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*Research article*

# Examining the Critical Success Factors of E-Learning Using Structural Equation Model: A Case Study on the Mandatory Use

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## Abstract

Several researchers have studied e-learning success factors. However, there is rare research linking the success factors from the student perceptions to their data stored in the e-learning system, i.e., the student usage behavior and learning achievement. In addition, there is little research in the literature on mandatory use contexts. Thus, this study aimed to systematically examine and investigate the critical success factors (CSFs) of e-learning used for e-learning evaluation, using an e-learning system in mandatory use as a case study. The study is based on the D&M IS success model, the user satisfaction model, and success factors of e-learning systems. A structural equation model was used to analyze the data collected from 221 undergraduate students who used the system. The results indicated that e-learning success factors were information quality, system quality, instructor characteristics, diversity of assessment, system use, user satisfaction, benefits, and learning performance. In addition, system use has a highly positive and significant effect on learning performance, whereas the perceived benefits are determined by system use, instructor characteristics, information quality, and user satisfaction. Besides, instructor characteristics, system quality, and diversity of assessment had positive impact on user satisfaction. The findings provide insights to practitioners, academics, and policymakers to help them focus on factors that can be used to improve and evaluate the e-learning system. Our study contributes to the body of knowledge on e-learning system success and evaluation in mandatory use contexts.

**Keywords**

critical success factors (CSF);

e-learning success factors;

information systems success;

e-learning evaluation;

structural equation modeling (SEM)

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## 1. Introduction

Nowadays, e-learning plays a significant role in higher education, especially in the new normal environment of the COVID-19 pandemic. It can be considered a powerful medium for effective learning. It encourages and motivates both teachers and students through active teaching and learning. Universities also gain benefits from using resources efficiently. Consequently, universities have adopted e-learning or blended learning in order to increase their competitiveness [1, 2]. Most universities have adopted e-learning systems to enhance their overall education system and to improve the learning performance of students. To achieve these goals, universities have increased the functionality and the capabilities of e-learning by providing several different types of content, including exercises, assignments, quizzes, examinations, and adaptive learning modules such as that used in our system [3]. However, the development and maintenance of e-learning requires much effort and considerable resources. In addition, e-learning ultimately needs to meet student expectations and provide student satisfaction [4]. Therefore, identifying the critical success factors (CSFs) and evaluating the e-learning system is essential for maximizing its utility and ensuring an effective learning system if an organization wants to be successful. Most previous studies have evaluated e-learning based on the perceptions of students using the structural equation model (SEM). SEM is a sophisticated multivariate method and analytical technique package used to test the relationships between observed and latent variables that permits accurate estimates to be obtained simultaneously.

Two model frameworks have commonly been used to assess the efficacy of e-learning. First, the D&M IS Success model was proposed by DeLone and McLean [5]. This model has a limited ability to explain the relationship between e-learning systems and the outcomes of the e-learning process. Second, the Technology acceptance model (TAM) was originally proposed by Venkatesh and Davis [6]. However, TAM is integrated into a broader set of human and social change processes [7] and is not appropriate for the e-learning context. Other approaches studied e-learning success via user satisfaction models [8]. In higher educational context, recent studies determined the critical success factors from student and academic staff perspectives. One example is the study of Alhabeeb and Rowley [9], who used the IS success model, and stated that the CSFs common to both groups were student characteristics, instructor characteristics, ease of access, and support and training. Soleimani *et al.* [10] showed that there was a correlation between the perceptions of students and academic staff regarding instructor quality, information quality and the benefits of e-learning systems. Truong *et al.* [11] identified that five dimensions of CSFs for e-learning at university level (UTE-DN case study) from student perspectives were course features, technology infrastructure, instructor features, learner features, and system quality. Do *et al*. [12] studied the use factor analysis to extract the factors influencing the e-learning system usage during the COVID-19 pandemic from student perspectives. The results indicated that the factors affecting student satisfaction, i.e., perceived usefulness, ease of use, system and technical dimension, and instructor characteristics. König *et al.* [13] used a mixed method approach with one quantitative student survey, two rounds of expert interviews, and a literature study classified the CSFs for individual digital study assistants in higher education according to the Updated DeLone and McLean IS Success model. They concluded that the essential critical success factors were skilled and reliable higher education institution personnel, well-organized and useful content, cross-platform usability, ease of use, and student social factors.

There have been several studies of CSFs and challenges for e-learning in many platforms such as web-based learning and m-learning, but no study has been done that explicitly addresses specific CSFs for individual digital study assistants [13]. Moreover, previous studies have contributed only limited information about the effectiveness of e-learning in the mandatory use context, and in the Thailand context. Furthermore, the studies concluded that numerous factors contributed to shape the educational environment. However, most of the success factors were similar. On the other hand, factors such as personalized learning and diversity of assessment, which are vital to current e-learning, were only studied in a few papers. Moreover, based on the review, we found that the academic achievement of students was rarely considered in studies of the e-learning success model. Motivated by these gaps, this research aimed to study the CSFs of e-learning using a case study on an anonymous system that is a web-based and adaptive e-learning system (individual digital study assistants) for a database course at an anonymous university in Thailand. The students must use the system for their learning activities, particularly for doing practical, assignments, quizzes, and examinations. It is crucial to have a more detailed understanding of the influencing factors for e-learning success. Therefore, the objectives of this study were (1) to examine and analyze the factor influencing the success of e-learning and (2) to develop an e-learning success model for an anonymous system and classify the results according to the IS success model in a mandatory e-learning context. The study contributes by providing theoretical and empirical evidence for the factors that contribute to the successful implementation and evaluation of an adaptive e-learning system for higher education in a mandatory use context. The proposed model includes the factors mentioned above; personalized learning, diversity of assessment, and learning performance in order to fill in the identified gaps in the research in the evaluation of the success of an e-learning system.

## 2. Materials and Methods

This study was approved by the Forum for Ethical Review committees in Thailand and KMITL Research and Innovation Services (KRIS), King Mongkut's Institute of Technology Ladkrabang.

