



Evaluating the Effectiveness of a Cloud Computing-Based LMS in Developing Learning Skills in Accounting Major

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ABSTRACT

Purpose of the study: This study aims to evaluate the factors influencing student acceptance and satisfaction with SIPDA, a cloud-based Learning Management System (LMS), among accounting majors at the Faculty of Economics, Universitas Negeri Medan.

Methodology: A quantitative research design was employed using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with SmartPLS. The study involved 213 accounting students from both regular and non-education programs, selected through a total sampling approach. Data were collected using structured questionnaires that measured five core constructs: instructor quality, content quality, perceived usefulness, satisfaction, and self-regulation. The collected data were analyzed using SEM-PLS to test the hypothesized relationships and assess model validity and reliability.

Main Findings: Of the seven hypotheses tested, six were found to be positive and statistically significant. Instructor and content quality had strong positive effects on perceived usefulness and satisfaction, while perceived usefulness significantly enhanced satisfaction. However, self-regulation showed an adverse indirect effect on satisfaction through perceived usefulness ($\beta = -0.061$), indicating that highly self-regulated students are more critical when the LMS fails to meet their expectations. The model demonstrated high predictive validity ($R^2 = 0.790$) and fulfilled all reliability and construct validity criteria.

Novelty/Originality of this study: This study reveals a counterintuitive relationship between self-regulation and satisfaction. While self-regulation typically fosters positive outcomes, students with greater autonomy and digital literacy are dissatisfied when LMS responsiveness and personalization are lacking. The findings emphasize the need for adaptive, learner-centered LMS designs tailored to self-regulated learners in higher education.

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1. INTRODUCTION

The technological revolution in education has profoundly transformed teaching and learning methods across academic disciplines, including accounting [1]-[3]. This transformation presents significant challenges for higher education institutions in Indonesia to produce graduates who are adaptable to a dynamic digital environment that demands both technical and non-technical competencies [4]-[6]. In response, universities have adopted cloud-based Learning Management Systems (LMS) such as SIPDA and Google Classroom (GCR) to support the government's digital transformation agenda in education. The urgency of this research lies in understanding how the effective implementation of LMS guided by the Information System Success Model

(ISSM) developed by DeLone and McLean can enhance teaching quality, accessibility, and student engagement in Indonesia's post-pandemic learning landscape. Despite widespread LMS adoption, its success depends on multiple factors, including instructor quality, information content quality, perceived usefulness, and student self-regulation [7]-[9].

The research problem addressed in this study lies in the limited empirical understanding of how these pedagogical, informational, and psychological factors collectively determine the effectiveness of LMS in accounting education. Although previous studies have explored LMS adoption from technological and behavioral perspectives mainly emphasizing perceived ease of use and perceived usefulness [10], [11], there remains a research gap in integrating multiple dimensions of LMS success into a unified evaluative model. Furthermore, this study incorporates the concept of academic optimism, which assumes that students' positive beliefs, motivation, and confidence in their learning abilities can enhance satisfaction and perceived usefulness within digital learning environments [12], [13]. This theoretical lens supports the integration of cognitive and emotional factors in understanding LMS success, particularly when applied to specific contexts such as accounting education, which requires both conceptual reasoning and technological adaptability.

The rationale behind this study rests on the need for a holistic evaluation model that captures not only the technical aspects of LMS but also the pedagogical and psychological dimensions influencing user experience. The accounting discipline, which requires strong theoretical foundations and practical applications, depends heavily on the instructor's ability to deliver high-quality content and create meaningful engagement through LMS platforms. Therefore, understanding how instructor quality, information content quality, and student self-regulation interact to shape perceived usefulness and satisfaction becomes crucial for improving LMS-based learning strategies [14]-[16].

To address this gap, this study applies the Information System Success Model (ISSM) developed by DeLone and McLean as a comprehensive framework to evaluate SIPDA, a cloud-based LMS. The objectives of this research are threefold: (1) to analyze the direct and indirect relationships among instructor quality, information content quality, perceived usefulness, self-regulation, and satisfaction; (2) to identify the most influential factors affecting student satisfaction with LMS use; and (3) to provide empirical evidence supporting the applicability of the ISSM model in accounting education [17]-[19]. The significance of this study lies in its theoretical and practical contributions. Theoretically, it expands the ISSM framework by incorporating pedagogical and psychological constructs including optimism and self-regulation to explain LMS effectiveness within higher education settings [20], [21]. Practically, the study provides actionable insights for improving LMS design, emphasizing the importance of instructor competence, content quality, and learner autonomy. The findings are expected to guide educators and policymakers in creating adaptive, learner-centered digital learning environments that enhance both engagement and satisfaction among students [22]-[24].

A Learning Management System (LMS) is defined as a digital platform designed to manage, distribute, and monitor online learning activities [25]. Through LMS, students and lecturers can share resources, complete assignments, take quizzes, and interact in discussion forums without requiring physical meetings, thereby supporting learning flexibility in terms of time and location [26]-[28]. Many universities in Indonesia have adopted cloud-based LMS platforms such as SIPDA (*Sistem Pembelajaran Daring*) and Google Classroom to promote digital transformation and enhance post-pandemic learning accessibility. The success of such systems depends on the quality of their infrastructure, the relevance of the content provided, and the capacity of users to manage their learning processes independently [29], [30]. The development of cloud computing has further enhanced LMS performance by offering web-based access, real-time data analytics, and adaptive features that facilitate personalized learning experiences [31]-[33].

