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Evaluating the Success of Learning Management Systems using the EESS Model and Expected Confirmation Theory

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Abstract

E-learning and LMS (Learning Management Systems) have been implemented in most universities to modernize learning and assist in the learning process of university students. This study aims to explore the factors that can be used to measure e-learning system success using the EESS (Evaluating E-learning System Success) model and Expectation and Confirmation Theory (ECT). A quantitative research method was employed, using questionnaires to collect data on users' perceptions of LMS. The collected data were then statistically analyzed using the PLS-SEM method with SmartPLS 3.2.9. Results revealed that out of 29 hypotheses, 16 were accepted and 13 were rejected. A novel discovery was that ECT can be implemented in the EESS model. Three hypotheses involving expectation confirmation had p-values of 0.001, 0.000, and 0.000, indicating significant roles. The study concluded that incorporating expectation confirmation quality into the EESS model enhances its effectiveness by providing a comprehensive perspective.

Keywords: E-learning; LMS; EESS; PLS-SEM; ECT

1. Introduction

With the progress of time, the implementation of technology and digitization has become prevalent in various domains, including education or e-learning. From elementary to higher education levels, Learning Management Systems (LMS) are increasingly being adopted to facilitate teaching and learning activities (Rosetta et al., 2020) Nevertheless, the adoption of a technology inherently necessitates its own acceptance and adjustment period. The success of a system's implementation can be gauged through user satisfaction and their perceptions of the system (Rosetta et al., 2020). In the context of the Learning Management System (LMS), the system's success can be gauged through the perceptions of both students and instructors. Evaluating the success of the LMS is essential to determine the sustainability of a system, considering that the implementation and development of university-level LMS systems entail significant costs and time investment.

Previous research on LMS evaluation has explored the E-learning Evaluation System Success (EESS) model, providing a suitable framework for assessing LMS success. Studies based on the EESS model have identified various factors for measuring LMS success from students' perspectives in multiple higher education institutions. These factors include Technical System Quality, Information Quality, Service Quality, Educational System Quality, Support System Quality, Learner Quality, Instructor Quality, Perceived Satisfaction, Perceived Usefulness, and System Use. However, there is a limitation in that the perceptions of other LMS users, namely instructors or lecturers, have not yet been examined or understood.

In the conducted study utilizing the EESS model, various variables and factors leading to hypotheses for measuring an LMS were identified. The EESS model itself is a research model derived from the DeLone and McLean model, the Technology Acceptance Model, the User Satisfaction Model, and the E-learning Quality Model (Al-Fraihat et al., 2020). Derived from these four models, a unified model with 11 dimensions was created for comprehensive Learning Management System (LMS) evaluation. However, further investigation into the Expectation-Confirmation Theory (ECT) revealed that the expectation-confirmation factor of a system influences user satisfaction, which is one dimension of the EESS model. This suggests that the expectation of system quality may be integrated into the EESS model. ECT itself is a theory that elucidates how the confirmation of user expectations regarding a system affects user satisfaction and their willingness to use a particular system or technological device (Hsu and Lin, 2015).

The fundamental concept of ECT posits that individuals hold specific expectations about a product

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or service, and their perceptions and attitudes towards it are shaped by the extent to which these expectations are confirmed or disconfirmed. These expectations are grounded in prior experiences, information, and beliefs, guiding individuals' perceptions, judgments, and behaviors. Confirmation bias is a cognitive mechanism that elucidates how individuals tend to seek, interpret, and remember information that confirms their expectations while disregarding or neglecting information that contradicts them (Park, 2020).

Empirical evidence of the ECT (Expected Confirmation Theory) indicates that individual expectations and their confirmation or disconfirmation significantly influence their attitudes and behaviors towards a product or service. Research has shown that when people's expectations are met or exceeded, they tend to have a more positive attitude, higher satisfaction, and a stronger intention to use or repurchase the product or service. Conversely, when their expectations are not met, they tend to have a more negative attitude, lower satisfaction, and a weaker intention to use or repurchase the product or service (Hsu and Lin, 2015).

The proposed research will encompass a comprehensive examination of the academic community's perceptions of the existing Learning Management System (LMS) with the incorporation of the Expectation-Confirmation Theory (ECT) into the model. This is grounded in the limitations highlighted in previous research on the EESS model, as well as the theoretical foundation that expectation confirmation can influence user satisfaction. Therefore, several research questions can be formulated from this study:

1) Does the comprehensive perception of the academic community as a whole result in distinct analyses compared to previous research?
2) Does the Technical System Quality of the Learning Management System (LMS) influence Perceived Satisfaction, Perceived Usefulness, and Actual Use?
3) Does the Information Quality of the LMS affect Perceived Satisfaction, Perceived Usefulness, and Actual Use?
4) Does the Service Quality of the LMS impact Perceived Satisfaction, Perceived Usefulness, and Actual Use?
5) Does the Educational System Quality of the LMS influence Perceived Satisfaction, Perceived Usefulness, and Actual Use?
6) Does the Support System Quality of the LMS affect Perceived Satisfaction, Perceived Usefulness, and Actual Use?
7) Does the Learner Quality of the LMS impact Perceived Satisfaction, Perceived Usefulness, and Actual Use?
8) Does the Instructor Quality of the LMS influence Perceived Satisfaction, Perceived Usefulness, and Actual Use?
9) Does the Expected Confirmed Quality of the LMS affect Perceived Satisfaction, Perceived Usefulness, and Actual Use?
10) Does the user's Perceived Satisfaction influence the Benefits derived from using the LMS?
11) Does the user's Perceived Usefulness influence Perceived Satisfaction, Actual Use, and Benefits from using the LMS?
12) Does the Actual Use of the LMS impact the Benefits derived from its use?

Based on the aforementioned question, it can be stated that the purpose of this research is to examine the EESS model with a collective group of respondents, namely, the academic community. Additionally, it aims to test the hypothesis of adopting variables originating from the ECT into the EESS model, investigating their role and influence on the evaluation of Learning Management Systems (LMS).

The novelty of this research lies in its integration of the Expectation-Confirmation Theory (ECT) with the EESS model, which has not been previously explored in the context of LMS evaluation. By examining the comprehensive perceptions of the academic community, including both students and instructors, this study aims to provide a more holistic understanding of LMS success factors. This approach not only addresses the limitations of past research but also offers a more robust framework for assessing and improving LMS implementations in higher education.

2. Literature Review

2.1. E-learning

According to the oxford learners dictionary, e-learning is defined as a system of learning that uses electronic media, typically over the internet. A previous study has mentioned that e-learning was defined as a result of the merging of several disciplines, including computer science, communication technology, and pedagogy, as all the gathered definitions incorporated traits from multiple disciplines, the new dynamic that defines educational systems at the beginning of the twenty-first century (Sangrà et al., 2012). E-learning has been implemented in most of universities due to the situation of the recent pandemic and also lets it to develop into a crucial part of the learning environment.

2.2. Evaluating E-learning System Success Model

The Evaluating E-learning System Success (EESS) model is a comprehensive theoretical framework grounded in key concepts from information systems and educational technology. It provides a structured approach to assessing the success of e-learning platforms by integrating multiple dimensions of quality, user acceptance, perceived usefulness, social influences, user satisfaction, and the benefits of system use (Al-Fraihat et al., 2020).

From the perspective of models and information systems, the EESS model draws on several foundational theories. One of the primary theories informing the EESS model is the DeLone and McLean Information Systems Success Model, which emphasizes the role of system quality, information quality, and service quality in determining system success (Petter et al., 2012). The EESS model builds on this by incorporating seven independent constructs representing critical quality factors: technical system quality, information quality, service quality, educational system quality, support system quality, learner quality, and instructor quality. These factors align with the Technology Acceptance Model (TAM), which explores how perceived ease of use and perceived usefulness drive user acceptance of technology (Turner et al., 2010).