In this section, we first systematically review the literature to examine how to evaluate or measure the success of e-learning and identify the critical factors that drive the e-learning success. Next, we briefly describe the anonymous system background. Finally, we present the theoretical models, constructs and their indicators, and path hypotheses. Data collection and statistical analysis are also described. The main findings of the literature are presented below:

### 2.1 E-learning success factors

This review is based on the study of Al-Fraihat *et al.* [7], who described four approaches for measuring the success of e-learning: the D&M IS success model, TAM, the user satisfaction model, and the e-learning quality model. However, our study reviewed 25 studies related to e-learning success. Most studies used one of the two major models that were relevant to the information system context, i.e., the use of the D&M IS success model [8, 14] or the TAM. Studies related to four models are presented in the following section.

#### 2.1.1 Information systems success model

One of the most well-known models for assessing information systems is the D&M Information success model, proposed and updated by DeLone and McLean [5]. The IS success model identified six dimensions of IS success measurements, i.e., information quality, system quality, service quality, intent to use/system use, user satisfaction, and net benefits. The developers have since replaced the term “Net Benefits” with the term “Net Impacts” in the modified model as shown in Figure 1 [15]. The study found that: (i) information quality, system quality, service quality, and net benefits were drivers of the user satisfaction, intention to use, and, in turn, system use; (ii) the system use and user

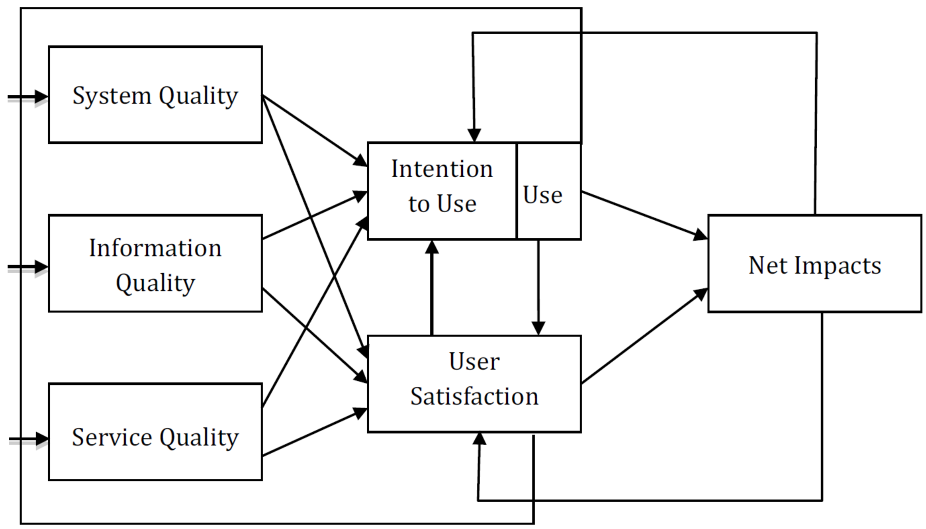


**Figure 1.** Updated DeLone and McLean IS success model (modified in 2016) [15]

satisfaction provided feedbacks enabling system quality, information quality, and service quality improvement; (iii) the determinants of the net impact were system use and user satisfaction; and (iv) system use, user satisfaction, and net impacts affect one another. Our research framework to identify the CSFs of e-learning was based on this model.

### 2.1.2 Technology acceptance model

The TAM model [6] explores the factors affecting an individual's use of new technology and system adoption factors. Venkatesh and Davis developed the original TAM and TAM2, and TAM3 was developed by Venkatesh and Bala. The general extended technology acceptance model for e-learning (GETAMEL) [16] was developed by Abdullah and Ward. The TAM model consists of five factors, i.e. external variables, perceived usefulness, perceived ease of use, intention to use, and usage behavior. Perceived usefulness and ease of use have a direct influence on behavioral intentions. In addition, intention to use has a direct influence on usage behavior. However, this model was not chosen for our research, although TAM is a useful model, it has been designed to be integrated into a broader situation that includes variables related to both human and social change processes [7].

### 2.1.3 User Satisfaction Model

The user satisfaction approach provides another significant direction for information systems research. "Satisfaction is a fundamental measure in the success, effectiveness, usage, and acceptance of information systems" [7]. Previous studies have used this model to assess e-learning systems, such as the study of Hew *et al.* [17], who used it to define MOOC success. In addition, several studies have confirmed that user satisfaction with e-learning can be widely used to evaluate the success of e-learning [8]. This approach evaluates system success in accordance with the D&M IS success model; therefore, our research incorporated user satisfaction as a factor that measures the success of e-learning.

#### 2.1.4 E-learning quality model

Most universities provide e-learning systems to enhance the overall education system and improve student performance. Hassanzadeh *et al.* [18] proposed the measuring e-learning systems success (MELSS) model and found that the achievement of educational and personal goals was suitable for measuring the success of e-learning systems. Raspopovic *et al*. [8] and Freeze *et al*. [19] evaluated the success of an e-learning system using the net benefit factors through academic performance achievements. In addition, one major deficiency of the D&M IS success model is its limited ability to assess e-learning systems based on e-learning outcomes [7]. Thus, our research was based on this approach to fill in the gap in the D&M IS success model. We used learning performance as the key factor in our e-learning evaluation model.

Many previous studies have used the SEM to validate the success factors for e-learning. Cidrala *et al.* [20] proposed a theoretical model integrating recent theories of information system satisfaction and success in e-learning systems. This study found that the e-learning success determinants are system quality, information quality, collaboration quality, instructor attitude towards e-learning, diversity in assessment, and learner-perceived interaction with others or the learning community. Other studies such as Aparicio *et al.* [21], demonstrated that common important factors were system quality, information quality, service quality, and instructor characteristics. Martins *et al.* [22] mentioned that when assessing information system quality, the inherent variables, i.e., information quality, system quality, and service quality, must be analyzed. Many studies have focused on developing e-learning systems with personalized learning mechanisms for adaptive learning such as the studies of Nalintippayawong *et al*. [3]. This factor was defined as the driver of learner satisfaction [8]. In addition, a study by Martina *et al.* [23] indicated that course assessment was linked to overall learner satisfaction.

In conclusion, the literature review above indicates that the key measures of e-learning success were system use, user satisfaction, benefits, and academic achievement/learning performance. The major e-learning success drivers were system quality, information quality, service quality, instructor characteristics, learning community, personalization, and course assessment.