The DeLone and McLean Information System Success Model (ISSM) provides a theoretical basis for evaluating information system effectiveness through six key dimensions: system quality, information quality, service quality, use, user satisfaction, and net benefits [34], [35]. Previous studies applying the ISSM in e-learning contexts confirmed that system and information quality have significant positive effects on perceived usefulness and user satisfaction [36]-[38]. However, these studies have largely focused on general education settings rather than specialized disciplines such as accounting, where instructor quality and self-regulation play more critical roles. Instructor quality encompasses the lecturer's competence in utilizing digital tools to manage materials, foster communication, and deliver feedback effectively, while information content quality determines the relevance, clarity, and accuracy of learning materials. High-quality instructional content enhances perceived usefulness and satisfaction, whereas poor content quality can diminish student engagement even when the system operates efficiently.

Another important construct influencing LMS effectiveness is self-regulation, defined as students' ability to plan, monitor, and control their learning processes independently. While self-regulation generally improves learning outcomes, previous research suggests that highly self-regulated students may exhibit lower satisfaction when LMS features fail to meet their expectations for autonomy, flexibility, or interactivity. This paradox aligns with optimism theory, in which motivated learners with high self-expectations may become less satisfied when the digital environment does not provide sufficient autonomy or challenge [39]-[41]. This finding

highlights the complex and sometimes dual role of self-regulation as both a predictor and moderator of satisfaction in digital learning environments.

Building on these theoretical insights, the present study integrates the ISSM framework with pedagogical, informational, and psychological dimensions to assess the success of SIPDA as a cloud-based LMS. Using a quantitative approach and Structural Equation Modeling–Partial Least Squares (SEM-PLS), data were collected from 213 accounting students across two programs through total sampling. The study evaluates seven hypotheses that examine the direct and indirect effects of instructor quality, information content quality, and self-regulation on perceived usefulness and satisfaction.

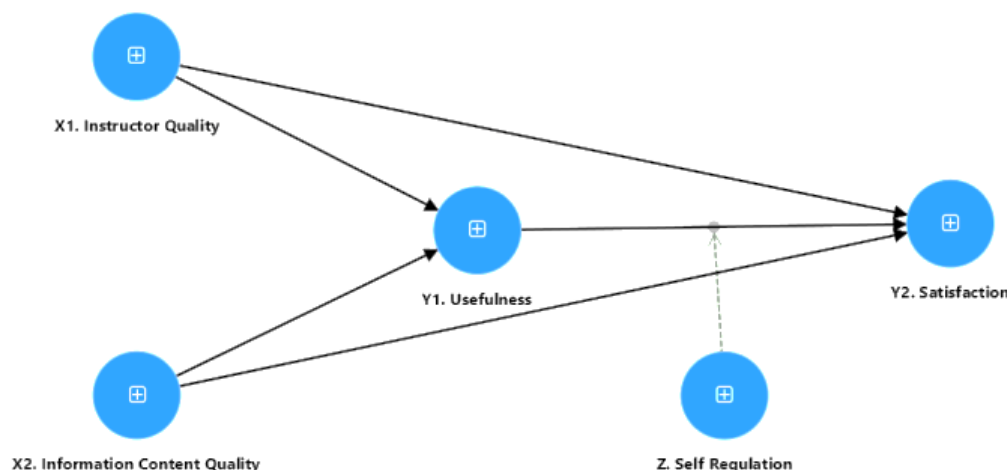


Figure 1. Conceptual framework

This conceptual framework illustrates the interrelationships among the key variables examined in the study. Instructor Quality and Information Content Quality act as exogenous variables that positively influence Perceived Usefulness and Satisfaction, while Self-Regulation functions as both an independent and mediating variable. Perceived Usefulness serves as a mediator linking the quality factors to user Satisfaction. The framework reflects the integration of pedagogical and technological perspectives within the ISSM model, suggesting that LMS effectiveness in Indonesia is determined not only by technical performance but also by instructional design and learners' capacity for self-directed learning. By analyzing these relationships, the study provides a comprehensive understanding of LMS implementation in Accounting Major and offers practical recommendations for improving digital learning environments in Indonesian higher education.

2. RESEARCH METHOD

This study employed a mixed-method research design, combining quantitative and qualitative approaches to obtain a comprehensive understanding of the factors influencing students' acceptance and satisfaction in using the SIPDA Learning Management System (LMS). The quantitative approach was used to test the proposed hypotheses statistically through the Structural Equation Modeling–Partial Least Squares (SEM-PLS) method, while the qualitative approach explored students' experiences and contextual perceptions in greater depth. This design was selected to integrate objective measurement and interpretive insights, ensuring both the validity and richness of findings.

This research is explanatory and confirmatory, aiming to test the causal relationships between instructor quality, information content quality, perceived usefulness, self-regulation, and satisfaction with the use of a cloud-based LMS. The population comprised all students enrolled in the Accounting and Non-Education Accounting programs between the 2022 and 2024 academic years. A total sampling technique was employed, resulting in a sample of 213 students, all of whom had direct experience using SIPDA in their coursework. This number exceeds the minimum requirement based on power analysis, where for a model with five constructs, a minimum of 150 samples is required to achieve a statistical power of 0.95 at a 5% significance level. In addition, 15 participants were selected through purposive sampling for semi-structured interviews to provide qualitative depth, representing students with varying levels of LMS engagement and performance.

Two main instruments were used: a structured questionnaire and an interview guide [8]. The questionnaire consisted of five constructs measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) in Table 1.

Table 1. Research Instrument Grid and Construct Indicators

Construct	Variable Code	Number of Items	Indicator Focus
Instructor Quality	X1	6	Lecturer feedback, communication, and guidance
Information Content Quality	X2	6	Clarity, relevance, and accuracy of materials
Perceived Usefulness	Y1	5	Perceived impact on learning outcomes
Satisfaction	Y2	5	Enjoyment and usefulness of system experience
Self-Regulation	Z	6	Planning, monitoring, and controlling learning

The instrument demonstrated high internal consistency with Cronbach's alpha values ranging from 0.83 to 0.92, exceeding the reliability threshold of 0.70. The interview guide included open-ended questions on instructor student interaction, content relevance, system responsiveness, and learning autonomy. Interviews were conducted virtually, recorded with consent, and transcribed for analysis. Quantitative data were collected online through SIPDA and Google Forms, ensuring convenience and inclusivity. Qualitative interviews were conducted after the survey phase to triangulate findings and explain patterns observed in the statistical model. Instrument validity was verified through content, construct, and convergent validity assessments. Three subject-matter experts in educational technology and accounting reviewed the questionnaire items for clarity and alignment. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were conducted to validate construct dimensions. All indicator loadings exceeded 0.70, and the Average Variance Extracted (AVE) values were greater than 0.50, confirming convergent validity. Composite reliability values exceeded 0.80, ensuring strong internal consistency.