Additionally, the EESS model resonates with the Unified Theory of Acceptance and Use of Technology (UTAUT**)**, which considers social influences, facilitating conditions, and the user's attitude towards technology as predictors of usage behaviour (Venkatesh et al., 2016). The model's inclusion of constructs like learner quality and instructor quality also reflects principles from Constructivist Learning Theory, where the interaction between the learner, the instructor, and the educational content is critical to the learning experience.

The dependent variables in the EESS model—perceived satisfaction, perceived usefulness, actual use, and benefits—are directly influenced by these quality factors, reflecting the model's alignment with these broader theories. By examining the interplay between these constructs, the EESS model offers a robust framework for understanding how various aspects of an e-learning system contribute to its overall success. This makes it a valuable tool for system designers, educators, and researchers aiming to optimize e-learning environments.

2.3. Expectation Confirmation Theory

The Expectation Confirmation Theory or ECT is a theory that was originally used for marketing in which it theorizes how the satisfaction of consumers are affected by their expectations towards the product (Hossain and Quaddus, 2012). It can be derived from the main theory that ECT affects perceived satisfaction. Moreover, previous studies has alson proven that ECT has an effect on perceived usefulness and use (Tam et al., 2020; Oghuma et al., 2016). This leads to one of the purpose of current study in improving the EESS model by implementing ECT into the model, since it has been shown that ECT has effects on constructs used in EESS model. A variable is added into the EESS model along with the other quality factors.

2.4. Structured Equation Modeling

Structural Equation Modeling (SEM) is a powerful statistical method that allows researchers to model and estimate complex relationships among multiple dependent and independent variables simultaneously. This method is particularly useful for testing and developing theories involving constructs that cannot be directly observed but are instead measured indirectly through various indicators. SEM enhances the accuracy and reliability of analysis by accounting for measurement errors in the observed variables, thus providing a more robust understanding of the relationships among constructs (Hair et al., 2021).

SEM is especially valuable for elucidating the relationships between dependent and independent variables, including latent factors or constructs that cannot be directly observed. These constructs are represented by multiple observed variables, making SEM unique in its combination of two well-established multivariate techniques: factor analysis and multiple regression analysis.

This study employs the Partial Least Squares Structural Equation Modeling (PLS-SEM) method, a variant of SEM particularly suited for theory development and exploratory research. PLS-SEM is chosen for its alignment with the research objective, which is to understand the success of e-learning media among the sample population through the lens of the expectation-confirmation theory (Hair et al., 2021).

To support this approach, the theoretical framework for PLS-SEM is charted, illustrating how constructs related to e-learning success are measured and linked within the model. This framework is essential for demonstrating how the observed variables serve as indicators for latent constructs, which in turn are used to predict the relationships and outcomes central to the research. By mapping these connections, the framework provides a clear visual and conceptual guide for interpreting the results of the PLS-SEM analysis, ensuring that the complex relationships between variables are comprehensively understood and effectively communicated.

3. Research Method

The proposed research uses the Behavioral Science Research approach along with quantitative methods through the use of questionnaires as a method for data collection. Collected data are further analyzed in a statistical analysis using PLS-SEM.

3.1 Research Stages

The research commenced with the selection of a topic, followed by defining the research scope. This study focuses on the Evaluation of Learning Management Systems within the context of Information System Evaluation. After determining the research scope and topic, the subsequent step involved conducting a literature review to establish the

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theoretical foundation for this study. The literature review concentrated on the E-Learning Evaluation System Success (EESS) model and the Expected Confirmation Theory (ECT), as they share a common variable and the potential for interconnection. Based on the literature review, hypotheses and the research direction were formulated.

With the theoretical framework, research hypotheses, and research questions in place, the study adopted a directed approach to Behavior Science Research (BSR) using quantitative methods. The research then progressed to the data collection phase, which involved the distribution of questionnaires utilizing a Likert scale for measurement. The gathered data were subsequently analyzed using Partial Least Squared Structural Equation Modeling (PLS-SEM) with the SmartPLS 3.2.9 application to identify any analysis gaps. The final stage of the research involves a discussion of the results and the formulation of conclusions, potentially resulting in a new model for the evaluation of Learning Management Systems. The research stages are displayed in Figure 1.

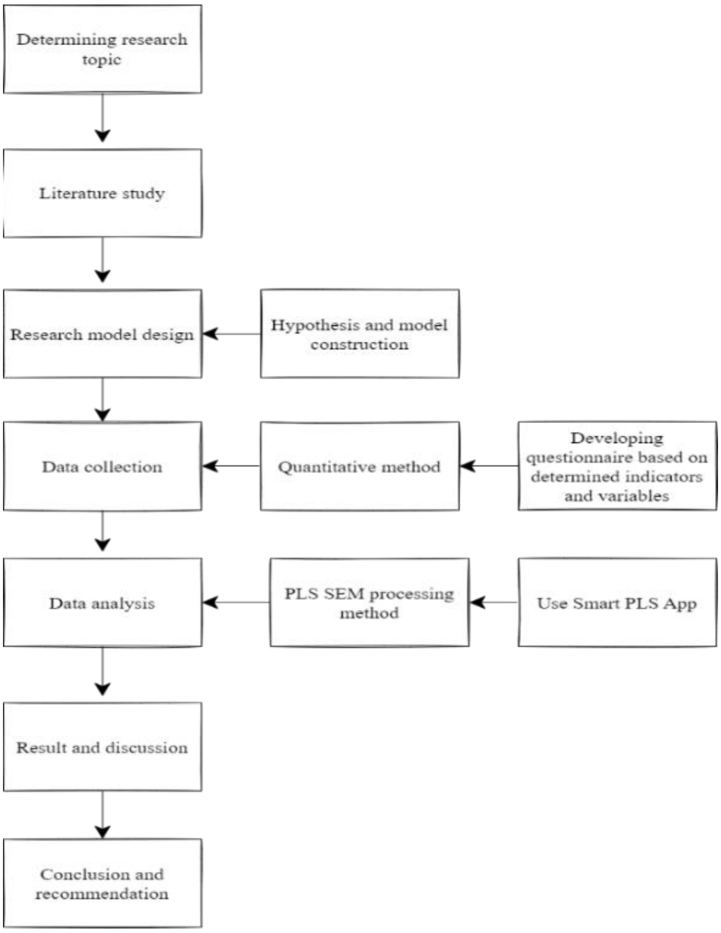

Figure 1. Research stages

3.2 *Sample and Population*

The objects of the study were LMS users who were lecturers and students at FTI UKSW (Faculty of Information Technology Universitas Kristen Satya Wacana). With the specific LMS that is being evaluated as the University developed LMS named FLearn. The total respondents that participated in the current study are 213 respondents.

In this research, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed. Although PLS-SEM does not require data to follow a normal distribution, in this study, the data was assumed to be normally distributed, enhancing the robustness of the analysis. The data collected was quantitative, making it suitable for this type of modeling. This approach allows for the effective examination of complex relationships among observed and latent variables, providing a comprehensive understanding of the LMS's effectiveness.

3.3 *Research Hypothesis*

In order to answer the proposed research questions, a research model was using EESS as the theoretical framework (Al-Fraihat et al., 2020) along with an added variable from ECT (Hsu and Lin, 2015). The research model itself consists of 8 independent variables and 4 dependent variables. The proposed model and hypothesis path are displayed in Figure 2.