### 2.2 Anonymous system background

The anonymous system is a web-based and adaptive e-learning platform for individual digital study assistants [3]. It has been used for the database course in blended learning since 2018, in the universities in Thailand. The system consists of general e-learning modules for the teachers and the students. The students can learn and practice SQL programming; the system can also generate adaptive questions that are suitable for the knowledge level of the student (enable individualized support through personalized recommendations), and the answers can be automatically scored [24]. Students can also design the database with a heuristic tool (conceptual design, logical design, and model mapping), which can automatically grade student design diagrams and send immediate feedback. In blended learning, students learned theory in the traditional classroom and have the option of using the system to review the contents, the form in the text, and video clips. However, students must use the system when doing practical, assignments, quizzes, and examinations, which together constitute the mandatory use context.

### 2.3 SEM analyses and software

SEM is a sophisticated multivariate method and analytical technique that permits accurate estimates to be obtained simultaneously. It is a statistical method used to test the relationships between observed and latent variables. Latent variables are not directly observable or measured but are inferred from a set of observed variables that are measured using surveys. The observed, measured, or indicator variables are a set of variables that are used to define or infer latent variables. The procedure of running the model using Amos graphic program proceeds according to five steps in SEM analyses [25]: model specification, model identification, model testing, model estimation, and model modification. For model specification, the researcher specifies the model, determining every relationship among variables relevant to their interest (drawing the path diagram). Identification refers to the fact that there is at least one unique solution for each parameter estimate in a SEM model. If a model is in the identified state, the parameter estimates can be trusted in the model estimation. Model testing (using the confirmatory approach) is done to test whether the data fits the model (different criterion can be checked). If model fit criterion is acceptable, the model can be accepted. Model modification may be required to obtain a better-fitting model. Amos enables the researcher to assess the expected model fit by showing each possible path that can be added to the model.

## 2.4 Theoretical models

Civelek [26] used SEM to propose a holistic success model for e-learning evaluation. However, the research model was mainly based on the four frameworks that most papers have referenced. The first study was the updated D&M IS success model [5]. The D&M IS success model measures the benefits at both the individual and organizational levels. However, our study measure benefit only at the individual impact on learners in perceived the benefits of e-learning. In the second study, Al-Fraihat *et al.* [7] reported that determinants of e-learning were perceived satisfaction of the technical system quality, information quality, service quality, support system quality, learner quality, instructor quality, and perceived usefulness. Next was the e-learning success determinants of Cidrala *et al.* [20]. The drivers of user satisfaction were information quality, system quality, instructor attitude towards e-learning, diversity in assessment, and learner community. Finally, the study based on e-learning quality models by Hassanzadeh *et al*. [18], who proposed the MELSS model and found that using e-learning systems directly affected student goal achievement.

In the next sections, the procedures of SEM are defining individual constructs, developing measurement models, producing empirical results, assessing measurement model validity, specifying the structural model, and assessing the structural model [27]. The research methodology conforms to these six stages.

## 2.5 Constructs and the measured indicators

The research model is mainly based on the studies mentioned previously in Section 2.4. Additional constructs and measured indicators were confirmed from prior studies in the e-learning context. The proposed model consisted of seven independent constructs: information quality (InfoQ), system quality (SysQ), service quality (SerQ), instructor characteristics (IC), learning community (LC), personalization (P), and diversity of assessment (DA). In addition, there were four dependent constructs: user satisfaction (US), system use (Use), benefits or positive individual impact (B), and learning performance (LP). The details of each construct and their indicators, and the supporting research are presented below:

Information quality is provided by the e-learning system, i.e., content, learning materials, and feedback. It must be useful, understandable, sufficient, reliable, and accurate [13, 20, 28].

System quality is the quality of the e-learning system. It is considered high when it is well-structured and reliable and when it responds quickly and provides the necessary functions that are both easy to use and navigate [21, 29].

Service quality refers to service staff having a service mind and knowing how to answer user questions. In addition, forms for online help are available and are the main measures of service quality [7, 30].

Personalization focuses on customizing learning cases based on different characteristics and requirements, such as fundamental knowledge and personalized entry pages [7, 31].

Instructor characteristics refer to the instructor's enthusiasm while teaching using e-learning tools and the instructor's ability to motivate students to use the e-learning system, including the instructor's ability to effectively use the e-learning system and the instructor's response time to student questions [7, 20]. “The more enthusiastic teachers are about e-learning, the more they will motivate students in all their educational practices” [12]. Instructor’s dimensions are one of the most significant factors during e-learning implementation [9, 32].

Learning community refers to the e-learning system and its ability to support different kinds of communication tools for interactivity between learners and instructors, which enable the learner to interact with a classmate or contact the instructor through e-learning [11, 14, 20].

Diversity of assessments refers to the diversity of ways that an online assessment, such as assignments, quizzes, tests, and various assessment types, can be completed. Diverse assessments allow instructors to quantify the effects of learning, and judge how different aspects of education vary in their effectiveness [7, 20].

User satisfaction refers to the way the system meets user requirements, and supports the course and the student enjoyment while using e-learning. System performance or efficiency is also included in this factor [16, 22].

System use focuses on the overall frequency of learning activities such as reading, practical, assignments, and quizzes attempted, and includes the number of exercises that students have completed on the e-learning system. System use is often an appropriate measure of success. Numerous previous studies have used this factor [19, 29].

Individual impact is the degree of benefits students perceive when using an e-learning system [20]. Benefits or positive individual impact in this study refer to the importance of students using an e-learning system that increases productivity in classwork or task performance. In addition, students can evaluate themselves using online exams, tests, homework, and other measures featured on the e-learning system. In accordance with the study of Martins *et al*. [22] and Martina *et al*. [23], individual impact has been considered beneficial.

Learning performance is important; consequently, e-learning should fulfill learning outcomes and aid the individual learning performance of students. Most of the literature has measured the success of the e-learning system based on student perception. However, only a few studies [8, 18] have used measures that reflect learning performance. Thus, our study assessed the success of e-learning by measuring actual learning performance as scores on practical and assignments, quizzes, and midterm examinations.

## 2.6 Structural model and path hypotheses

The structural model or constructs and their relationships were designed based on previous SEM e-learning literature and from exploration of empirical data from the case study of an anonymous system. Below, the relationships between constructs and formulated path hypotheses were discussed.