Quantitative analysis employed SEM-PLS using SmartPLS 4 software. The analysis was conducted in two phases. Outer model testing, to assess indicator reliability, discriminant validity, and convergent validity. Inner model testing, to evaluate the strength of relationships among constructs using R^2 , F^2 , path coefficients, and predictive relevance (Q^2). A bootstrapping procedure (5,000 resamples) was performed at a 5% significance level to test the statistical significance of each path. The final model showed $R^2 = 0.790$, indicating that 79% of the variance in satisfaction was explained by the independent variables, which demonstrates high predictive power. Qualitative data were analyzed thematically using the Miles and Huberman interactive model, which involves data reduction, data display, and conclusion drawing. Coding and theme generation were performed using NVivo software to ensure analytical rigor and traceability.

The use of 213 respondents exceeds the recommended sample size for SEM-PLS, providing strong statistical power (>0.95) and reducing the risk of Type II errors. The combination of quantitative modeling and qualitative triangulation strengthens both internal validity and interpretive depth, offering a robust mixed-method evaluation of LMS effectiveness.

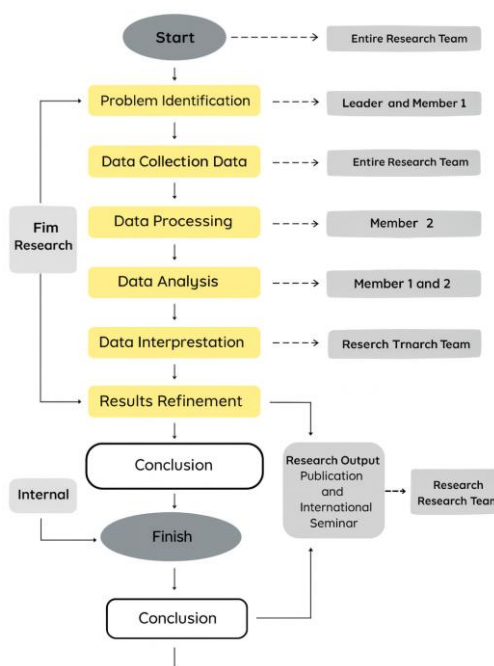


Figure 2. Research Flowchart

As shown in Figure 2, the research flow follows a systematic procedure to ensure methodological coherence and analytical accuracy. Each step is interconnected to produce valid and reliable findings, where quantitative and qualitative data were integrated to strengthen the interpretation of LMS effectiveness in accounting education. This flowchart also emphasizes the iterative nature of data validation and interpretation processes undertaken in the study.

3. RESULTS AND DISCUSSION

3.1. Evaluation of Measurement Model

The evaluation of the measurement model was conducted to ensure that each construct in the research framework met the criteria of reliability and validity before proceeding to structural model testing. Using SmartPLS 4.0, the measurement model was analyzed to verify that the latent variables were accurately represented by their observed indicators. The goal of this step is to confirm the internal consistency, convergent validity, and discriminant validity of all measurement items.

The research model developed in this study was analyzed using SmartPLS 4.0 to evaluate both the measurement and structural models. Before interpreting the results, it is important to visualize the relationships among the five key constructs: Instructor Quality, Information Content Quality, Perceived Usefulness, Satisfaction, and Self-Regulation. The following figure presents the complete structural model that reflects the hypothesized connections among these variables.

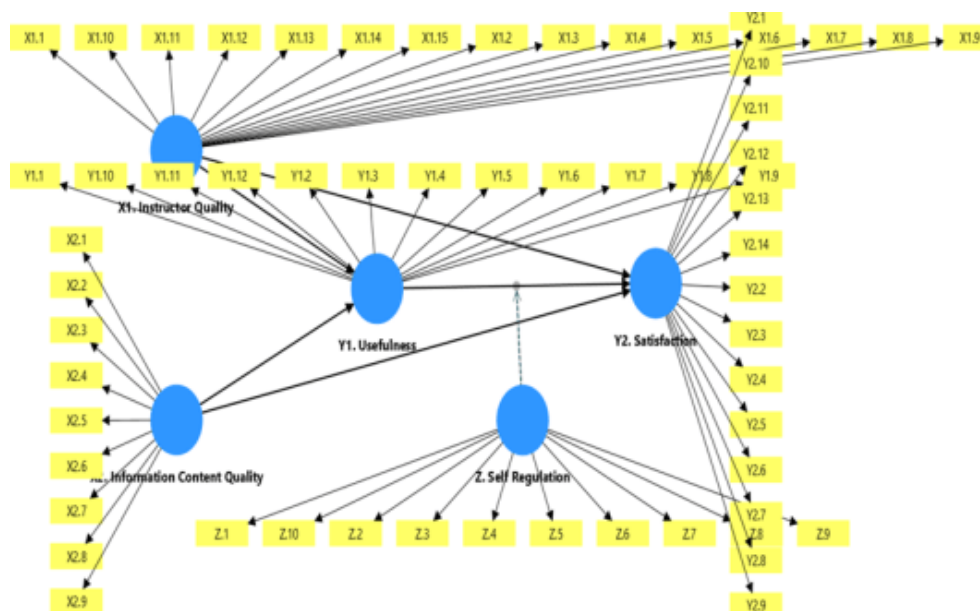


Figure 3. Research Model in Smart-PLS

As shown in Figure 3, each construct is connected through direct and indirect paths that represent the strength of their relationships. The figure illustrates that Instructor Quality and Information Content Quality positively influence both Perceived Usefulness and Satisfaction, while Self-Regulation has an indirect negative effect on Satisfaction through Perceived Usefulness. This visualization confirms that the research model is structurally sound and provides a strong basis for hypothesis testing in the subsequent analysis.