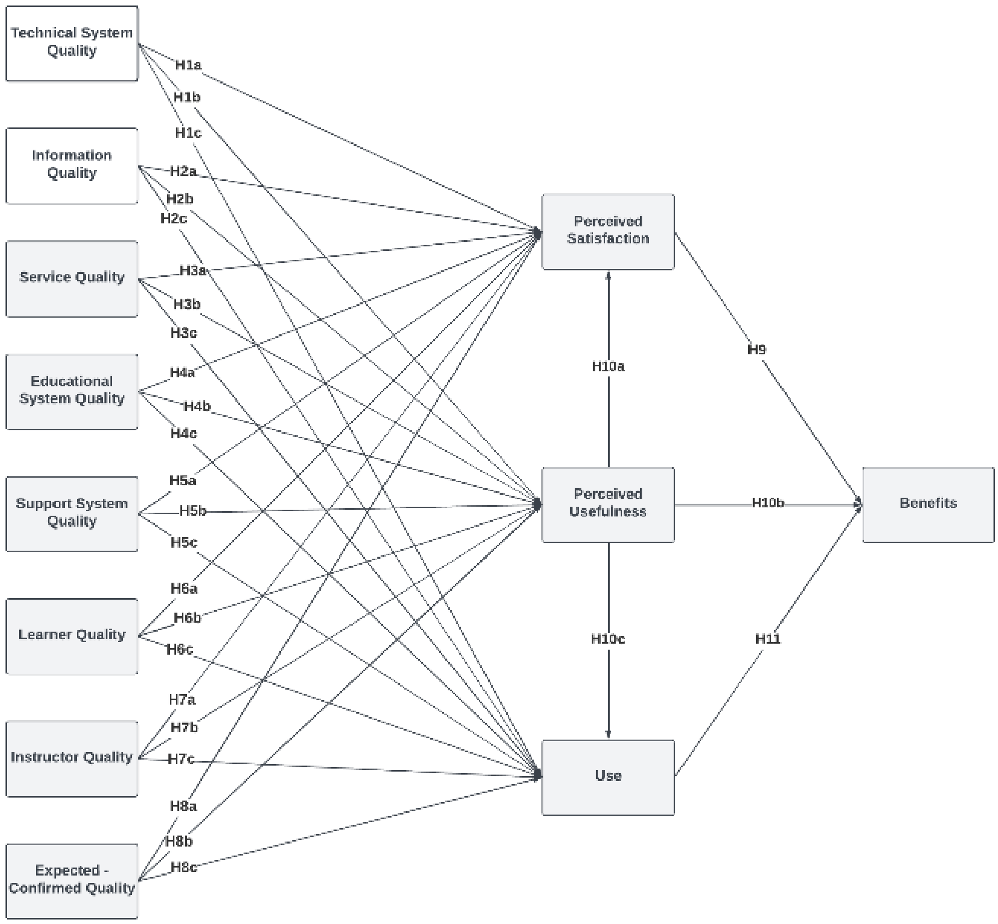

Figure 2. EESS model and research hypothesis

The hypotheses regarding the relationships in the research model with corresponding discussions are presented in this section. Each relationship between the model constructs is substantiated based on empirically demonstrated assumptions in the e-learning platform and information system success literature. Thus, the following hypothesis are as follows

H1a: The positive influence of technical system quality on the perceived satisfaction with the e-learning system is expected.

H1b: The positive influence of technical system quality on the perceived usefulness of the e-learning system is expected.

H1c: The positive influence of technical system quality on the use of the e-learning system is expected.

H2a: Positive information quality influences perceived satisfaction with the e-learning system.

H2b: Positive information quality affects perceived usefulness of the e-learning system.

H2c: Positive information quality impacts the use of the e-learning system.

H3a: Positive service quality influences the perceived satisfaction with the e-learning system.

H3b: Positive service quality influences the perceived usefulness of the e-learning system.

H3c: Positive service quality influences the use of the e-learning system.

H4a: A positive influence of educational system quality on the perceived satisfaction with the e-learning system is expected.

H4b: A positive impact of educational system quality on the perceived usefulness of the e-learning system is anticipated.

H4c: A positive relationship between educational system quality and the utilization of the e-learning system is expected.

H5a: Positive support system quality significantly influences perceived satisfaction with the e-learning system.

H5b: Positive support system quality significantly influences the perceived usefulness of the e-learning system.

H5c: Positive support system quality significantly influences the utilization of the e-learning system.

H6a: Positive learner quality positively influences the perceived satisfaction with the e-learning system.

H6b: Positive learner quality positively influences the perceived usefulness of the e-learning system.
H6c: Positive learner quality positively influences the use of the e-learning system.
H7a: A positive influence of instructor quality on the perceived satisfaction with the e-learning system is expected.
H7b: A positive influence of instructor quality on the perceived usefulness of the e-learning system is expected.
H7c: A positive influence of instructor quality on the actual use of the e-learning system is expected.
H8a: Expected-Confirmed Quality positively influences perceived satisfaction with the e-learning system.
H8b: Expected-Confirmed Quality positively influences perceived usefulness with the e-learning system.
H8c: Expected-Confirmed Quality positively influences the usage of the e-learning system
H9: Positive perceived satisfaction with the e-learning system significantly influences student benefits.
H10a: The perceived usefulness influences the perceived satisfaction with the e-learning system.
H10b: The perceived usefulness of the e-learning system affects the benefits for students.
H10c: The perceived usefulness of the e-learning system influences its usage.
H11: The utilization of the e-learning system influences the benefits for students and lecturers.

4. Result and Discussions

4.1. Respondent Demographic Data Analysis

The data collection method used in this research is an online questionnaire. Data collection through the questionnaire commenced from January 18th 2024 until February 14th 2024. The demographic of the respondents for this research can be seen in Table 1.

Table 1. Respondent demographic data

Category	Items	Frequency	Percentage
Respondent Type	Student	208	97.6%
	Lecturer	5	2.4%
Batch	2020	78	37.5%
	2021	48	23%
	2022	19	9.2%
	2023	63	30.3%
Study Program	Informatics Systems	92	44.2%
	Informatics Technology	79	38%
	Visual Communication Design	29	14%
	Public Relations	8	3.8%

The data collection process, a total of 213 responses were obtained from 5 lecturers and 208 students. According to the data collected, the majority of the respondents are mainly students. The comparison between student and lecturer are 1 to 40. This represents current situation of the faculty in which a class with 1 lecturer can have up to 40 students.

The student batch that participated in the questionnaire ranges from 4-year batches. Students from the 2020 batch had the most respondents (37.5%), followed by the 2023 batch (30.3%), 2021 batch (23%), and 2022 batch (9.2%). Current research mainly uses student batches with majority of active students, the 4 student batches also are the students that uses the Learning Management System (FLearn) for a longer period since its implementation in 2020. In addition, the student from 4 different batches also represented a variety of study programs at FTI UKSW. The study programs that participated in said research area informatics systems study program (44.2%), informatics technology (38%), Visual Communication Design (14%), and Public Relations (3.8%).

4.2. Measurement Model (Outer Model)

Measurement is an essential component of research since it helps to identify latent variables that are employed in the actual study (Hair et al., 2021) . Current research utilizes PLS SEM as the main technique for testing the model due to its nature being multivariant and its complexity with 12 constructs 60 indicators, and 29 relationships. Indicators are measured to indicate its validity for the research. There are 2 stages of testing for the measurement model. The first one is to test reliability by looking at the outer loading value, the Cronbach's alpha value, and the Composite Reliability's value. The second one is to test validity by assessing the Average Variance Extracted (AVE), Cross-loadings and Fornell-Lacker criterion value

4.2.1. Reliability Testing

Reliability testing is conducted to see whether the research items are consistent and accurate to measure the research constructs. First of all, the reliability testing is done by analyzing the outer loading according. Based on its value certain actions can be performed according to these criteria of the outer loading (Hair et al., 2021) indicates that if the outer loading is < 0.40 delete the indicator. If the outer loading is ≥ 0.70 retain the indicator. If the outer loading us ≥ 0.40 but < 0.70 then further analysis regarding the impact of indicator deletion based on AVE and composite reliability. Once the other measures reach the thresholds then retain the indicators, otherwise consider delete the indicators.

The result of the reliability test is displayed on table 2. Based on the data, an indicator from the

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construct Learner Quality (LER) namely LER 3, can be deleted due to the outer loading value is less than 0,40. Furthermore, internal consistency reliability is also tested by looking into Cronbach's Alpha and Composite Reliability of each construct. The threshold for both tests is ≥ 0.70 (Urbach and Ahlemann, 2010)Based on the test result all the constructs are reliable, with educational system quality (ESQ) construct having the lowest value of both tests and perceived satisfaction (SAT) construct having the highest value of both.