### 2.6.1 System use, benefits, and learning performance

The actual system usage or “Use” measures individuals' actions when using the e-learning system to perform their learning tasks, such as retrieving contents, completing practical, and completing assignments [29]. If using the e-learning system is in line with student needs, then students will be more successful in the modules and achieve their learning goals, increasing the usage of the e-learning system and, in turn, the benefits that students receive [7]. This is in agreement with Freeze *et al*. [19], who mentioned that if students perceive that usage adds value to their ability to improve performance in the course and consider it as a benefit, the e-learning system will be perceived as successful; consequently, the results shown that system use has an impact on the benefits. Thus, this study proposed the following hypothesis:

H1a: Use has a positive influence on learning performance.

Benefits (B) were examined in several studies and the fulfillment of learning outcomes was perceived as a benefit from students' perspectives [22]. Benefits are one of the critical factors that impact academic success and are used in the final stage for evaluating the success of the e-learning system [7]. Thus, this study proposed the following hypothesis:

H2: Benefit has a positive influence on learning performance.

As an academic achievement, learning performance (LP) is an expected educational outcome. Previous studies found a positive relationship between use and learning performance. The case study shows that more interest in using e-learning systems will directly contribute to user goals [18]. Therefore, the perceived benefits of using the e-learning system can affect learning performance. Thus, this study proposed the following hypothesis:

H1b: Use has a positive influence on perceived benefit.

#### 2.6.2 User satisfaction, system use, and benefits

One of the determinants is user satisfaction, which positively impacted individual benefits [14]. In addition, user satisfaction is an essential predictor of success [7]. Therefore, it is better to examine the vital role of satisfaction in influencing the learning benefits. In the D&M IS success model [5], user satisfaction is closely related, and positive experiences using the system will lead to higher user satisfaction. In the context of university e-learning, system use is required to complete the coursework and does not depend on voluntary use by the user [19]. With mandatory use of the anonymous system, user satisfaction is more critical. Consequently, hypotheses were defined as follows:

H3a. User satisfaction has a positive influence on the benefits.

H3b. User Satisfaction has a positive influence on Use.

#### 2.6.3 Information quality, system use and user satisfaction

Several researchers have examined e-learning system success based on the D&M IS success model. Their studies revealed a positive relationship between use and information quality [20, 21]. Furthermore, information quality also has a positive influence on benefits [22]. In addition, some studies have found that information quality and user satisfaction also have a positive relationship [19, 31]. Thus, this study proposed the following hypotheses:

H4a. Information quality has a positive influence on use.

H4b. Information quality has a positive influence on benefits.

H4c. Information quality has a positive influence on user satisfaction.

### 2.6.4 System quality, system use, and user satisfaction

Previous studies have shown that system quality has a positive impact on the use of e-learning [22, 29] and user satisfaction [14, 31]. In terms of the relationship between system quality and benefits, a study showed that if users find the e-learning system compatible with their requirements, they will consider it useful, and utilize it [7]. Consequently, the study hypothesized that:

H5a: System quality has a positive influence on use.

H5b: System quality has a positive influence on benefits.

H5c: System quality has a positive influence on user satisfaction.

### 2.6.5 Service quality, system use, user satisfaction

Service quality is an important quality determinant that should be measured. It affects subsequent use and user satisfaction [5]. Many previous studies revealed a significant relationship between service quality and use; in addition, service quality also significantly impacted user satisfaction [21, 29]. Thus, this study includes the following hypotheses:

H6a. Service quality has a positive influence on use.

H6b. Service quality has a positive influence on user satisfaction.

### 2.6.6 Instructor characteristics, user satisfaction, and benefits

In online learning, learners can access material or content for classes and interact with their classmates or instructors. Previous study identified the determinants of user-perceived satisfaction, use, and the individual impact of e-learning [20]. The instructor's attitude towards e-learning is one of the most significant drivers of user-perceived satisfaction; in addition, student perception of the benefit has highlighted the important role of instructors during the course process [5]. A study mentioned that if the instructor provided enough time to interact with students during the learning process and responded promptly through the e-learning system, learners would increase their level of satisfaction [1]. Another study showed that instructor quality positively influenced student satisfaction with the e-learning system [7]. Thus, this study hypothesized that:

H7a. Instructor characteristics have a positive influence on user satisfaction.

H7b. Instructor characteristics have a positive influence on benefits.

### 2.6.7 Learning community and user satisfaction

E-learning involves interacting with a computer and having e-learning tools for community interaction. Thus, learners can communicate with peers and faculty. However, the learning community has only recently been seen as a determinant of user-perceived satisfaction. Online learning needs a system that includes e-mail, chatroom, and webboard to support the interaction between teachers and students in order to promote a virtual classroom environment. In accordance with Hew *et al*. [17] and Martina *et al*. [23], learner-instructor interaction and learner-learner interaction can affect learner satisfaction in conventional online courses. Studies have shown that the relationship between a learning community and user satisfaction is positive one [7, 20]. Thus, this study hypothesized that:

H8. Learning community has a positive influence on user satisfaction.

#### 2.6.8 Personalized and user satisfaction

A study of qualities in international e-learning benchmarking projects showed that various aspects of personalization should be embedded in all levels of management and services for e-learning in higher education [8]. Many researchers have focused on developing e-learning systems with personalized learning mechanisms to assist online learning and adaptively provide learning paths to promote individual learner learning performance [31]. For example, the anonymous system has also considered learner knowledge level to promote personalized learning performance [3]. Previous study found a significant relationship between personalization and learner satisfaction [8]. Thus, this study hypothesized that:

H9. Personalization has a positive influence on user satisfaction.

#### 2.6.9 Diversity in assessment and user satisfaction

Digital assessment tools are handy from the instructors' perspective given that they allow students to reflect on their progress and keep track of their learning; however, if the assessment of student learning is not reflective of the learning process, students often feel reluctant to participate [32]. One of the main recommendations revealed that instructors should use various assessments to assess students including quizzes, discussion forums, exams, final papers, position papers, final projects, peer assessments, self-assessments, and reflection. Information from completing the assessment is useful for evaluating the online course in order to achieve student learning outcomes. Other researchers observed that a diversity of assessment methods in online courses was linked to overall learner satisfaction [7, 22]. Thus, this study hypothesized that:

H10. Diversity of assessment has a positive influence on user satisfaction.