3.1.1. Outer Model Testing

Convergent Validity

Convergent validity was assessed by examining item reliability, as indicated by the *loading factor* values that show the correlation between a question item and its construct indicator. According to Hair et al. (2009), an initial examination of loading factors below 0.3 is considered minimal, around 0.4 is acceptable, and above 0.5 is generally considered significant. Therefore, this study follows the loading factor threshold of 0.7 as recommended in the Smart-PLS 4.0 application [35].

Table 2. Convergent Validity Results

Indicator	Outer loadings	Description
X1.11 <- X1. Instructor Quality	0.718	Meets
X1.12 <- X1. Instructor Quality	0.713	Meets
X1.13 <- X1. Instructor Quality	0.779	Meets
X1.14 <- X1. Instructor Quality	0.589	Not Meets
X1.15 <- X1. Instructor Quality	0.656	Not Satisfied
X1.1 <- X1. Instructor Quality	0.682	Not Satisfied
X1.2 <- X1. Instructor Quality	0.705	Meets
X1.3 <- X1. Instructor Quality	0.741	Meets
X1.4 <- X1. Instructor Quality	0.809	Meets
X1.5 <- X1. Instructor Quality	0.732	Meets
X1.6 <- X1. Instructor Quality	0.777	Meets
X1.7' <- X1. Instructor Quality	0.729	Meets
X1.8 <- X1. Instructor Quality	0.752	Meets
X1.9 <- X1. Instructor Quality	0.741	Meets
X1.10 <- X1. Instructor Quality	0.517	Not Meets
X2.1 <- X2. Information Content Quality	0.652	Not Satisfied
X2.2 <- X2. Information Content Quality	0.775	Meets
X2.3 <- X2. Information Content Quality	0.843	Meets
X2.4 <- X2. Information Content Quality	0.839	Meets
X2.5 <- X2. Information Content Quality	0.821	Meets
X2.6 <- X2. Information Content Quality	0.856	Meets
X2.7 <- X2. Information Content Quality	0.807	Meets
X2.8 <- X2. Information Content Quality	0.864	Meets
X2.9 <- X2. Information Content Quality	0.822	Meets
Y1.10 <- Y1. Usefulness	0.814	Meets
Y1.11 <- Y1. Usefulness	0.796	Meets
Y1.12 <- Y1. Usefulness	0.795	Meets
Y1.1 <- Y1. Usefulness	0.679	Not Meets
Y1.2 <- Y1. Usefulness	0.672	Not Met
Y1.3 <- Y1. Usefulness	0.803	Meets
Y1.4 <- Y1. Usefulness	0.795	Meets
Y1.5 <- Y1. Usefulness	0.767	Meets
Y1.6 <- Y1. Usefulness	0.533	Not Meets
Y1.7 <- Y1. Usefulness	0.800	Meets
Y1.8 <- Y1. Usefulness	0.815	Meets
Y1.9 <- Y1. Usefulness	0.853	Meets
Y2.1 <- Y2. Satisfaction	0.813	Meets
Y2.10 <- Y2. Satisfaction	0.862	Meets
Y2.11 <- Y2. Satisfaction	0.806	Meets
Y2.12 <- Y2. Satisfaction	0.810	Meet
Y2.13 <- Y2. Satisfaction	0.784	Meets
Y2.14 <- Y2. Satisfaction	0.854	Meets
Y2.2 <- Y2. Satisfaction	0.863	Meets
Y2.3 <- Y2. Satisfaction	0.850	Meets
Y2.4 <- Y2. Satisfaction	0.824	Meets
Y2.5 <- Y2. Satisfaction	0.847	Meets
Y2.6 <- Y2. Satisfaction	0.832	Meets
Y2.7 <- Y2. Satisfaction	0.608	Not Meets
Y2.8 <- Y2. Satisfaction	0.824	Meets
Y2.9 <- Y2. Satisfaction	0.818	Meets
Z. Self Regulation x Y1. Usefulness -> Z. Self Regulation x Y1. Usefulness	1.000	Meets
Z.10 <- Z. Self Regulation	0.831	Meets

Indicator	Outer loadings	Description
Z.1 <- Z. Self Regulation	0.596	Not Meets
Z.2 <- Z. Self Regulation	0.720	Meets
Z.3 <- Z. Self Regulation	0.732	Meets
Z.4 <- Z. Self Regulation	0.805	Meets
Z.5 <- Z. Self Regulation	0.832	Meets
Z.6 <- Z. Self Regulation	0.736	Meets
Z.7 <- Z. Self Regulation	0.749	Meets
Z.8 <- Z. Self Regulation	0.799	Meets
Z.9 <- Z. Self Regulation	0.607	Not Met

The data processing results using Smart-PLS 4.0 show that the majority of indicators for each variable have a loading factor value greater than 0.7, thus meeting the validity criteria. However, eleven indicators were found to have loading factor values less than 0.7, namely indicators X1.1, X1.10, X1.14, and X1.15 on the *Instructor Quality* variable (X1); indicator X2.1 on the *Information Content Quality* variable (X2); indicators Y1.1, Y1.2, and Y1.6 on the *Usefulness* variable (Y1); indicator Y2.7 on the *Satisfaction* variable (Y2); and indicators Z.1 and Z.9 on the *Self Regulation* variable (Z). Therefore, these indicators were removed from the model, and the test was repeated to ensure convergent validity in the revised model.