Table 2. Validity and Reliability Test Results (first stage test)

Indicator	*Loading Factor*	*Cronbachs' Alpha*	*Composite Reliability*	*AVE*
TSQ 1	**0.706**			
TSQ 2	**0.694**			
TSQ 3	**0.749**			
TSQ 4	**0.756**			
TSQ 5	**0.722**			
TSQ 6	**0.701**	**0.869**	**0.895**	**0.441**
TSQ 7	**0.711**			
TSQ 8	**0.654**			
TSQ 9	**0.421**			
TSQ 10	**0.509**			
TSQ 11	**0.599**			
INQ 1	**0.811**			
INQ 2	**0.717**			
INQ 3	**0.773**			
INQ 4	**0.787**	**0.862**	**0.895**	**0.549**
INQ 5	**0.760**			
INQ 6	**0.670**			
INQ 7	**0.655**			
SRQ 1	**0.787**			
SRQ 2	**0.761**			
SRQ 3	**0.842**	**0.880**	**0.913**	**0.678**
SRQ 4	**0.870**			
SRQ 5	**0.850**			
ESQ 1	**0.624**			
ESQ 2	**0.791**	**0.734**	**0.833**	**0.557**
ESQ 3	**0.778**			
ESQ 4	**0.781**			
SUP 1	**0.718**			
SUP 2	**0.837**	**0.782**	**0.858**	**0.603**
SUP 3	**0.746**			
SUP 4	**0.800**			
LER 1	**0.868**			
LER 2	**0.869**			
LER 3	**0.222**	**0.773**	**0.846**	**0.552**
LER 4	**0.738**			
LER 5	**0.811**			
INS 1	**0.685**			
INS 2	**0.845**			
INS 3	**0.825**	**0.851**	**0.893**	**0.627**
INS 4	**0.765**			
INS 5	**0.829**			
ECQ 1	**0.914**			
ECQ 2	**0.909**	**0.892**	**0.933**	**0.822**
ECQ 3	**0.898**			
SAT 1	**0.891**			
SAT 2	**0.926**	**0.908**	**0.936**	**0.785**
SAT 3	**0.835**			
SAT 4	**0.890**			
USF 1	**0.857**			
USF 2	**0.907**			
USF 3	**0.911**	**0.905**	**0.934**	**0.779**
USF 4	**0.854**			
USE 1	**0.866**			
USE 2	**0.879**	**0.841**	**0.904**	**0.758**
USE 3	**0.866**			
BNT 1	**0.827**			
BNT 2	**0.896**			
BNT 3	**0.756**	**0.884**	**0.915**	**0.685**
BNT 4	**0.780**			
BNT 5	**0.871**			

4.2.2. Validity Testing

The validity test is performed with the purpose to see that the constructs/variables used are correlated. The test itself subsist of convergent validity and discriminant validity. Convergent validity has a basis in which each construct should be highly correlated to one another, as a result the criteria for the test are determined based on the AVE should be greater than 0.50 (Fornell and Larcker, 1981). On the contrary, discriminant validity proposes that correlations between constructs/variable should not be high. The Fornell Lacker Criterion is used as a criterion on the discriminant validity test, where one construct is considered to be valid if its value is greater than the correlation values of another construct. The discriminant validity also can be determined by looking into the cross-loading value.

Outcomes of the convergent validity tests are displayed in Table 3. The construct TSQ had an AVE value of 0.447. This resulted to a deletion of two indicators that belonged to the TSQ which are TSQ 9 (0.421), TSQ 10 (0.509), and TSQ 11 (0.599). The aforementioned indicators have the lowest outer loading value of said construct and have shown significant impact on the AVE value, thus the deletion of the indicators is required to keep the reliability and validity of the research items. After the removal of said indicators all the research constructs met the criteria of having an AVE value ≥ 0.50. This deemed the convergent validity of all the research construct as valid.The discriminant test result can be seen on table 3 for the Fornell Lacker criterion. The second stage test for Fornell Lacker Criterion contains two variables that does not met the minimum criterion, the aforementioned variables are TSQ and INQ. Thus, in order to resolve said issue, both variables AVE needed to be raised by removing several indicators that have significant impact on the AVE value (Hair et al., 2021). After the adjustment are completed, the Cross-loading test is also performed and has satisfactory outcome. The result from both tests can be seen in the valid research model in figure 3. This EESS Model, integrating concepts from the Expectation Confirmation Theory (ECT) with the addition of Expected Confirmation Quality (ECQ) as a critical independent variable. This framework aims to evaluate how various quality dimensions—such as Teaching Service Quality, Information Quality, System Response Quality, Educational Service Quality, Support Quality, Learner Quality, and Instructor Quality—affect key success metrics in an LMS, including user satisfaction (SAT), perceived usefulness (USF), and intention to use (USE). The introduction of ECQ, derived from ECT, emphasizes the role of users' expectations and their subsequent confirmation in shaping satisfaction and perceived usefulness, which are crucial mediators leading to the ultimate outcome of Net Benefits (BNT). By incorporating ECQ, the model extends its theoretical foundation to better capture the dynamics between user expectations, quality perceptions, and the overall effectiveness of the e-learning system.

Table 3. Fornell – Lacker Criteria (Second Stage test)

x	BNT	ECQ	ESQ	INQ	INS	LER	SAT	SRQ	SUP	TSQ	USE	USF
BNT	**0.828**											
ECQ	0.764	**0.907**										
ESQ	0.647	0.579	**0.747**									
INS	0.696	0.708	0.722	**0.741**								
INQ	0.702	0.565	0.612	0.697	**0.792**							
LER	0.686	0.627	0.686	0.751	0.677	**0.824**						
SAT	0.755	0.757	0.677	0.812	0.654	0.809	**0.886**					
SRQ	0.620	0.634	0.541	0.692	0.648	0.552	0.631	**0.823**				
SUP	0.638	0.617	0.519	0.665	0.666	0.644	0.708	0.706	**0.776**			
TSQ	0.660	0.666	0.633	0.819	0.631	0.674	0.752	0.683	0.649	**0.724**		
USE	0.636	0.652	0.381	0.482	0.508	0.429	0.535	0.489	0.479	0.543	**0.870**	
USF	0.796	0.744	0.605	0.693	0.701	0.723	0.812	0.601	0.658	0.667	0.632	**0.883**