Malkanthie [33] performed a preliminary SEM using empirical data as part of their model-generating approach and found a correlation between instructor characteristics and other factors, including information quality, system quality, and diversity of assessment. Therefore, this study includes these correlations in the research model. There could also be a correlation between instructor characteristics and information quality. Generally, instructors need to create the course materials; the quality of information or content thus highly depends on the knowledge of instructors. Likewise, the quality of content may affect the instructors. They can improve themselves through feedback from students. Like the correlation with system quality, if the system is of high quality, this can affect the quality of teaching. Moreover, sufficiently diverse assessments depend on instructors given that they are responsible for assessing the students. Thus, this study hypothesized that:

H11. System quality and information quality are interrelated with each other.

H12. Instructor characteristics and information quality are interrelated with each other.

H13. Instructor characteristics and system quality are interrelated with each other.

H14. Instructor characteristics have a positive influence on diversity of assessment.

In addition, Malkanthie [33] also found a correlation between diversity of assessment, system quality, and information quality. Specifically, if a high-quality system can provide various assessment types, this can affect the diversity of assessments; conversely, the availability of various types of assessment can increase system quality. A similar correlation was observed with information and content quality. A sufficient assessment covering overall content throughout the course can affect overall information quality; however, the quality of information can also impact diversity of assessments (e.g., feedback from the system for assessments). Thus, this study hypothesized that:

H15. Diversity in assessment and system quality are interrelated with each other.

H16. Diversity in assessment and information quality are interrelated with each other.

The research model derived from the literature and research hypotheses is shown in Figure 2.

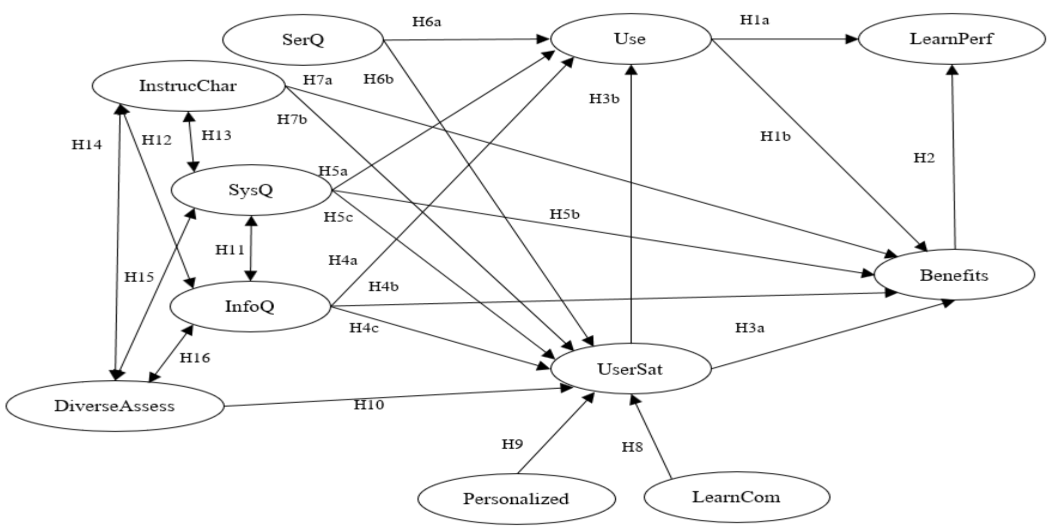


**Figure 2.** Research model

## 2.7 Data collection and analysis

The research design, which was consistent with most studies and featured best practices, made use of the SEM method and AMOS software to construct and validate the research model. In addition, a survey was conducted to collect data for the empirical evaluation of the theoretical model. Below is a description of the data collection, and statistical analysis used for assessing the model.

#### 2.7.1 Data collection

First, the academic performance data, i.e., quizzes, midterms, and practical, were collected to assess their efficacy as indicators of the learning performance. Additionally, this study retrieved usage behavior using different features, such as content reading and participation in quizzes and practical. Second, data were collected from participants through a voluntary online survey. Survey items adapted from the literature were used to develop the research model. A 28-item questionnaire was used to construct the instrument, which included the multi-item Likert scale. Data were collected from undergraduate students enrolled in the anonymous system for the database course, and a total of 221 valid samples (79.5% of the population) were included. Kline [34] suggested that a minimum sample size of at least 200 cases was needed to advance to the next step of SEM. Furthermore, according to Abdul-Aziz *et al*. [35], "information obtained from the census is likely to be more valid and reliable." Thus, these samples were considered sufficient for the SEM analysis.

#### 2.7.2 Model-fit criteria

SEM was used to test theoretical models and examine the relationships between constructs. Model fit criteria commonly used include chi-square ($X^2$) p-value > 0.05, goodness-of-fit index (GFI) 0.95 and adjusted goodness-of-fit index (AGFI) 0.95, normed fit index (NFI) 0.95, root-mean-square residual (RMR) and standardized root-mean-square residual (SRMR) 0.05, comparative fit index (CFI) 0.97, RMSEA 0.08 [25], relative chi-square (CMIN/DF) 3, GFI 0.90, AGFI 0.85, CFI 0.95, and RMSEA 0.08 [33]. This study used the CFA approach and tested the effects of factors based on the Maximum Likelihood Estimates method.

## 3. Results and Discussion

SEM consists of two sub models: the measurement model and the structural model. The measurement model shows the relationship between observed and latent variables. The structural model shows the relationship between latent variables. This study examined data via both sub models.

### 3.1 Measurement model assessment

The research used a CFA to assess eleven theoretical measurement models with thirty observed variables. Table 1 summarizes the results of the model assessment. Below, the model reliability, validity testing, and factor loading for each construct are discussed.

#### 3.1.1 Internal consistency reliability

We calculated Cronbach's alpha coefficient to determine the reliability of the measurement models. Values 0.70 or higher indicate more stringent reliability according to Hair *et al.* [27]. Table 1 shows the Cronbach values of construct variables ranged between 0.746-0.887. These results indicated that all values met the minimum requirement. Next, squared multiple correlations ($R^2$), which indicated communality ranged between 0.395-0.854; all variables were greater than the 0.3 threshold mentioned by Holmes [36], results which showed that indicator were reliable.

