model (TAM) and its extension (TAM2), the unified theory of acceptance and use of technology, the theory of reasoned action, the decomposed theory of planned behavior, and the IDT [18-19]. Bandura [8] developed the SCT, which is the most widely used method for measuring users' behavior of information technology/system and is commonly applied various empirical studies [20]. Nevertheless, we observed that an integrated theoretical model for the students' learning performance of OLSs in healthcare educational contexts is absent in the existing literature.

To identify the key personal and environmental/ technological factors regarding adopting an OLS, we incorporated the IDT [21] and TPB [22] to develop an integrated theoretical model to investigate students' learning performance based on the framework proposed by SCT. Additionally, previous studies have widely used the TPB to explain information technology's adoption [5]. TPB incorporates three core factors: attitude, subjective norms, and perceived behavioral control, and emphasizes that all individuals' attitudes can reflect their behavior tendency and behavior. Subjective norms can affect one's behavior and perceived behavioral control. This study first adopted attitude-induced factors, compatibility to evaluate whether the OLSs match the students' current utility values, needs, and perceived usefulness (as the appraisal of useful beliefs) to explore student differences in using OLSs. Previous study reveals that attitude is one of the main factors affecting students' learning performance or technology acceptance [20]. Additionally, to consider the concept of perceived behavioral control, we adopted the factor of convenience to assess the degree of student-perceived ease of use regarding the OLSs.

Moreover, IDT, which is grounded in the perspective of sociology, is a useful model for understanding the process by which the use of innovations spread within and between social systems [21]. Agarwal and Prasad [23] pointed out that personal innovativeness must be integrated into research models to measure educational innovation, an efficient way to analyze the users' critical factors. Additionally, prior studies indicated that well-designed

OLSs that are convenient to use and have high levels of compatibility with users' utility values and needs could generate the relationship between user beliefs and learning outcomes [2]. Therefore, based on IDT, this study investigated the impact of compatibility, convenience, and personal innovativeness on the behavior of OLS users in an online learning environment.

3 Development of the Research Model and Hypotheses

To contribute to the prior OLS literature, this study proposed a multidimensional research model consisting of six constructs, including personal innovativeness, compatibility, convenience, perceived usefulness, continued intention, and learning performance (see Figure 1) to explore students' learning experiences of OLSs in healthcare educational settings.