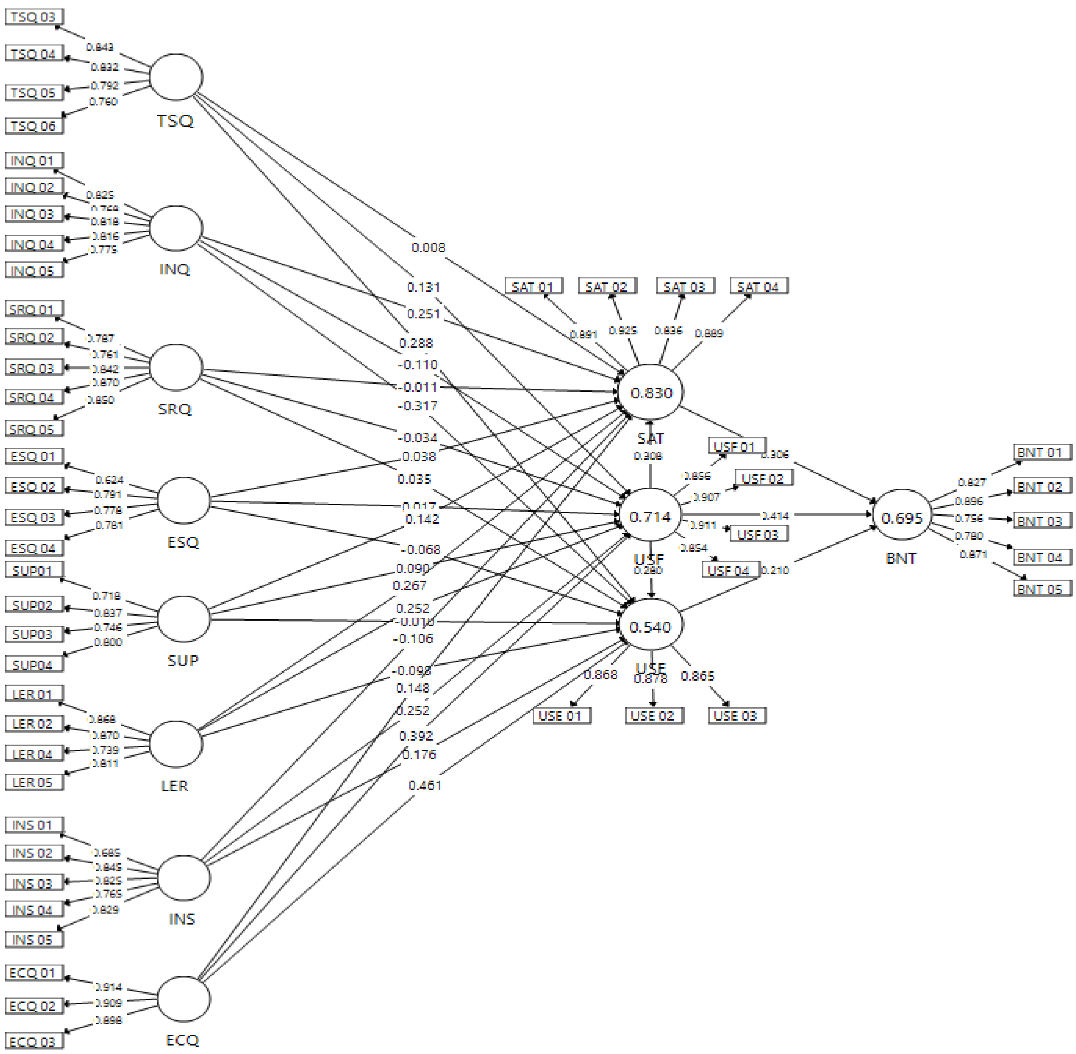

Figure 3. Valid Research Model (Third Stage)

4.3. *Structural Model (Inner Model)*

Structural model testing is the following step succeeding the measurement model testing of the model evaluation. The structural model is assessed through several criteria (Hair et al., 2021). First, examine collinearity issues with the threshold of VIF < 5. Second, assess the influence of relationships of the structural model or also known as hypothesis testing ($p < 0.05$). Third, Asses the value of R^2 by categorizing into three categories and thresholds, respectively 0.19 (weak), 0.33 (moderate), 0.67 (substantial). Fourth, assessment designated for the value of Q^2 to measure the predictive relevance of the structural model, and the assessment has a threshold of greater than zero.

Finally, the last assessment to be done in the on the structural model is to examine the model fit, the assessment aims to measure how well the structural model represents the data for the theory that is being tested (Hooper et al., 2008). Current study is also considering the indirect effects value as an additional indicator.

4.3.1. *Collinearity Testing*

Collinearity testing takes a look into the variance inflation factor or VIF. If a construct withholds a value of VIF ≥ 5 it indicates the potential of collinearity issues. After retrieving the result of collinearity testing, all constructs have possessed VIF value within the threshold. Thus, the data and construct does not contain any collinearity issue. The result for the collinearity test is shown in Table 4.

Table 4. Collinearity tests result

Construct	*SAT*	*USE*	*USF*	*BNT*
BNT				
ECQ	2.805	2.805	2.267	
ESQ	2.414	2.414	2.413	
INQ	3.512	3.512	3.469	
INS	2.781	2.781	2.559	
LER	3.176	3.176	2.953	
SAT				2.945
SRQ	2.610	2.610	2.606	
SUP	2.687	2.687	2.658	
TSQ	2.677	2.677	2.617	
USE				1.667

4.3.2. *Hypothesis Test Result*

Hypothesis testing was also conducted on this research by looking into the significance level of the path coefficient value. Utilizing a T-value of 1.96 along with a significance level of 5% on a two tailed test type. This approach allows for the determination of whether the path coefficients are significantly different from zero, providing insights into the relationships among the variables in the EESS model. To ensure the validity of the T-test results, the assumption of normally distributed data was made. This assumption is crucial for the accuracy of the T-test. It was assumed that the sample data follows a normal distribution, which supports the reliability of the hypothesis testing process.

The result of hypothesis tests is displayed on table 5. The T-test in this study was utilized using Equation (1).

$$t = \frac{O}{STDEV} \quad (1)$$

This T-test is calculated by using the Observed Value or in the current study case labeled as path coefficient and divided by the standard deviation of the path. An example for said calculation for the first path TSQ → SAT having the patch coefficient value of 0.008 (rounded) and a standard deviation value of 0.057, if calculated it would result to the value of the T-statistics 0.132 displayed on Table 5.

Table 5. Path Coefficient tests result

Path	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
H1a: TSQ -> SAT	0.057	0.132	0.895
H1b: TSQ -> USF	0.075	1.731	0.083
H1c: TSQ -> USE	0.076	3.785	0.000
H2a: INQ -> SAT	0.066	3.785	0.000
H2b: INQ -> USF	0.072	1.520	0.129
H2c: INQ -> USE	0.097	3.275	0.001
H3a: SRQ -> SAT	0.053	0.215	0.830
H3b: SRQ -> USF	0.059	0.568	0.570
H3c: SRQ -> USE	0.078	0.455	0.649
H4a: ESQ -> SAT	0.053	0.707	0.479
H4c: ESQ -> USF	0.065	0.264	0.792
H4c: ESQ -> USE	0.076	0.89	0.374
H5a: SUP -> SAT	0.051	2.766	0.006
H5b: SUP -> USF	0.060	1.502	0.133
H5c: SUP -> USE	0.076	0.136	0.892
H6a: LER -> SAT	0.061	4.390	0.000
H6b: LER -> USF	0.075	3.383	0.001
H6c: LER -> USE	0.084	1.162	0.245
H7a: INS -> SAT	0.913	2.126	0.034
H7b: INS -> USF	0.105	3.504	0.000
H7c: INS -> USE	0.05	1.68	0.093
H8a: ECQ -> SAT	0.072	3.212	0.001
H8b: ECQ -> USF	0.065	6.015	0.000
H8c: ECQ -> USE	0.046	5.407	0.000
H9: SAT -> BNT	0.069	4.431	0.000
H10a: USF -> SAT	0.062	5.002	0.000
H10b: USF -> BNT	0.074	5.611	0.000
H10c: USF -> USE	0.096	2.917	0.004
H11: USE -> BNT	0.051	4.123	0.000

Based on the path coefficient test value, presented are the acquired hypothesis tests result: H1a, H1b, and H1c assumed that the construct technical system quality (TSQ) had significant effect towards perceived satisfaction (SAT), perceived usefulness (USF), and use (USE) respectively. The test resulted in H1a and H1b possessed a p-value of 0.895 and 0.083 respectively, that are both greater than the threshold of 0.05. Both hypotheses also had a t-statistical value lower than 1.96 (0.132 and 1.731 respectively). Whereas H1c possessed a p-value of 0.000 and at statistical value greater than 1.96. H1a and H1b are rejected, however H1c is accepted. Thus, it was concluded that technical system quality prompts a significant effect on use, nonetheless it does not prompt a significant effect on perceived satisfaction and perceived usefulness according to the perception of the tested LMS users H2a, H2b, and H2c assumed that the construct information quality (INQ) had significant effect towards perceived satisfaction (SAT), perceived usefulness (USF), and use (USE) respectively. The test resulted in H2a and H2b possessed a p-value of 0.00 and 0.001 respectively, both hypotheses' value met the threshold being less than 0.05. Also, H2a and H2b had a t-statistical value greater than 1.96 (3.785 and 3.275 respectively). However, H2c possessed a p-value of 0.129 that is greater than the threshold, and a t-statistical value that is lower than 1.96 (1.520). H2a and H2c are accepted, yet H2b is rejected. Thus, it was concluded that information quality prompts a significant effect on perceived satisfaction and use, nonetheless it does not prompt a significant effect on perceived usefulness according to the perception of the tested LMS users; H3a, H3b, and H3c assumed that the construct service quality (SRQ) had significant effect towards perceived satisfaction (SAT), perceived usefulness (USF), and use (USE) respectively. The resulted in H3a, H3b, and H3c possessed a p-value of 0.830, 0.570, and 0.649 respectively. All three hypotheses do not meet the threshold for its p-value test. Also, H3a, H3b, and H3c possessed a t-statistical value that are lower than 1.96 (0.215, 0.568, and 0.455). H3a, H3b, and H3c are all rejected. Thus, it was concluded that service quality does not prompt significant effect towards perceived satisfaction, perceived usefulness, and use according to the perception of the tested LMS user.