#### 3.1.2 Discriminant validity

A cross-loadings method was utilized to assess the loading of each indicator. Extraction with Maximum Likelihood and Promax rotation were used. The results indicated that factor loadings for each indicator were highest on the construct it was associated with, or the discriminant validity was achieved. Factors and their indicators are shown in Table 1.

#### 3.1.3 Standardized factor loadings

Table 1 shows the factor loading of items or indicators for each factor that appear in the research model. According to Hair [27], acceptable factor loadings for each indicator must be at least 0.4 for a sample size of more than 200. The research model results met the minimum requirements of the above threshold and were thus considered acceptable. However, three constructs were not significant for the structural model: personalization, learning community, and service quality (discuss in next section). Thus, these factors are not presented in the Table. The results indicated that the information quality factor was strongly affected by usefulness at 0.73 and completeness at 0.70, and it was moderately affected by reliability at 0.68 and understandability at 0.66; the system quality factor was strongly affected by well-structured and reliable indicator at 0.80 and the easy to use and navigate at 0.76, and it was moderately affected by necessary functions at 0.69 and quick response at 0.65; the instructor characteristics was strongly affected by instructor's self-efficiency at 0.86, ability to motivate the student to us e-learning at 0.76, and instructor's enthusiasm at 0.74, and it was moderately affected by instructor's response time at 0.69. The diversity of assessment factor was strongly affected by availability of sufficient assessment at 0.85, and it was moderately affected by variety of types of assessment at 0.68; the user satisfaction factor was strongly affected by enjoyment at 0.93 and system performance at 0.87, and it was moderately affected by system functionality at 0.62; the benefit factor was strongly affected by learning performance (perceived) at 0.82, and increasing of class work performance at 0.81, the students evaluate themselves at 0.76, and the increased transparency in evaluation at 0.71; the using of system factor was strongly affected by the frequency of doing practical at 0.93, and it was moderately affected by frequency use (overall attempts) at 0.62; and the learning performance factor was strongly affected by practical performance at 0.72 whereas the quiz performance indicator had a moderate effect on the learning performance factor, scoring at 0.59.

### 3.2 Structural model assessment

The CFA was used to test the structure model; Figure 3 shows the findings. The overall model fit was evaluated to ascertain whether it met the statistical criteria [25, 33]. The results were: CMIN/DF, 1.240; RMR, 0.04; GFI, 0.90; AG, 0.98; CFI, 0.98; AIC, 455.365; BIC, 689.839; RMSEA, 0.03; and Hoelter, 205; thus, all statistical values of the research model were acceptable. The results of the path analysis and the hypotheses testing are summarized in Table 2. Statistical results supported fourteen hypotheses: H1a, H1b, H3a, H5c, H7b, and H11–H16, which were significant at p-values $< 0.001$; H4b and H10, which were significant at p-values $< 0.01$; and H7a, which was supported by significant p-values $< 0.05$. The relations of factors are presented in Table 3. In summary, the results showed that the system quality, diversity of assessment, and instructor characteristics had a positive influence on user satisfaction; the information quality, instructor characteristics, and user satisfaction had a positive influence on the benefits; and using the system had a positive influence on perceived benefits and learning performance.

**Table 1.** Results of the measurement model

| **Factors** | **Code** | **Indicators** | **Squared Multiple Correlation** > 0.30 | **Factor Loading** > 0.40 | **Cronbach Alpha** > 0.70 |
|---|---|---|---|---|---|
| Information Quality: IQ (Content and Feedback) | IQ1 | Usefulness | 0.518 | 0.73 | 0.80 |
| | IQ2 | Understandability | 0.457 | 0.66 | |
| | IQ3 | Completeness | 0.467 | 0.70 | |
| | IQ4 | Reliability | 0.459 | 0.68 | |
| System Quality: SQ | SQ1 | Well-structured and reliable | 0.640 | 0.80 | 0.81 |
| | SQ2 | Quick response | 0.405 | 0.65 | |
| | SQ3 | Necessary functions | 0.445 | 0.69 | |
| | SQ4 | Easy to use and navigate | 0.550 | 0.76 | |
| Instructor Characteristics: IC | IC1 | Instructor's enthusiasm | 0.566 | 0.74 | 0.84 |
| | IC2 | Can motivate the student to use e-learning | 0.532 | 0.76 | |
| | IC3 | Instructor's self-efficiency | 0.695 | 0.86 | |
| | IC4 | Instructor's response time | 0.506 | 0.69 | |
| Diversity of Assessment: DA | DA1 | Availability of sufficient assessment | 0.665 | 0.85 | 0.75 |
| | DA2 | Variety of types of assessment | 0.533 | 0.71 | |
| User Satisfaction: US | US1 | System functionality | 0.763 | 0.62 | 0.85 |
| | US2 | Enjoyment | 0.600 | 0.93 | |
| | US3 | System performance | 0.607 | 0.87 | |
| Benefit: B (Positive individual impact) | B1 | Increase class work performance | 0.652 | 0.81 | 0.85 |
| | B2 | Students evaluate themselves | 0.565 | 0.76 | |
| | B3 | Increased transparency in evaluation | 0.497 | 0.71 | |
| | B4 | Learning performance (perceived) | 0.676 | 0.82 | |
| Use System: USE | USE1 | Frequency use (Overall attempts) | 0.395 | 0.62 | N.A. |
| | USE2 | Frequency of doing practice | 0.854 | 0.93 | |
| Learning Performance: LP | LP2 | Quiz performance | 0.325 | 0.59 | N.A. |
| | LP3 | Practice performance | 0.482 | 0.72 | |