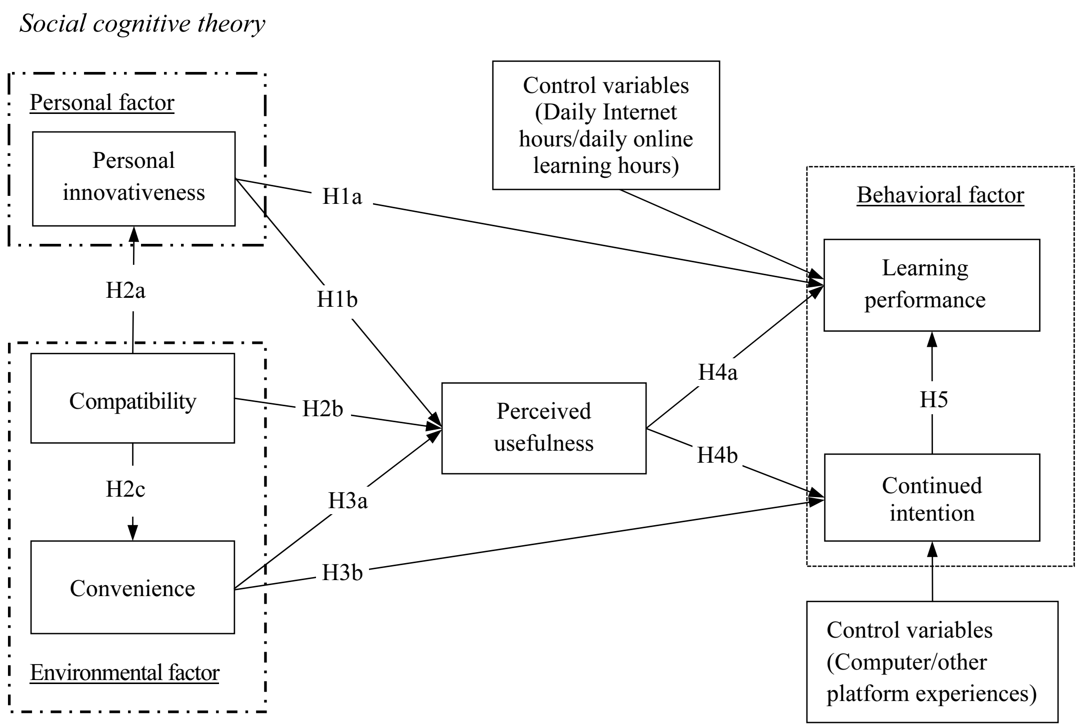


Figure 1. A multidimensional research model adapted SCT, TPB and IDT

3.1 Personal Dimension

The construct of personal innovativeness has been described as an individual's inherent tendency to seek challenges, novelties, and new learning opportunities. Because of the variety of the types of professional expertise that healthcare students are required to learn. The use of an OLS can provide students with a broad range of knowledge to enhance their professional cognitive reasoning and critical-thinking skills to satisfy their diverse learning needs than traditional lecture-based learning activities. In this case, students are more likely to engage in innovate learning contexts that stimulate their beliefs and thus affect learning performance [24]. Indeed, innovativeness is affected by personal experiences, which also influence an individual's technological beliefs, and can lead to better learning performance [25]. Accordingly, the following hypothesis is proposed:

H1a. Personal innovativeness has a positive effect on students' learning performance.

Innovative students are more willing to incorporate new learning technologies into their learning process, and thus simultaneously develop their professional competencies and practices in responding to the uncertainty situations. If the functions of an OLS (e.g., offering convenient accesses to various online professional databases/networks) are stable and meet the current requirements of innovative students. They will then perceive more utility values of OLSs to support their learning tasks in a fast-paced and complex environment. Many studies have verified that personal innovativeness can significantly affect perceived usefulness [26-28]. Accordingly, the following hypothesis is developed:

H1b. Personal innovativeness has a positive effect on perceived usefulness.

3.2 Environmental/Technological Dimension

Compatibility involves the OLS users' evaluation of the degree to which an OLS innovation is consistent with their learning processes, experiences, and existing utility values [29]. When an OLS can provide functions (e.g., creating 3D visual images and convenient accesses to or useful information of other online/offline learning resources), enabling a high level of personalization, this kind of OLS use might be compatible with the learners' utility needs and values. A previous study indicated that compatibility is consistently associated with innovation adoption [23]. Parasuraman [30] argued that early adopters are likely to accept new technology because they tend to possess a high level of technology readiness (e.g., optimism, innovativeness, discomfort, and security) than others. Because the concept of compatibility is similar to that of technology readiness [31], it can thus be inferred that an OLS possesses a high level of compatibility with healthcare students' needs. They can have more confidence in the OLS's effectiveness and are more likely to readily accept the OLS as a result of the enhanced personal innovativeness. Accordingly, the following hypothesis is developed:

H2a. Compatibility has a positive effect on personal innovativeness.

When an OLS is compatible with a student's skills, utility values, and accessible learning styles, the students will perceive that they can put less effort into completing academic tasks, focus on what they want to achieve, and learn more effectively. If students regarded OLSs as compatible with their professional learning activities, they would perceive the OLSs' usefulness [29]. Currently, making system-related learning tools compatible with students' learning patterns and needs (e.g., large storage capacity and easy access) is an essential factor in ensuring the learning process's effectiveness. The OLSs can be conveniently used anywhere and downloaded anytime from websites for supporting the learning process of healthcare students [32]. They can then thus personalize their learning tools for accomplishing learning tasks; for instance, by adding personal annotations and highlighting important 3D visual images or sentences [33]. Consequently, when online tools are compatible with individuals' lifestyles and experiences, users perceive those tools' convenience [34]. Accordingly, the following hypotheses are proposed:

H2b. Compatibility has a positive effect on perceived usefulness.

H2c. Compatibility has a positive effect on convenience.