H4a, H4b, and H4c assumed that construct the education system quality (ESQ) had significant effect towards perceived satisfaction (SAT), perceived usefulness (USF), and use (USE) respectively. The resulted in H4a, H4b, and H4c possessed a p-value of 0.479, 0.792, and 0.374 respectively. All three hypotheses do not meet the threshold for its p-value test. Also, H4a, H4b, and H4c possessed a t-statistical value that are lower than 1.96 (0.707, 0.264, and 0.890). H4a, H4b, and H4c are all rejected. Thus, it was concluded that education system quality does not prompt significant effect towards perceived satisfaction, perceived usefulness, and use according to the perception of the tested LMS users H5a, H5b, and H5c assumed that the construct support system quality (SUP) had significant effect towards perceived satisfaction (SAT), perceived usefulness (USF), and use (USE) respectively. The test resulted in H5a possessed a p-value of 0.006, meaning that it met the threshold of being lower than 0.05. H5a also had a t-statistical value greater than 1.96 (2.766). Whereas H5b and H5c possessed a p-value of 0.133 and 0.892 respectively, that does not meet the threshold that should be lower than 0.05. Also, both hypotheses had a t-statistical value that are lower than 1.96 (1.502 and 0.136 respectively). H5a is accepted, however H5b and H5c are rejected. Thus, it was concluded that support system quality prompts a significant effect on perceived satisfaction, nonetheless it does not prompt a significant effect on perceived usefulness and according to the perception of the tested LMS users; H6a, H6b, and H6c assumed that the construct learner quality (LER) had significant effect towards perceived satisfaction (SAT), perceived usefulness (USF), and use (USE) respectively. The test resulted in H6a and H6b possessed a p-value of 0.00 and 0.001 respectively, both hypotheses' value met the threshold being less than 0.05. Also, H6a and H6b had a t-statistical value greater than 1.96 (4.390 and 3.383 respectively). However, H6c possessed a p-value of 0.245 that is greater than the threshold, and a t-statistical value that is lower than 1.96 (1.162). H6a and H6b are accepted, yet H6c is rejected. Thus, it was concluded that learner quality prompts a significant effect on perceived satisfaction and perceived usefulness, nonetheless it does not prompt a significant effect on use according to the perception of the tested LMS users.

H7a, H7b, and H7c assumed that the construct instructor quality (INS) had significant effect towards perceived satisfaction (SAT), perceived usefulness (USF), and use (USE) respectively. The test resulted in H7a and H7b possessed a p-value of 0.034 and 0.000 respectively, both hypotheses' value met the threshold being less than 0.05. Also, H7a and H7b had a t-statistical value greater than 1.96 (3.504 and 3.212 respectively). However, H7c possessed a p-value of 0.093 that is greater than the threshold, and a t-statistical value that is lower than 1.96 (1.680). H7a and H7b are accepted, yet H7c is rejected. Thus, it was concluded that instructor quality prompts a significant effect on perceived satisfaction and perceived usefulness, nonetheless it does not prompt a significant effect on use according to the perception of the tested LMS users; H8a, H8b, and H8c assumed that the construct expected confirmation quality (ECQ) had significant effect towards perceived satisfaction (SAT), perceived usefulness (USF), and use (USE) respectively. The resulted in H8a, H8b, and H8c possessed a p-value of 0.001, 0.000, and 0.000 respectively. All three hypotheses met the threshold for its p-value test. Also, H8a, H8b, and H8c possessed a t-statistical value that are greater than 1.96 (3.212, 6.015, and 5.407). H8a, H8b, and H8c are all accepted. Thus, it was concluded that expected confirmation quality prompts significant effect towards perceived satisfaction, perceived usefulness, and use according to the perception of the tested LMS users; H9 assumed that the construct perceived satisfaction (SAT) had significant effect towards benefits (BNT). The resulted in H9 possessed a p-value of 0.000. All three hypotheses do not meet the threshold for its p-value test. Also, H9 possessed a t-statistical value that are greater than 1.96 (4.431). H9 is accepted, and it was concluded that perceived satisfaction prompts significant effect towards benefits according to the perception of the tested LMS users.

H10a, H10b, and H10c assumed that the construct perceived usefulness (ECQ) had significant effect towards perceived satisfaction (SAT), benefits (BNT), and use (USE) respectively. The resulted in H10a, H10b, and H10c possessed a p-value of 0.000, 0.000, and 0.004 respectively. All three hypotheses met the threshold for its p-value test. Also, H10a, H10b, and H10c possessed a t-statistical value that are greater than 1.96 (5.002, 5.611, and 2.917). H10a, H10, and H10c are all accepted. Thus, it was concluded that perceived usefulness prompts significant effect towards perceived satisfaction, benefits, and use according to the perception of the tested LMS users; H11 assumed that the construct use (USE) had significant effect towards benefits (BNT). The resulted in H11 possessed a p-value of 0.000. All three hypotheses do not meet the threshold for its p-value test. Also, H11 possessed a t-statistical value that are greater than 1.96 (4.123). H11 is accepted, and it was concluded that use prompts significant effect towards benefits according to the perception of the tested LMS users.

4.3.3. R-Square Test Result

The R-squared test was utilized and aims to look into how well the independent variables are able to describe or explain the variation of the dependent variables. The R-squared test is used to explain the relationship between independent and dependent variables in any model. For instance, in a simple linear regression model where Y is predicted from X, the R-squared value measures the proportion of variance in Y that is predictable from X, ranging from 0 to 1It helps assess the goodness of fit, evaluate model performance, and compare models, though a higher R-squared does not necessarily imply the best model, as it could also indicate overfitting. R-square values can be categorized into several groups based on the cut-off levels as follows: 0.190 (weak), 0.333 (moderate),and 0.670 (substantial) (Hamid and Anwar, 2019). Results for the R-square tests are displayed in Table 6.

Table 6. R-square test results

Dependent Variable	R-Square	Category
Benefits	0.695	Substantial
Perceived Satisfaction	0.830	Substantial
Use	0.540	Moderate
Perceived Usefulness	0.714	Substantial

Benefits (BNT) variable acquired an R-square value of 0.695 that puts it in the substantial category. It can be derived that the independent variables managed to explain the variation changes in the BNT variable by 69.5%. Perceived satisfaction (SAT) variable acquired an R-square value of 0.830 that puts it in the substantial category. It can be derived that the independent variables managed to explain the variation changes in the SAT variable by 83%. Use (USE) variable acquired an R-square value of 0.540 that puts it in the moderate category. It can be derived that the independent variables managed to explain the variation changes in the USE variable by 54%. Perceived usefulness (USF) variable acquired an R-square value of 0.714 that puts it in the substantial category. It can be derived that the independent variables managed to explain the variation changes in the USF variable by 71.4%. Based on the R-square test results, it was concluded that most of the dependent variables leaned more towards possessing a substantial R-square value, as 3 dependent variables (BNT, SAT, USF) acquired substantial that also includes the target variable (BNT) and 1 acquired moderate level (USE).