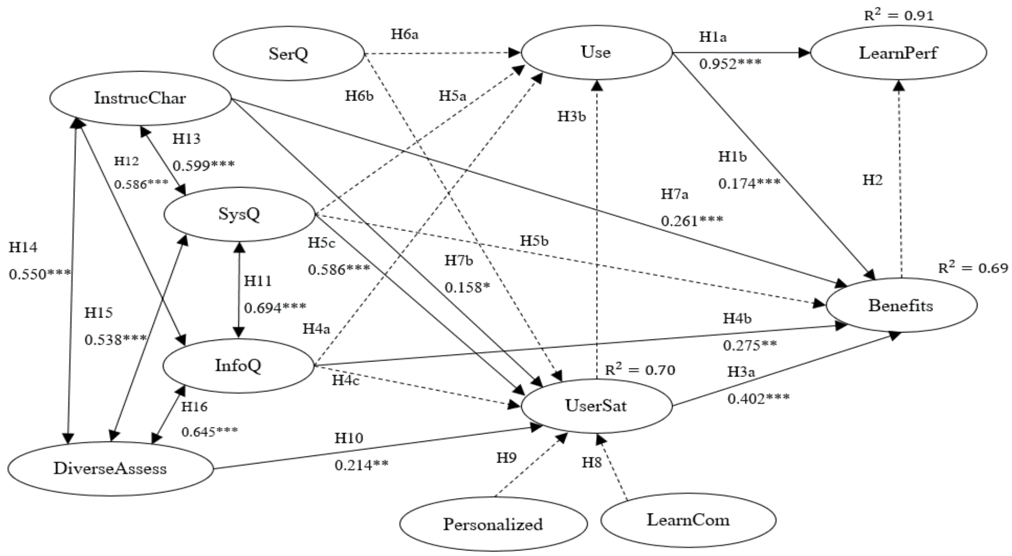


**Figure 3**. Results of the research model

p-values; ***p < 0.01; **p < 0.05; *p < 0.01

**Table 2.** Verification of hypotheses

| Hypotheses | Paths | β Coefficients | P-values | Results |
|---|---|---|---|---|
| H1a | Use → LP | 0.952 | *** | Supported |
| H1b | Use → B | 0.174 | *** | Supported |
| H2 | B → LP | 0.054 | 0.377 | Rejected |
| H3a | US → B | 0.402 | *** | Supported |
| H3b | US → Use | 0.152 | 0.188 | Rejected |
| H4a | IQ → Use | 0.068 | 0.337 | Rejected |
| H4b | IQ → B | 0.275 | 0.002** | Supported |
| H4c | IQ → US | 0.088 | 0.121 | Rejected |
| H5a | SQ → USE | -0.152 | 0.108 | Rejected |
| H5b | SQ → B | 0.134 | 0.212 | Rejected |
| H5c | SQ → US | 0.586 | *** | Supported |
| H6a | SerQ → USE | 0.005 | 0.935 | Rejected |
| H6b | SerQ → US | -0.012 | 0.804 | Rejected |
| H7a | IC → US | 0.158 | 0.045* | Supported |
| H7b | IC → B | 0.261 | *** | Supported |
| H8 | LC → US | 0.089 | 0.465 | Rejected |
| H9 | P → US | 0.082 | 0.321 | Rejected |
| H10 | DA → US | 0.214 | 0.006** | Supported |
| H11 | SQ ↔ IQ | 0.694 | *** | Supported |
| H12 | IC ↔ IQ | 0.586 | *** | Supported |
| H13 | IC ↔ SC | 0.599 | *** | Supported |
| H14 | IC → DA | 0.550 | *** | Supported |
| H15 | DA ↔ SQ | 0.538 | *** | Supported |
| H16 | DA ↔ IQ | 0.645 | *** | Supported |

***P < .001, **P<.01, *P<.05

**Table 3.** Results of the structural model assessment

| Relations of factors | Significant p-values |
|---|---|
| Using the system has a positive influence on learning performance.<br>Using the system has a positive influence on perceived benefit.<br>User satisfaction has a positive influence on the benefits.<br>System quality has a positive influence on user satisfaction.<br>Instructor characteristics have a positive influence on benefits. | < 0.001 |
| Information quality has a positive influence on benefits.<br>Diversity of assessment has a positive influence on user satisfaction. | > 0.01 |
| Instructor characteristics have a positive influence on user satisfaction. | > 0.05 |

## 3.3 Discussion

The statistical results showed the success factors of the e-learning anonymous system: system quality, information/content quality, benefits/individual impact in line with Soleimani *et al*. [10], Do *et al*. [12] and König *et al*. [13], instructor characteristics in accordance with Soleimani *et al*. [10] and Do *et al*. 12]; system use and user satisfaction consistent with König *et al*. [13], and diversity of assessment and learning performance, which were new factors in our model. However, service quality was not in line with Soleimani *et al*. [10] and König *et al*. [13], and learning community, and personalization did not significantly affect user satisfaction in our model; thus, these constructs were not included in the success model of the system. Comparison of our success factors with recent studies which used different methods are shown in Table 4.

**Table 4.** Comparison of the CSF of e-learning with recent studies

| | Our Research (SEM) | König *et al.* [13] (Survey & Interview) | Soleimani *et al.* [10] (Survey & Descriptive Analysis) | Do *et al.* [12] (Multiple regressi analysis) |
|---|---|---|---|---|
| Information quality | √ | √ | √ | √ |
| System quality | √ | √ | √ | √ |
| Net benefits/impacts | √ | √ | √ | √ |
| Instructor characteristics | √ | | √ | √ |
| System use | √ | √ | | |
| User satisfaction | √ | √ | | |
| Diversity of assessment | √ | | | |
| Learning performance | √ | | | |
| Service quality | × | √ | √ | |
| learning community | × | | | |
| personalization | × | | | |
| Student characteristics* | | | √ | |
| Technology infrastructure* | | | | √ |

* Did not include in the research model

The proposed model strongly explained 91% of the variation in learning performance, 69% of the perceived benefits, and 70% of the variation in student satisfaction. Below, the relationships between the various factors are discussed.

There was a highly positive relationship between system use and learning performance. The first hypothesis (H1a) received empirical support. There was a positive relationship between system use and learning performance with a regression coefficient of 0.952 ($P < 0.001$), which indicated a strong direct effect of 95.20%. This relationship was consistent with studies by Cidrala *et al*. [20] and Martins *et al*. [22], demonstrating that system use has a positive impact on individual performance. In accordance with Hassanzadeh *et al*. [18], more interest in using e-learning systems facilitates user goals. However, the benefits failed to support hypothesis H2: the result indicates that perceived benefits of using the e-learning system did not have a significant impact on the actual learning performance.