Prior research stated that five characteristics are critical determinants for the OLS's continued intention, such as time, place, usage, execution, and obtainment [35]. These characteristics enable students to access learning courses with saving time and effort. Research indicated that convenience could directly and positively affect perceived usefulness and continued intention toward using an OLS in the mobile English learning context [36]. An OLS needs to provide convenience with easy access to content in a learning content database and provide independence from time and place constraints. Furthermore, convenience is tangible support in the online learning area, and students' perceived convenience for the OLS can positively affect their perceived usefulness and behavioral intention [34, 37]. Accordingly, the following hypotheses are developed:

H3a. Convenience has a positive effect on perceived usefulness.

H3b. Convenience has a positive effect on students' continued intention.

Perceived usefulness refers to an individual who believes that a specific technology can improve their performance or work productivity in a given task [22, 38]. When students perceive that new OLSs have a high level of usefulness, their learning experiences would positively enhance their beliefs. Since OLSs are likely to help learners reach their learning goals and learning performance would, in turn, be positively affected [39]. Therefore, the following hypothesis is proposed:

H4a. Perceived usefulness has a positive effect on students' learning performance.

Perceived usefulness is an antecedent of continued intention and is commonly mentioned in prior studies [10]. It is also a strong predictor for new technology acceptance compared to other variables. Research showed that perceived usefulness directly impacts continued intention using an OLS [39-41]. This study expects that healthcare students' perceived usefulness for the OLSs would be affected by their perceived benefits. For example, a high-quality and well-designed user-friendly interface of OLS allows students to access course content or materials and participate in learning activities at a location of their preference or anytime, enhancing their continued intention using the OLSs [18-19]. Accordingly, the following hypothesis is proposed:

H4b. Perceived usefulness has a positive effect on students' continued intention.

3.3 Behavioral Dimension

If an OLS meets students' requirements, they would likely use an OLS as one of the learning tools for their learning tasks and improve their learning performance [42-43]. The use of learning technology provides a flexible learning process that extends in-class learning and deepens learning [44]. It is feasible to generate benefits for students, such as a change in learning status or pattern (time or effort saving, interaction quality, and learning performance) or an expectation of performance/feedback [17]. Specifically, a learning process can be used to achieve a specific learning outcome [2], which is characterized as a measure of the continued intention to use learning technologies [43].

Accordingly, the following hypothesis is proposed:

H5. Students' continued intention has a positive effect on their learning performance.

4 Methodology

4.1 Participants and Procedures

In this study, the data were collected using an online survey by Google Forms, which was analyzed to validate the proposed model shown in Figure 1. The participants were recruited from two universities, one medical and the other pharmacology. The survey goal was to invite healthcare students who had experience enrolling in online courses to participate in this study. These online courses include face-to-face lectures, asynchronous online course sessions, traditional assessment measures, and other tools (e.g., Q & A forum, messages, or discussions) supported by the OLSs.

Several procedures were used to assess the participants' experience of enrolling in online courses before questionnaires were distributed to the healthcare students taking online courses. First, using the principles of semi-structured interviews, the instructors were interviewed better to understand the online course context regarding online education quality. Second, a pilot test of our questionnaire conducted with 42 healthcare students was conducted to examine the instruments' reliability and validity. Third, invitation letters were sent to the instructors of some online courses to acquire their permission to allow us to recruit students in their classes to participate in this study as our survey respondents. Eventually, instructors of six online courses (with approximately 300 enrolled students) agreed to participate in this study and provide us with the grades of the midterm and final exams of the students who agreed to participate in this study. The six courses were related to optometry, biostatistics, healthcare, and medical computer applications. We distributed our questionnaire via the Google Form service. We asked the participants to provide their student ID and fill out the questionnaire based on their experience in one particular online course to eliminate duplicate responses. Finally, we identified and excluded the responses from students who failed to report crucial demographic information or did not take the midterm exam and/or final exam.

At the beginning of the questionnaire, short instructions were given to request the participants answering the survey questions based on their experience of enrolling in online learning with an OLS. All participants' responses were anonymous, and they voluntarily responded to this survey, and can withdraw at any time. Ethical approval for this study was obtained from NCKU University Human Research Ethics Committee (HREC-109-088-2).