4.3.4. Indirect Effect

Indirect relationships between the variables in the valid research model was looked into. The test was done between the independent variables (TSQ, INQ, SRQ, ESQ, SUP, LER, INS, and ECQ) and the target variable (BNT). The test result is displayed on Table 7.

Table 7. Indirect effect tests result

Path	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
TSQ -> BNT	0.051	2.660	0.008
INQ -> BNT	0.055	0.942	0.346
SRQ -> BNT	0.045	0.337	0.736
ESQ -> BNT	0.046	0.155	0.877
SUP -> BNT	0.046	2.028	0.043
LER -> BNT	0.054	3.789	0.000
INS -> BNT	0.049	2.982	0.003
ECQ -> BNT	0.048	7.672	0.000

According to the test results, it can be derived that: Indirect relationship between technical system quality (TSQ) and benefits (BNT) possessed a t-statistical value that is greater than the threshold (1.96), it also had a p-value of 0.008 that proves its significance. Therefore, it can be concluded that the technical system quality significantly affects the benefits felt by the users of said LMS indirectly; Indirect relationship between information quality (INQ) and benefits (BNT) possessed a t-statistical value that is lower than the threshold (1.96), it also had a p-value of 0.346 that shows that the relationship is not significant. Thus, it can be concluded that the information quality does not significantly affect the benefits felt by the users of said LMS; Indirect relationship between service quality (SRQ) and benefits (BNT) possessed a t-statistical value that is lower than the threshold (1.96), it also had a p-value of 0.736 that shows that the relationship is not significant. Thus, it can be concluded that the service quality does not significantly affect the benefits felt by the users of said LMS; Indirect relationship between education system quality (ESQ) and benefits (BNT) possessed a t-statistical value that is lower than the threshold (1.96), it also had a p-value of 0.877 that shows that the relationship is not significant. Thus, it can be concluded that the education system quality does not significantly affect the benefits felt by the users of said LMS; Indirect relationship between support system quality (SUP) and benefits (BNT) possessed a t-statistical value that is greater than the threshold (1.96), it also had a p-value of 0.043 that proves its significance. Therefore, it can be concluded that the support system quality significantly affects the benefits felt by the users of said LMS indirectly; Indirect relationship between learner quality (LER) and benefits (BNT) possessed a t-statistical value that is greater than the threshold (1.96), it also had a p-value of 0.000 that proves its significance. Therefore, it can be concluded that the learner quality significantly affects the benefits felt by the users of said LMS indirectly; Indirect relationship between instructor quality (INS) and benefits (BNT) possessed a t-statistical value that is greater than the threshold (1.96), it also had a p-value of 0.003 that proves its significance. Therefore, it can be concluded that the instructor quality significantly affects the benefits felt by the users of said LMS indirectly; Indirect relationship between expectation-confirmation quality (ECQ) and benefits (BNT) possessed a t-statistical value that is greater than the threshold (1.96), it also had a p-value of 0.008 that proves its significance. Therefore, it can be concluded that the expectation confirmation quality significantly affects the benefits felt by the users of said LMS indirectly.

4.3.5. *Q^2 Test Result*

Predictive relevance test was done on current study constructs resulting in their Q^2 value. The threshold for the Q^2 value is greater than zero. The result is displayed in table 8 where a test for both cross validated redundancy and cross validated communality. Results shows that all of the Q^2 value surpassed the threshold.

The cross validated redundancy aims to measure the capability of target variables predictive power. The result from the test shows that all of the target variables (BNT, SAT, USF, USE) possesses predictive power (Threshold for strong predictive $Q^2 > 0.35$)

Cross validated communality was also calculated and aims to measure the model's predictive power for all variables. Results show that there are 9 variables with strong predictive power and 2 variables possessed moderate predictive power. Thus, results from both tests deemed the model possesses considerable predictive power.

Table 8. Q^2 tests result

Variables	**Predictive Relevance Q^2**			
	Construct Crossvalidated Communality		**Construct Crossvalidated Redundancy**	
BNT	0.524	Strong predictive power	0.467	Strong predictive power
ECQ	0.608	Strong predictive power	-	
ESQ	0.268	Moderate predictive power	-	
INQ	0.455	Strong predictive power	-	
INS	0.441	Strong predictive power	-	
LER	0.461	Strong predictive power	-	
SAT	0.624	Strong predictive power	0.638	Strong predictive power
SRQ	0.510	Strong predictive power	-	
SUP	0.342	Moderate predictive power	-	
TSQ	0.413	Strong predictive power	-	
USE	0.492	Strong predictive power	0.385	Strong predictive power
USF	0.614	Strong predictive power	0.543	Strong predictive power

4.3.6. *Model Fit Test Result*

The last part of the structural model testing is the model fit test. It was determined that the model fit is able to be measured by looking into the Goodness of Fit (GoF) value. GoF was described as the average R-square value $(\overline{R^2})$and the mean of average communality $(\overline{AVE})$ (Tenenhaus et al., 2005) as expressed in Equation (2).

$$GoF = \sqrt{\overline{AVE} \times \overline{R^2}} \qquad (2)$$

The calculation was done on the model's value and resulted with a 0.692 of GoF. Based on the result of the calculation the model fit is categorized as large.

4.3.7. *Discussion*

Current research has tested a total of 29 hypotheses from 11 variables, the results are as follows. Results from H1a, H1b, H1c proved that technical system quality did not affect users' satisfaction and perception of usefulness from using the system, but it affected the willingness to use the LMS. These resulst was in complete contrast to the previous research (Al-Fraihat et al., 2020). Users of the of the tested LMS seemed to be more driven towards the fact that only when the system is used often would they feel the benefits of the system. All of the result might occur due external influence that the use of the tested LMS is mandatory however improvements regarding to the system was rarely made by the time this research was done; Results from H2a, H2b, and H2c proved that the quality of information that is provided by the LMS proved to satisfy the users and increases their willingness to use the LMS and further extends to the benefits of using. However, information quality does not affect users' perception of usefulness towards the system. It also aligned with a previous study that proved information significantly affect users' satisfaction and willingness to use (Al-Fraihat et al., 2020). Possible reasons for the rejection of H2b could be the fact that the system was mainly used for assignments, handing out teaching materials, and in some cases, tests. In cases of information regarding the class and announcements, communication was rarely done through the LMS, thus information quality does not significantly affect the user's perception regarding the system's usefulness. This is because users primarily value the LMS for its functional utility in efficiently handling assignments and materials, rather than the quality of supplementary information such as announcements; Results from H3a, H3b, and H3c was in contrast with the expected relationship. Compared to the previous research, only H3a had a contrast which it was accepted in the prior study. (Al-Fraihat et al., 2020). This discrepancy suggests that the services provided by the system do not significantly contribute to user satisfaction, perception of the system's usefulness, or the overall utilization of the system. Despite the anticipated positive impact, the findings indicate that other factors may play a more critical role in influencing these aspects of user experience. Thus, the current study challenges previous assumptions about the direct impact of service quality on user outcomes in LMS environments.