There were no determinants that affected system use. This study examined the relationship of information quality, system quality, service quality, and user satisfaction with system use. The results were that none of these hypotheses were supported. Information quality had no significant impact on use (H4a), a result which was in accordance with Al-Fraihat *et al*. [7]. This result indicated that providing high-quality information does not influence student use of the e-learning system. Moreover, the result showed that system quality did not significantly affect the use of the e-learning system (H5a); a similar nonsignificant relationship was found by Al-Fraihat *et al*. [7] and Aparicio *et al*. [21]. The study revealed that student use of the e-learning system was independent of the perceived quality of the system. The service quality had no significant impact on use (H6a); this result was consistent with the studies of Cidrala *et al*. [20]. The quality of services delivered to students by IT staff did not contribute to student attitudes towards e-learning. User satisfaction did not significantly affect the use of the e-learning system (H3b). This result was consistent with previous studies [29]. The explanation for these points of non-significance (H4a, H5a, H6a) might be that the use of the anonymous system by students was mandatory; students had to use the system regardless of its quality, whereas in a voluntary context, quality criteria may well influence users' decisions to use the system.

Service quality had no significant impact on user satisfaction. The results also indicated that service quality had no significant impact on user satisfaction (H6b). This finding was consistent with the results of Cidrala *et al*. [20]. An anonymous system such as the one we used is a specific system used for a specific course and is different to general e-learning systems used for all students at a university, which are supported by an IT service center. The service of the system is provided by teacher assistants (TA). In addition, students have sufficient IT skills, and thus they do not need much service. Therefore, the service quality did not have an impact on user satisfaction.

The perceived benefits were influenced by system use, instructor characteristics, information quality, and user satisfaction. The results showed that students could perceive benefits if they used the e-learning systems (H1b), which was in accordance with previous studies [7, 9]. However, it had a smaller effect with a regression coefficient of 0.174 ($P < .001$), meaning its direct effect of 17.4%. Instructor characteristics had a positive influence on benefits (H7b) with a regression coefficient of 0.261 ($P < .001$) and thus a direct effect of 26.1%, which is considered a low rate in accordance with Yakubu *et al*. [29]. Information quality positively influenced the benefits (H4b) with a regression coefficient of 0.275 ($p = 0.002$), or a direct effect of 27.5%, which is considered low. This finding was in line with Martins *et al.* [22]. User satisfaction positively influenced benefits (H3a) with a regression coefficient of 0.402 ($P < .001$) and a direct effect of 40.2%, which is considered a moderate effect. These results were consistent with most other studies [19-21]. However, this study found that system quality was not a good predictor of net benefits (H5b), a conclusion that was revealed by previous studies [22, 29].

Instructor characteristics, system quality, and diversity of assessment positively impacted user satisfaction. The results found that instructor characteristics positively influenced user satisfaction (H7a), as was reported in a previous study [1, 20, 32]. However, it had a regression coefficient of 0.158 ($p = 0.045$), or a direct effect of only 15.8%, which is considered a low rate. System quality positively and significantly influenced user satisfaction (H5c) with a regression coefficient of 0.586 ($P < 0.001$) and a direct effect of 58.6%, which is considered a moderate rate, and in accordance with most previous studies [21, 29, 31]. Diversity of assessment positively influenced user satisfaction (H10) with a regression coefficient of 0.214 ($P = 0.006$) or a direct effect of only 21.4%, which is considered a low rate. However, user satisfaction was not affected by service quality and information quality. This finding is in accordance with previous studies [20]. The results also showed that learning community and personalization did not have significant effects on user satisfaction. Since the anonymous system does not focus on community features for the students, the class interaction consisted in Facebook instead, and the system does not yet have many personalized features for the students to help them perceive that they are gaining benefit and satisfaction.

The hypotheses from the empirical data experiment for the system evaluation (i.e., H11 to H16), instructor characteristics, system quality, information quality, and diversification of assessments were all supported, and it was indicated that they were interrelated. System quality and information quality were interrelated (H11) with a regression coefficient of 0.694, or a direct effect of 69.4%, which was considered a moderate rate. Instructor characteristics and information quality were interrelated (H12) and had a regression coefficient of 0.586 or 58.6%, which was considered a moderate rate. Instructor characteristics and system quality were interrelated (H13) with a regression coefficient of 0.599, or a direct effect of 59.9%, which was considered a moderate rate. Instructor characteristics positively influenced the diversity of assessments (H14), with a regression coefficient of 0.550, or a direct effect of 55%, which was considered a moderate rate. Diversity of assessment and system quality were interrelated (H15) with a regression coefficient of 0.538, or a direct effect of 53.8%, which was a moderate rate. Diversity of assessment and information quality were interrelated (H16) with a regression coefficient of 0.645 or a direct effect of 64.5%, which was considered a moderate rate.

In summary, the use of e-learning is a critical factor that influences learning performance. However, information quality, service quality, system quality, and user satisfaction did not significantly impact system use. Moreover, in an educational context where usage is mandatory, the results revealed no relationship between system use and user satisfaction.

### 3.4 Implications for practices

Based on our CSF finding, a number of practical implications can be drawn. Frist of all, we used these CSFs for evaluating an anonymous system for system improvement. Second, we found that using the sytem was an important for student learning achievement, so instructors should continuously motivate and encourage students to use the system. Finally, the solution on information quality, system quality, instructor characteristics, diversity of assessment, system use, user satisfaction, benefits, and learning performance should be considered and implemented to improve the quality of e-learning and the student learning process, particularly for individual digital study assitants in the manditory use context. Therefore, other types of e-learning settings should be incorporated with the CSFs in order to increase student satisfaction and e- learning efficiency.

## 4. Conclusions

In this research, we examined e-learning critical success factors for system evaluation, using a case study on anonymous system in mandatory use contexts. The study clearly defined the e-learning success measurement and success determinants, and thus provides insights for practitioners, academics, and policymakers on how to implement and evaluate the e-learning system. Furthermore, this research expands the success metrics used for e-learning evaluation, including the actual system use and learning performance. Stakeholders should focus on CSFs to meet the expectations of students and improve their academic achievement. Theoretically, this study contributes to the body of knowledge of e-learning success by empirically validating the D&M IS success model in a different context: specifically, e-learning with mandatory use. The main limitations of this study were that the sample size was limited, and the e-learning platform was used only for a specific course. Future studies should focus on the drivers of system use that have a highly positive impact on the learning achievement, including factors from instructors' perspectives.

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