Of the 169 (56.33% response rate) questionnaires received, 25 problematic or incomplete questionnaires were removed, yielding 144 valid questionnaires with an overall response rate of 46.67%. The sample comprised 61.81% females and 38.19% males. The participants' average age was 19.51 years (standard deviation = 0.68), with a range of 19 to 23 years old. Of the participants, 12.5% spent less than two hours, 45.83% spent 2-5 hours, 25.0% spent 5-8 hours, 11.11% spent 8-10 hours, and 5.56% spent more than 10 hours per day online (DOH). Additionally, 74.31% spent less than two hours, 19.44% spent 2-5 hours, 4.17% spent 5-8 hours, 1.39% spent 8-10 hours, and 0.69% spent more than 10 hours per day on online courses (DIH). Therefore, it can be inferred that most of the participants had experience with computers/internet, which indicated that they had the necessary skills for learning and using OLSs. Moreover, 27.28% of the participants had experience using other online learning platforms (OPs). Additionally, 7.64% of the participants had experience using internet/computer-based applications (IAEs), such as Google DOC, instant messaging services, emails, and other internet-based applications, to support their learning during the progress of online courses.

In this study, we were interested in the relationship between independent variables and the dependent variable. Previous studies recommended that students' demographic information be controlled to avoid their potential influence on continued intention and learning performance [45-47]. Therefore, the questionnaire covered DOH, DIH, IAEs, and OP in demographic information to obtain students' profile data and control them in the research model.

4.2 Instruments

The instruments of the proposed research model were adapted from the previous literature. The wording of all questions was slightly modified to fit the specific context of this study. The personal innovativeness construct was measured using three-item scales adapted from Agarwal and Prasad [23]. The construct of compatibility was measured using three-item scales taken from Lai and Chang [34]. The questions for measuring convenience were assessed via four questions from Chang et al. [36]. The perceived usefulness construct was determined via three questions extracted from Davis, Bagozzi, and Warshaw [48]. The continued intention construct was measured three-item scales adapted from Wang and Wang [49]. Finally, the students' midterm exam and final exam scores evaluated the construct of learning performance. To avoid content overlapping between items, we invited two scholars, who major in the field of online learning and education, to examine the questionnaire's clarity (its logical consistency, contextual relevance, and ease of understanding). Likewise, to ensure the questionnaire items' internal consistency and reliability, five of the 23 questions were removed from the original questionnaire based on the procedures of the confirmatory factor analysis (CFA) and the mentioned above procedures. All questions were measured using a five-point Likert scale ranging from (1) strongly disagree to (5) strongly agree, except the construct of learning performance. The scores of students' midterm exam and final exam were measured from 0 to 100 score. All survey items are listed in Table 1.

Table 1. Survey items and factor loading

Construct	Items	Factor loading
Personal innovativeness	If I heard about a new online learning course, I would look for a way to gain experience with it.	0.74
	Among my peers, I am usually the first to try out a new online learning course.	0.92
	I like to experiment with a new online learning course.	0.91
Compatibility	Using OLSs provided by the school for my learning is more suitable for my learning style.	0.83
	Using OLSs provided by the school is more suitable for my lifestyle.	0.93
	The learning format of OLSs provided by the school meets my learning needs very well.	0.91
Convenience	I can perform my learning anywhere via the OLSs.	0.83
	Using OLSs is convenient for me to engage in my learning.	0.87
	I feel that OLSs are convenient for me to accomplish my learning.	0.81
	I can perform my learning at any time via the OLSs.	0.85
Perceived usefulness	Using OLSs improves my learning performance.	0.86
	Using OLSs enhances my learning efficiency	0.90
	Using OLSs can help me increase my learning effectiveness.	0.87
Continued intention	I intend to use OLSs to perform my learning activities and communicate with my classmates.	0.94
	I will use OLSs to perform different learning-related activities.	0.96
	I intend to increase my use of OLSs in the future.	0.94
Learning performance	The midterm examination score of your in this course:	0.89
	The final examination score of your in this course:	0.91

Note. All factor loadings are significant at 0.001 level.