To assess the validity of the measurement model, the convergent validity test was performed using the outer loading values of each indicator. Indicators are considered valid if their loading values exceed 0.70, indicating that each item reliably measures its corresponding construct. The results of the convergent validity test are presented in Table 3.

Table 3. Second Literacy Model Convergent Validity Results

Indicator	Outer loadings	Description
X1.11 <- X1. Instructor Quality	0.718	Meets
X1.12 <- X1. Instructor Quality	0.713	Meets
X1.13 <- X1. Instructor Quality	0.779	Meets
X1.2 <- X1. Instructor Quality	0.705	Meets
X1.3 <- X1. Instructor Quality	0.741	Meets
X1.4 <- X1. Instructor Quality	0.809	Meets
X1.5 <- X1. Instructor Quality	0.732	Meets
X1.6 <- X1. Instructor Quality	0.777	Meets
X1.7' <- X1. Instructor Quality	0.729	Meets
X1.8 <- X1. Instructor Quality	0.752	Meets
X1.9 <- X1. Instructor Quality	0.741	Meets
X2.2 <- X2. Information Content Quality	0.775	Meets
X2.3 <- X2. Information Content Quality	0.843	Meets
X2.4 <- X2. Information Content Quality	0.839	Meets
X2.5 <- X2. Information Content Quality	0.821	Meets
X2.6 <- X2. Information Content Quality	0.856	Meets
X2.7 <- X2. Information Content Quality	0.807	Meets
X2.8 <- X2. Information Content Quality	0.864	Meets
X2.9 <- X2. Information Content Quality	0.822	Meets
Y1.10 <- Y1. Usefulness	0.814	Meets
Y1.11 <- Y1. Usefulness	0.796	Meets
Y1.12 <- Y1. Usefulness	0.795	Meets
Y1.3 <- Y1. Usefulness	0.803	Meets
Y1.4 <- Y1. Usefulness	0.795	Meets
Y1.5 <- Y1. Usefulness	0.767	Meets
Y1.7 <- Y1. Usefulness	0.800	Meets
Y1.8 <- Y1. Usefulness	0.815	Meets
Y1.9 <- Y1. Usefulness	0.853	Meets
Y2.1 <- Y2. Satisfaction	0.813	Meets
Y2.10 <- Y2. Satisfaction	0.862	Meets
Y2.11 <- Y2. Satisfaction	0.806	Meets
Y2.12 <- Y2. Satisfaction	0.810	Meets
Y2.13 <- Y2. Satisfaction	0.784	Meets
Y2.14 <- Y2. Satisfaction	0.854	Meets

Indicator	Outer loadings	Description
Y2.2 <- Y2. Satisfaction	0.863	Meets
Y2.3 <- Y2. Satisfaction	0.850	Meets
Y2.4 <- Y2. Satisfaction	0.824	Meets
Y2.5 <- Y2. Satisfaction	0.847	Meets
Y2.6 <- Y2. Satisfaction	0.832	Meets
Y2.8 <- Y2. Satisfaction	0.824	Meets
Y2.9 <- Y2. Satisfaction	0.818	Meets
Z. Self Regulation x Y1.Usefulness -> Z. Self Regulation x Y1.Usefulness	1.000	Meet
Z.10 <- Z. Self Regulation	0.831	Meets
Z.2 <- Z. Self Regulation	0.720	Meets
Z.3 <- Z. Self Regulation	0.732	Meets
Z.4 <- Z. Self Regulation	0.805	Meets
Z.5 <- Z. Self Regulation	0.832	Meets
Z.6 <- Z. Self Regulation	0.736	Meets
Z.7 <- Z. Self Regulation	0.749	Meets
Z.8 <- Z. Self Regulation	0.799	Meets

As shown in Table 3, all indicators have outer loading values greater than 0.70, confirming that every observed variable meets the convergent validity criteria. This demonstrates that each construct Instructor Quality, Information Content Quality, Perceived Usefulness, Satisfaction, and Self-Regulation has a strong and reliable relationship with its respective measurement items. Consequently, the model fulfills the requirements for convergent validity and can be further analyzed in the structural model stage.

Construct Reliability and Validity

To further assess the discriminant validity of the measurement model, an evaluation of the Average Variance Extracted (AVE) was conducted. This step compares the square root of the AVE value for each construct with the correlations between constructs. According to Fornell and Larcker (1981), a construct achieves adequate discriminant validity if the square root of its AVE exceeds its correlations with other constructs, and the AVE value itself is greater than 0.50 [36], [37]. The results of the AVE analysis are presented in Table 4.

Table 4. AVE Value Results

Variable	Variance extracted (AVE)
X1. Instructor Quality	0.556
X2. Information Content Quality	0.687
Y1.Usefulness	0.647
Y2. Satisfaction	0.689
Z. Self Regulation	0.590

As shown in Table 4, all constructs have AVE values above 0.50, ranging from 0.556 to 0.689. These results indicate that each latent variable explains more than half of the variance of its observed indicators. Therefore, the model satisfies both convergent and discriminant validity criteria, confirming that the measurement model is reliable and suitable for further structural analysis.

Internal Consistency Reliability

Internal consistency reliability measures how well the indicators consistently represent their latent constructs. This was evaluated using Cronbach's alpha. A Cronbach's alpha value between 0.6–0.7 is considered acceptable, while values above 0.7 indicate good reliability.

Table 5. Internal Consistency Reliability Results

Variable	Cronbachs alpha	Description
X1. Instructor Quality	0.920	Meets
X2. Information Content Quality	0.935	Meets
Y1.Usefulness	0.932	Meets
Y2. Satisfaction	0.962	Meets
Z. Self Regulation	0.913	Meets

As shown in Table 5, all constructs Instructor Quality, Information Content Quality, Perceived Usefulness, Satisfaction, and Self-Regulation have Cronbach's alpha values above 0.90, which demonstrates a

high level of internal consistency. These results indicate that all indicators are reliable and consistently measure their respective constructs, ensuring the robustness of the measurement model for further structural analysis.