H4a, H4b, H4c predictions did not align with its test results. However, compared to the previous study H4a and H4b possessed the same result and H4c possessed a contrast result (Al-Fraihat et al., 2020). This indicates that the quality of the educational system does not significantly impact user satisfaction, perception of the system's usefulness, or the willingness to use the system. One possible reason for this is that the educational system's uses are still being explored and developed, and the current study's LMS is undergoing continuous improvements over time. Consequently, users may not yet fully appreciate the system's quality due to its evolving nature. Also, the contrast result from the previous might occur due to the difference state of development between the 2 LMS; H5a acquired support, while H5b and H5c did not receive support. Thus, it can be concluded that knowledge and information regarding ethical and legal issues on the system affects user's satisfaction. However, it does not affect the perception of usefulness and the will to use the system. The finding of H5a aligns with the previous research, while H5b and H5c finding are in contrast (Al-Fraihat et al., 2020). The contrast of findings found in H5a is assumed to be mainly caused due to a difference in ethical and legal issues presented in different educational institution or culture and might cause a different level of satisfaction; H6a, and H6b managed to receive support, while H6c does not. This proves that a learner's attitude and enthusiasm towards using an LMS affects the user's satisfaction and perception of usefulness towards the system. However, it does not affect the users' will to use the system. The result of H6c is in contrast with previous research regarding the relationship, where it showed that satisfaction was affected by learners' attitude towards the system (Al-Fraihat et al., 2020; Üstünel, 2016; Chen and Tat Yao, 2016). A possible reason for this could be due to lecturers and students mainly uses the system for assignments and tests and not a main source of learning. As a result, learners might engage with the LMS out of necessity rather than a desire to explore and utilize its full potential for educational enrichment. This utilitarian approach to using the LMS means that while learners' attitudes can enhance their satisfaction and perception of usefulness when they interact with the system, it does not necessarily translate into a greater willingness to use the system beyond these mandatory tasks. The system's role as a supplementary tool rather than a central learning platform could thus explain why learners' s willingness to use does not significantly influence their overall willingness to engage with the LMS.

Derived from analyzed data H7a, and H7b had aligned with initial prediction, nonetheless H7c had contrary result. It can be concluded that an instructor's support and attitude towards the use of an LMS contribute to users' satisfaction and perception of the system's usefulness. This outcome makes sense because when students and lecturers provide support and cooperate in using the LMS, both parties tend to feel more satisfied and recognize the system's usefulness during the learning process. The positive reinforcement and encouragement from instructors can enhance the overall learning experience, making the LMS seem more beneficial. However, the support and positive attitude from instructors do not appear to affect the users' willingness to use the LMS. One reason for this might be similar to the rationale in the previous hypothesis: the LMS is primarily used for assignments and tests, not as the main source of learning. This limited use case means that students and lecturers interact with the LMS out of necessity rather than choice. As a result, their willingness to use the system is not significantly influenced by the support and attitude of the instructors. The necessity-driven interaction limits the impact of external encouragement on their willingness to use the LMS.

Additionally, the same results for H7a, H7b, and H7c were observed in previous studies, indicating that these findings are consistent and support the initial assumptions. The recurring patterns suggest that while instructor support enhances satisfaction and perceived usefulness, it does not translate into a greater willingness to use the LMS. This reinforces the notion that the role of the LMS as a supplementary tool, mainly for administrative and assessment purposes, shapes users' engagement and willingness to use it beyond required tasks. (Al-Fraihat et al., 2020). H8a, H8b, and H8c were all supported from the statistical view. This proves that a users' expectation and confirmation regarding an e-learning system greatly affects its success. H8a, H8b, and H8c was not tested in previous studies. However, similar results can be found in different studies with a similar relationship of variables (Tam et al., 2020; Oghuma et al., 2016). Thus, it can be taken into perspective that users' expectations and its confirmation can affect the levels of satisfaction, perceived usefulness, and willingness to use the system that leads to measure how successful an LMS have been implemented. Furthermore, this discovery marks that expectation-confirmation factor can be taken into consideration into improving the evaluation model for e-learning system's success;

The result for H9 was as expected, confirming that satisfaction has a significant influence on the benefits that users attain from the system. In other words, the greater the users' satisfaction, the more substantial the benefits they will experience. This finding aligns with the discoveries of previous studies Cidral et al., (2018), Aparicio et al., (2017), and Al-Fraihat et al., 2020), reinforcing the conclusion that user satisfaction positively impacts the perceived benefits of using the system. When users are satisfied with the LMS, they are more likely to engage deeply and effectively with its features, leading to enhanced learning outcomes, better management of assignments and materials, and a more streamlined educational experience. This positive correlation highlights the importance of prioritizing user satisfaction to maximize the advantages offered by the LMS. By continuously improving the system to meet users' needs and expectations, institutions can ensure that users derive the maximum possible benefits. The consistency of this result with prior research underscores its validity and emphasizes the critical role of satisfaction in determining the overall success and utility of the LMS. Hypotheses H10a, H10b, and H10c all received support, proving that if users deem the system to be useful, students are more likely to use the system extensively. This demonstrates that perceived usefulness is a critical factor in driving user engagement with the LMS. When the system increases efficiency and accessibility in the learning process, students are more likely to feel satisfied with it. The better the system is at meeting these criteria, the higher the level of user satisfaction. Furthermore, the benefits that users achieve from the system are closely tied to their perception of its usefulness. The results for H11 aligned with the hypothesis, confirming that the usage of the LMS is beneficial to users when it meets their needs. This means that when the system is tailored to address users' specific requirements and preferences, it becomes a valuable tool in their educational journey. Consequently, the rate of use directly influences the benefits achieved by users. The more frequently and effectively users engage with the LMS, the greater the benefits they experience, including enhanced learning outcomes, better management of academic tasks, and improved access to educational resources. This underscores the importance of a user-centric design and continuous adaptation of the LMS to meet evolving needs, ensuring it remains an integral part of their academic routine and maximizes the educational advantages it provides.

The outcome of the study managed to discover the perception of both students and lecturers on the success of the LMS used for day-to-day learning activity. Thus, the success of the studied LMS have been measured and factors that contributes to its success. According to the findings of this study, a variable pointing on expectation and confirmation quality is implemented in the EESS model. Current study also conducted testing the relationship between the 11 variables of theorized EESS model. There are a total of 29 hypotheses, with 16 out of 29 hypotheses managed to be accepted. The study also managed to answer the research question that involved expectation and confirmation theory to be incorporated into the EESS model, and found that expected confirmation quality significantly affects satisfaction, perception of usefulness, and utilization of the tested e-learning system. Expectations from the e-learning users and its confirmation plays a role in the factors of achieved benefits. Therefore, it can be said that it is crucial to have information regarding what are the expectations of the e-learning system from the user's perspective and is it possible to fulfill it prior to implementing or developing and updating an e-learning system. Present study also incorporated lecturers as respondents and managed to discover some differences in test result compared to prior researches. It can be said that the inclusion of lecturers or instructors as part of respondents are a major point of measuring an e-learning system's success, since lecturers plays a major role in the learning process and also one of the main users of the system.

Current study acquired a couple of contributions for the implementation, development and maintenance of an LMS. First of all, university executives and head of technology department would find it useful to know the factors that measures up the implementation and development of an LMS. By knowing prior to implementation certain factors such as expectation and confirmation, technical system quality, and users' attitude about having and using the LMS would pushes the development into the factors that can achieve more benefits for the users. Second, in an event of further developing the current LMS, it is crucial to focus on features that enhances satisfaction and perception of usefulness for the student and lecturers. Reason being that both satisfaction, and perception has more effect on the achieved benefits.

5. Conclusion

Based on the results of the current study, it was discovered that expectation confirmation quality significantly influences perceived usefulness, satisfaction, and system utilization. System utilization is primarily affected by technical system quality, information quality, and perceived usefulness, while perceived usefulness is mainly influenced by instructor quality and learner quality. Satisfaction is impacted by information quality, support system quality, learner quality, instructor quality, and perceived usefulness. However, education system quality and service quality do not significantly affect LMS success, likely due to the absence of a dedicated IT team and insufficient user training on LMS features. From the aforementioned findings it can be said that the research question managed to be answered. Furthermore, to improve the LMS at Universitas Kristen Satya Wacana, providing comprehensive information and training on LMS features and establishing dedicated IT support are recommended. The study's limitations include a restricted population size, which future research should expand to include the entire university population and a larger sample size. Additionally, future studies could explore incorporating new variables into the EESS model to better measure e-learning system success and identify factors for further development to enhance LMS effectiveness.

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