A pilot test of the 23 survey items was conducted using a convenience sample of 42 healthcare students. The results revealed that the Cronbach's alpha statistics of the constructs investigated, ranging from 0.8 to 0.86, were higher than the recommended level of 0.7. Additionally, the values of Kaiser-Meyer-Olkin were all greater than the recommended level of 0.5 (ranging from 0.67 to 0.77). Additionally, the results of Bartlett's tests of all the constructs in our research model were significant ($p < 0.001$), indicating that there existed significant intercorrelation among constructs in our research model. Finally, the percent of variance explained by all the constructs ranged from 68.27% to 78.85%, indicating an acceptable explanatory power level. Overall, the above results indicated that these items had adequate reliability and validity levels and could be used in our main data collection process.

4.3 Data Analysis Method

To avoid spurious effects, we integrated the four variables (internet experience, daily online learning hours, daily internet hours, and experience with other online learning platforms) into this proposed model as control variables. Similarly, to avoid common method variance (CMV) affecting our proposed hypotheses, certain procedures, such as hiding the meaning of the constructs, anonymizing all survey responses, and gathering data from different respondent groups, were deployed. Moreover, we tested CMV using Harman's one-factor analysis [50], which showed that the total variance explained was 45.14%. Therefore, the results suggested that CMV is absent from this study.

To understand the effects of the multiple relationships between the independent, mediating, and dependent variables in our proposed model, partial least squares structural equation modeling (PLS-SEM) was used for the data analysis. We employed PLS-SEM because it is appropriately used when the working data is non-normal and small or concerns theoretical discussions and simulations. It is also a component-based SEM method that transforms non-normal data following the central limit theorem [51]. First, we used both the Kolmogorov-Smirnov test ($p < 0.000$) and the Shapiro-Wilk test ($p < 0.000$) to test the survey sample. The results showed a non-normal distribution, thereby significantly suggesting PLS-SEM can be considered to test the proposed hypotheses, as opposed to the covariance-based SEM (CB-SEM) method for this study. Then, the overall model fit, reliability, and validity of this model must be examined, for which CFA assessed the measurement model. Finally, the t-values regarding the structural model's path coefficients were determined using the bootstrapping method, which was fixed at 5000, as recommended in a previous study.

5 Results

5.1 Measurement Model

As previously recommended, each construct used three or more indicators to increase the internal consistency of these measures and address its concept, except for the learning performance construct which had only two indicators. The individual Cronbach's alpha coefficients were tested first, all of which were greater than 0.7 (ranged from 0.75 to 0.94). Fornell and Lacker [52] have noted that first-order reflective constructs were assessed in terms of convergent and discriminant validity. Convergent validity can be evaluated by three measures: (a) the criteria of average variance extracted (AVE) values are greater than 0.5; (b) the criteria of composite reliability (CR) values are greater than 0.7; and (c) the criteria of factor loading values which should be greater than 0.7. Table 1 shows that all factor loadings ranged from 0.74 to 0.96, which were all significant and higher than 0.7. The CR values ranged from 0.89 to 0.96, which were all larger than 0.7; meanwhile, the AVE values ranged from 0.69 to 0.89, which also all were higher than 0.5. In addition, the discriminant validity can be checked by Heterotrait-Monotrait ratios, which is a statistical test based on the bootstrapping procedure. The ratios must be lower than 0.90 [53] and the confidence interval of bootstrapping should not include the value 1 [54]. When the criterion is satisfied for each construct, and the discriminant validity is supported. Therefore, all constructs had adequate convergent validity and the discriminant validity of the measures was adequately demonstrated (see Table 2).

Table 2. Descriptive statistics, correlations, HTMT, AVE, Cronbach's alpha, and CR

	Mean	SD	1	2	3	4	5	6
1. Personal innovativeness	3.64	0.62	0.74					
2. Compatibility	3.68	0.57	0.32 (0.67)	0.79				
3. Convenience	3.58	0.55	0.27 (0.62)	0.57 (0.85)	0.70			
4. Perceived usefulness	3.78	0.62	0.27 (0.60)	0.26 (0.58)	0.39 (0.72)	0.77		
5. Continued intention	3.61	0.69	0.19 (0.48)	0.18 (0.46)	0.38 (0.69)	0.43 (0.72)	0.89	
6. Learning performance	73.73	16.05	0.01 (0.07)	0.01 (0.13)	0.01 (0.13)	0.01 (0.15)	0.00 (0.04)	0.81
Cronbach's alpha			0.82	0.87	0.86	0.85	0.94	0.76
Composite reliability (CR)			0.89	0.92	0.90	0.91	0.96	0.89

Notes. N = 144; SD = standard deviation; Heterotrait-Monotrait (HTMT) ratios are in parentheses; the average variance extracted (AVE) is on the diagonal; the other matrix entries are the squared factor correlations.