Composite Reliability

After assessing internal consistency reliability through Cronbach's alpha, this study also examined composite reliability to ensure that all constructs consistently represent their respective latent variables. Composite reliability provides a more accurate estimate of construct reliability than Cronbach's alpha, particularly in models using SEM-PLS. A construct is considered reliable if its composite reliability value exceeds 0.70. The results of this analysis are summarized in Table 6.

Table 6. Composite Reliability Results

Variable	Cronbach's alpha	Description
X1. Instructor Quality	0.921	Meets
X2. Information Content Quality	0.936	Meets
Y1. Usefulness	0.932	Meets
Y2. Satisfaction	0.963	Meets
Z. Self Regulation	0.919	Meets

As shown in Table 6, all constructs have composite reliability values above 0.90, exceeding the recommended threshold of 0.70. This indicates that all indicators are consistently measuring their respective constructs, confirming the high internal consistency of the model. Overall, the measurement model demonstrates strong reliability and validity, ensuring that each construct accurately reflects its theoretical dimension and is appropriate for further structural testing.

3.1.2 Inner Model Testing

Analysis of Variance (R-Square)

After validating the measurement model, the next step is to evaluate the inner model, which represents the structural relationships among latent variables. This assessment includes testing the model's explanatory power (R^2), effect size (f^2), model fit indices, and hypothesis testing through bootstrapping procedures. The inner model analysis helps determine the strength and significance of the relationships between exogenous and endogenous constructs, thereby confirming the predictive capability of the model. The criteria: If the value of $R^2 = 0.75$ means *substantial* (large / strong), If the value of $R^2 = 0.50$ means *moderate* (medium), If the value of $R^2 = 0.25$ means *weak* (small)

Table 7. R-Square Value Results

Variable	R-square	Adjusted R-square
Y1. Usefulness	0.544	0.539
Y2. Satisfaction	0.790	0.785

The value with a determination of 0.544 for the *Usefulness* variable shows that the *Instructor Quality*, and *Information Content Quality* variables are able to explain changes, the *Usefulness* variable is 54.4% and the remaining 45.6% is explained by other variables outside of the literacy model used. While the *Satisfaction* variable shows that *Instructor Quality*, *Information Content Quality*, *Usefulness*, and *Self Regulation* are able to explain changes, the *Satisfaction* variable is 79% and the remaining 21% is explained by other variables. In accordance with existing criteria, the *Usefulness* variable has a *moderate* influence (moderate) and the *Satisfaction* variable has a *substantial* influence (strong).

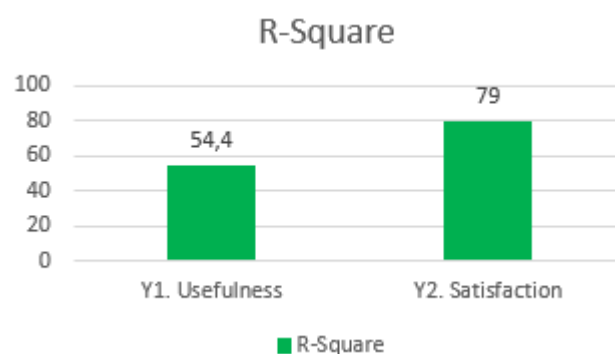


Figure 4. Diagram of R-Square Value Results

Smart-PLS gives an indication of *R-Square* from the color of the graph: green (indicating a good effect), red (bad). Thus, the *R-Square* for: R-Square Model Path I = 0.544 is green (good); R-Square of Path II Model = 0.790 in green (good)

F-Square Analysis

The *f-square* (f^2) value evaluates the effect size of each exogenous variable on the endogenous variables. It is used to measure the change in R^2 when a specific exogenous variable is omitted from the model [38], [39]. The f^2 thresholds are as follows: 0.02 (small effect), 0.15 (medium effect), and 0.35 (large effect). Values below 0.02 can be considered negligible.

Table 8. Results of F-Square Values

	<i>F-Square</i>
X1. Instructor Quality -> Y1.Usefulness	0.065
X1. Instructor Quality -> Y2. Satisfaction	0.068
X2. Information Content Quality -> Y1.Usefulness	0.130
X2. Information Content Quality -> Y2. Satisfaction	0.128
Y1.Usefulness -> Y2. Satisfaction	0.065
Z. Self Regulation -> Y2. Satisfaction	0.032
Z. Self Regulation -> Y1.Usefulness -> Y2. Satisfaction	0.044

The results in Table 7 reveal that all paths—*Instructor Quality* → *Usefulness*, *Instructor Quality* → *Satisfaction*, *Information Content Quality* → *Usefulness*, *Information Content Quality* → *Satisfaction*, *Usefulness* → *Satisfaction*, *Self Regulation* → *Satisfaction*, and *Self Regulation* × *Usefulness* → *Satisfaction*—have f^2 values greater than 0.02, indicating at least moderate effect sizes. These findings demonstrate that all independent variables significantly contribute to explaining the endogenous constructs.

The next stage of the inner model evaluation involves analyzing the *f-square* (f^2) values to determine the effect size of each exogenous variable on the endogenous variables. The f^2 value measures how much a predictor variable contributes to the explained variance of a dependent construct. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. The results of the *f-square* analysis are illustrated in Figure 5.

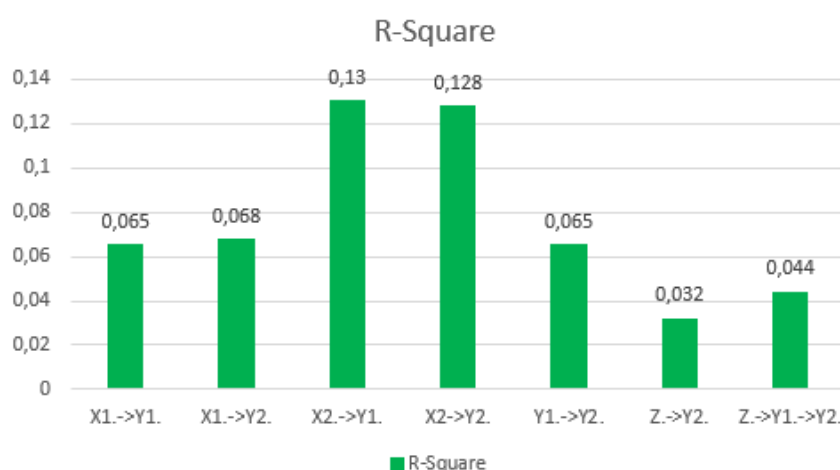


Figure 5. Diagram of F-Square Value Results

- X1. Instructor Quality -> Y1.Usefulness = Good
- X1. Instructor Quality -> Y2. Satisfaction = Good
- X2. Information Content Quality -> Y1.Usefulness = Good
- X2. Information Content Quality -> Y2. Satisfaction = Good
- Y1.Usefulness -> Y2. Satisfaction = Good
- Z. Self Regulation -> Y2. Satisfaction = Good
- Z. Self Regulation x Y1.Usefulness -> Y2. Satisfaction = Good

Model Fit

To determine whether the model achieves a satisfactory level of fit, several indices were evaluated: *SRMR* (Standardized Root Mean Square Residual), *d_ULS*, *d_G*, *Chi-square*, and *NFI* (Normed Fit Index). According to Cangur and Ercan (2015), an SRMR value below 0.05 indicates a good fit, while the SmartPLS guideline recommends RMS Theta < 0.102, SRMR < 0.10, and NFI > 0.90 as model fit criteria.

Table 9. Model Fit Results

	Saturated model (saturated)	Model estimates
SRMR	0.052	0.059
d_ULS	3.411	4.437
d_G	2.118	2.218
Chi-square	2258.471	2287.519
NFI	0.775	0.772

Table 8 shows that the SRMR value for both the saturated model (0.052) and the estimated model (0.059) are below the 0.10 threshold, meeting the model fit criterion. Although the NFI values (0.775 and 0.772) are slightly below 0.90, they are still within an acceptable range for PLS-SEM exploratory research. Thus, the model is considered fit for structural testing, particularly given its predictive-oriented nature.

Hypothesis Testing

Hypothesis testing is carried out based on the results of inner model testing which includes *r-square* output, parameter coefficients and t-statistics. To see whether a hypothesis is acceptable or not, among others, by paying attention to the significance value between constructs, t-statistics and *p-values*. Testing the hypothesis of this study is seen from the results of *bootstrapping* with a comparison of the t statistical value must be greater than 1.96 with a significance level of p-value of 5% and a positive beta coefficient.

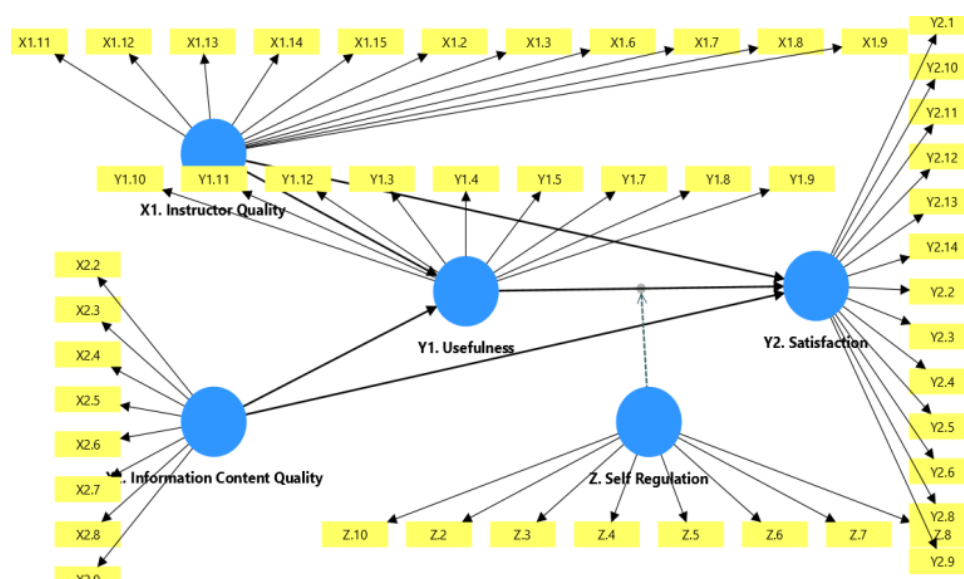


Figure 6. Bootstrapping Value Results

Based on this figure, it shows that all variables consisting of *Instructor Quality*, *Information Content Quality*, *Usefulness*, *Satisfaction*, and *Self Regulation* have *p-values* smaller than 0.05 such as the *Smart Governance* and *Smart Living* variables on the *Smart City Dimension & Development Strategy* variable.