5.2 Structural Model and Hypothesis Testing Analysis

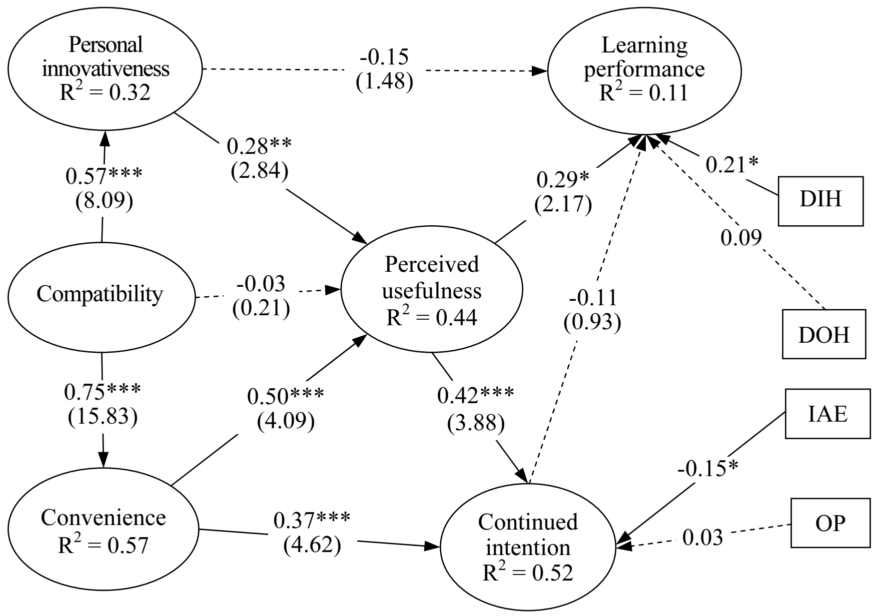
We adopted the PLS-SEM approach using the bootstrapping procedure to evaluate all hypotheses of the structural model. First, the R-square and the Q-square were used to assess the fit of the structural model. Figure 2 shows that the proposed model can be explained by the R-square values, which ranged from 0.11 to 0.57. Additionally, Stone-Geisser's Q-square values for all endogenous constructs should be above 0 [55-56]. The Q square values were calculated, which ranged from 0.06 to 0.45. Meanwhile, nonparametric bootstrapping with 5,000 samples and bias-corrected 95% confidence intervals were conducted to evaluate the proposed research hypotheses. Therefore, these results supported the fit of the structural model (see Figure 2).

As shown in Figure 2, perceived innovativeness did not significantly affect learning performance (H1a), but significantly affect perceived usefulness (H1b). Compatibility significantly affects personal innovativeness (H2a) and convenience (H2c) but did not significantly affect perceived usefulness (H2b). Further, convenience significantly affects perceived usefulness (H3a) and continued intention (H3b); meanwhile, perceived usefulness significantly affects learning performance (H4a) and continued intention (H4b). And, continued intention did not significantly affect learning performance (H5). Overall, most of the hypotheses were supported, except for hypotheses H1a, H2b, and H5.

6 Discussion

The research results indicate that personal innovativeness, compatibility, convenience, and perceived usefulness are the significant factors that directly or indirectly related to continued intention and learning performance.

First, we found that personal innovativeness significantly positively affects perceived usefulness (H1b) but did not significantly affect students' learning performance (H1a), which were consistent with the



Notes. ***Significant at < 0.001; ** Significant at < 0.01; * Significant at < 0.05; T-values are in parentheses.
DIH = daily internet hours; DOH = daily online learning hours; IE = internet experience; OP = experience with other online learning platforms

Figure 2. Hypotheses testing results

findings of previous studies of [26, 28] and [24], respectively. Therefore, we further investigated the potential mediating effect of perceived usefulness on the relationship between personal innovativeness and learning performance. The method of examining mediating effects was adopted from the work of Hayes [57], the results of which are given in Table 3. We found that perceived usefulness has a mediating effect on the relationship between personal innovativeness and learning performance. This mediation may be explained by the tendency of highly innovative students perceiving the usefulness and efficiency of OLSs. This finding implies that educators should foster healthcare students' innovativeness by adopting new learning technologies and further enhancing their beliefs in their professional cognitive reasoning and critical-thinking skills through OLSs, which may achieve a better learning performance.

Table 3. Examination of the mediating effects of the full sample

		Path		
		INN → PU → LP	**COM → INN → PU**	**COM → CONV → PU**
Indirect effect		0.10	0.31	0.69
se		0.05	0.10	0.13
Bias-corrected 90% or 95% CI	Lower	0.01	0.13	0.44
	Upper	0.22	0.55	0.96
z value		1.72	2.34	4.71
p value		0.08	0.02	0.000
Mediation supported: Yes/No		Yes	Yes	Yes

Notes. INN = personal innovativeness; PU = perceived usefulness; LP = learning performance; COM = compatibility; CONV = convenience.

Second, the results indicated that compatibility significantly affects personal innovativeness (H2a) and convenience (H2c), consistent with a previous study [23] and [34], respectively. On the other hand, compatibility did not significantly affect perceived usefulness (H2b), inconsistent with the findings of previous studies [27, 33]. As shown in Table 3, compatibility is positively and indirectly affects learning performance via perceived innovativeness and perceived usefulness. The possible reasons may be that the OLSs does not mitigate the potential problems (e.g., students' isolation, prompt feedback) in their learning process. In this case, technological issues are the most critical consideration in the OLSs of healthcare education settings. While compatibility also highlights the importance of integrating the IDT's variables in explaining the students' beliefs or reducing their learning loadings.

Third, convenience positively affects perceived usefulness (H3a) and continued intention (H3b), which is in line with previous studies [34-35, 37]. This study suggests that convenience can be considered a push effect enhancing students' adoption of an OLS and its perceived usefulness (namely, effort-saving, timesaving, and accuracy-seeking) and positively improving the learning process. Furthermore, H4a and H4b were supported and consistent with previous research [39] and [26, 28-29], respectively. This study suggests that perceived usefulness has a strong pull-effect on students' learning performance and continued intention using the OLS.

Finally, continued intention using an OLS did not significantly affect students' learning performance, consistent with previous research [42]. Table 2 shows that the square factor correlations were almost zero to all parameters compared to the learning performance. The main reason might be learning performance was measured by students' actual scores, which did not include the frequency of using OLSs. Additionally, students may have experience using various learning platforms that help to complete their learning tasks. Although the OLSs has many advantages for students, they still need to adjust to new learning strategies.

The results of the examination of the control variables are discussed as follows. First, students' OP was not significantly related to continued intention, which is consistent with a previous study [45]. Second, students' DOH was not significantly related to their learning performance. These OP and DOH results were reasonable because using information technologies as one of the essential tools for learning is common among students. Additionally, we found that students' DIH was significantly related to their learning performance. This result indicates that students' time and learning efforts in their online courses, positively influence their learning performance in the courses, consistent with a previous study [46]. Finally, we found that students' IAEs positively influenced their continued intention using the OLS. This indicates that students who have more IAEs are more likely to use OLS than those with fewer IAEs, which is consistent with the research results of a previous study [47]. This result suggests that educators or instructors need to consider their courses' designs, teaching strategies, and adapted support to encourage students to interact and communicate with their classmates in online courses using various internet/computer-based applications. This, in turn, can enhance the students' intention to continue to use the OLS.

6.1 Implications for Research

This study's results have several implications for research related to the validation of how individual beliefs can contribute to an understanding of the interaction between technological factors and the healthcare students' characteristics by integrating the three theories, namely SCT, TPB, and IDT. Based on the SCT, we developed and empirically validated a theoretical model that presents the critical causal relationships among the OLS use's critical factors. The proposed multi-theoretical model is effective in investigating the antecedents of student learning performance from a holistic view, which is missing from the existing healthcare education literature.

Additionally, we found that students who have a high level of personal innovativeness tend to be more willing to adopt new learning technologies for supporting their learning tasks for developing their professional cognitive reasoning and critical-thinking skills, such as the case of healthcare students illustrated in this study.

Finally, this study, from a relatively unique theoretical angle, focuses on the examination of the interactions among personal, environmental/technological, and behavioral factors, and the effects of these factors on students' learning performance, which is rarely studied in the literature of the OLS use in the contexts of healthcare education. These qualified or registered healthcare specialists are highly valued in many countries. They are responsible for the frontline tasks for patient care and initial screening and assessment of patient conditions before doctoral diagnosis.They need to possess high levels of professional cognitive reasoning and critical-thinking skills to handle those tasks effectively. Consequently, an OLS application to effectively support the basic/fundamental training activities included in the healthcare educational programs is important to healthcare students who engage in the professional healthcare examination works.

6.2 Implications for Practice

This research model extends those in previous studies by further confirming the crucial role of perceived usefulness in interpreting students' learning performance and the adoption of OLSs. First, OLSs are established to match personalized learning requirements and achieve the learning purposes they intend to achieve, all of which can increase their perceived usefulness of the OLSs. Additionally, OLSs allow instructors to integrate relevant learning materials and access other online information resources/databases/ networks (e.g., TED talks, YouTube, Wikis, and MOOCs) to perform their instructional practices. OLSs make it easier for the students to complete learning practices more conveniently.

Corresponding to the discussion above, it is recommended that the management of higher educational institutes actively encourage instructors and students to freely and actively use OLSs to support their teaching and learning processes by offering tangible and/or intangible benefits (e.g., including OLS use performance as a part of instructors' teaching evaluation, and offering distant-learning-based degree programs for part-time students via OLSs). This could be done by encouraging instructors to integrate external online/offline educational resources using OLSs and evaluate these methods' effectiveness by measuring system-usage rates or other system-use measures. Additionally, developers of OLSs can ensure positive user evaluations of the validity of OLSs by accessing procedures and provide appropriate system functions, high-quality user interfaces, online storage functions, and user guidelines (e.g., system-related problem-response modules, regular monitoring, and Q and A modules) to support students' learning activities on the OLSs.

Finally, OLS service providers should maintain and enhance useful functions (e.g., commenting, displaying graphics and animations, annotating/bookmarking contents, and other interactive programs) related to compatibility and convenience, which may remove specific barriers of system usage and provide reliable and satisfactory services for students. Additionally, these functions of OLSs should enable the OLSs to be simple and satisfy students' learning needs, which may encourage them to continue using OLSs to ensure favorable learning effectiveness.

6.3 Limitations

As with every research project, this study has its limitations. First, this study is the relatively small sample size and the cross-sectional analysis collected from the 144 healthcare students from a medical university and a pharmacology university in Taiwan. This survey suggests that future research could replicate and extend this research model of OLSs using samples collected from other areas. Second, the profile of samples shows that there is a higher number of females in this study. Future studies might need to consider the differences in this profile in their data. Third, this study only investigated students who had experience enrolling in six OLS-based courses. Thus, there is caution should be taken when generalizing the findings to other OLSs/services. Fourth, this study categorized the disciplines related to pharmacology as the subfields of healthcare education and did not specifically investigate the application of the OLS in the cases of students in pharmacology-related disciplines. The reason is that knowledge related to pharmacology is critical for healthcare students to develop professional healthcare abilities. Therefore, using OLSs or other e-learning technologies to support various teaching strategies might help healthcare students develop a good understanding of pharmacology and apply it in clinical practice [58-59]. However, future research can extend or refine our research findings by specifically investigating the use of OLSs in the context of pharmacological education. Finally, this study used only the conceptualization of convenience, compatibility, and perceived usefulness as the essential technological factors in this study. Future research could focus on the influence of other variables in similar contexts and the extent to which such conditions are recommended.

7 Conclusions

This study was a multi-theoretical integrated model of OLSs and conducted an empirical investigation through the use of PLS-SEM analysis, the findings of which provide educators, developers, and providers of OLS services with significant insights into OLS development of healthcare education. This study can also add important contributions to the existing literature as various OLSs (e.g., massive online open courses (MOOCs), social media) continue to influence learning patterns in healthcare education. The environmental/technological, psychological, and individual characteristic perspectives can help evaluate students' learning performance and adoption of OLSs, which enrich the OLS knowledge.

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