Table 10. Hypothesis Results

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
X1. Instructor Quality -> Y1.Usefulness	0.317	0.323	0.087	3.660	0.000
X1. Instructor Quality -> Y2. Satisfaction	0.234	0.237	0.066	3.521	0.000
X2. Information Content Quality -> Y1.Usefulness	0.450	0.446	0.088	5.095	0.000
X2. Information Content Quality -> Y2. Satisfaction	0.345	0.343	0.073	4.719	0.000
Y1.Usefulness -> Y2. Satisfaction	0.191	0.190	0.058	3.312	0.001
Z. Self Regulation -> Y2. Satisfaction	0.154	0.156	0.066	2.332	0.020
Z. Self Regulation -> Y1.Usefulness -> Y2. Satisfaction	-0.061	-0.060	0.019	3.267	0.001

The results in Table 10 show that all direct relationships are significant ($p < 0.05$). Specifically, *Instructor Quality* positively and significantly affects *Usefulness* ($\beta = 0.317$, $t = 3.660$, $p < 0.05$) and *Satisfaction* ($\beta = 0.234$, $t = 3.521$, $p < 0.05$). This indicates that the higher the instructor quality in managing LMS (SIPDA or Google Classroom), the greater the students' perceived usefulness and satisfaction. These results are consistent with previous studies that also found a positive influence of instructor quality on perceived usefulness and satisfaction [40].

Similarly, *Information Content Quality* has a significant positive effect on both *Usefulness* ($\beta = 0.450$, $t = 5.095$, $p < 0.05$) and *Satisfaction* ($\beta = 0.345$, $t = 4.719$, $p < 0.05$). This suggests that better information and content quality in LMS lead to greater perceived benefits and satisfaction among students, aligning with findings by Sun et al. (2008) and Roca et al. (2006). Furthermore, *Usefulness* significantly affects *Satisfaction* ($\beta = 0.191$, $t = 3.312$, $p < 0.05$), supporting the Technology Acceptance Model (TAM), which highlights the strong link between perceived usefulness and user satisfaction.

Interestingly, *Self Regulation* exhibits both direct and indirect effects on *Satisfaction*. Directly, it has a positive and significant effect ($\beta = 0.154$, $t = 2.332$, $p < 0.05$), indicating that students with high self-regulation tend to experience higher satisfaction. However, the indirect effect through *Usefulness* is negative and significant ($\beta = -0.061$, $t = 3.267$, $p < 0.05$), suggesting that highly self-regulated students may be more critical of the LMS's usefulness, potentially reducing their satisfaction. This is consistent with the findings of Lee (2010) and Joo et al. (2013), who observed that students with higher self-regulation often hold higher expectations toward LMS performance [41], [42]. Overall, these findings validate the hypothesized model and reinforce the relevance of TAM and ISSM frameworks in explaining LMS adoption. The results also highlight the interplay between instructional quality, content quality, and students' self-regulatory behaviors as key determinants of satisfaction.

Multicollinearity Testing

The assumption or requirement that must be met in the *outer model* analysis is that there is no multicollinearity problem. Namely a problem where there is an intercorrelation or strong correlation between indicators. The limitation is the correlation value > 0.9 which is usually characterized by the *Variance Inflating Factor* (VIF) value at the indicator level > 5 . So if there is an indicator VIF value > 5 then there is a multicollinearity problem. The consequence is that dropping or removing one of the strongly correlated indicators can be done. The following are the results of the VIF analysis at the indicator level.

Table 11. Multicollinearity Value Results

	VIF
X1. Instructor Quality -> Y1.Usefulness	3.415
X1. Instructor Quality -> Y2. Satisfaction	3.844
X2. Information Content Quality -> Y1.Usefulness	3.415
X2. Information Content Quality -> Y2. Satisfaction	4.441
Y1.Usefulness -> Y2. Satisfaction	2.680
Z. Self Regulation -> Y2. Satisfaction	3.525
Z. Self Regulation x Y1.Usefulness -> Y2. Satisfaction	1.203

The inner model results confirm that both *Instructor Quality* and *Information Content Quality* are key determinants of LMS effectiveness, influencing both perceived usefulness and satisfaction. *Self Regulation* acts as a dual-path factor, enhancing satisfaction directly but moderating perceived usefulness negatively. These

findings contribute to extending the TAM and ISSM frameworks by emphasizing the role of learner self-regulation as a moderating factor in digital learning environments.

3.2 Research Model Analysis

Direct Effects

The research model analysis aims to identify the direct, indirect, and predictive relationships among the variables in the model. Through Partial Least Squares–Structural Equation Modeling (PLS-SEM), the analysis evaluates both the magnitude and significance of path coefficients, as well as the predictive relevance of the model. This section provides a comprehensive overview of the direct and indirect effects and confirms the predictive strength of the structural relationships.

In PLS SEM analysis, the *direct effects* value is also called the *path coefficient*. Furthermore, the measurement of *path coefficients* between constructs is carried out to see the significance and strength of the relationship and also to test the hypothesis. The value of *path coefficients* ranges from -1 to +1. The value of *path coefficients* is closer to +1, the stronger the relationship between the two constructs. A relationship that is closer to -1 indicates that the relationship is negative. The results of the direct effects of the literacy model of this study are as follows Table 12.

Table 12. Results of Direct Effects Value

	Y1. Usefulness	Y2. Satisfaction
X1. Instructor Quality	0.317	
X1. Instructor Quality		0.294
X2. Information Content Quality	0.450	
X2. Information Content Quality		0.432
Y1. Usefulness		0.191
Z. Self Regulation		0.154

The results show that all variables—*Instructor Quality*, *Information Content Quality*, *Usefulness*, *Satisfaction*, and *Self Regulation*—have positive and significant direct effects:

- The direct effect of the *Instructor Quality* variable on the *Usefulness* variable is 0.317 which indicates that the higher the *Instructor Quality* variable, the more *Usefulness* variables will increase significantly.
- The direct effect of the *Instructor Quality* variable on the *Satisfaction* variable is 0.294, which indicates that the higher the *Instructor Quality* variable, the more significant the *Satisfaction* variable will be.
- The direct effect of the *Information Content Quality* variable on the *Usefulness* variable is 0.450, which indicates that the higher the *Information Content Quality* variable, the higher the *Usefulness* variable will be significantly.
- The direct effect of the *Information Content Quality* variable on the *Satisfaction* variable is 0.432, which indicates that the higher the *Information Content Quality* variable, the more significant the *Satisfaction* variable will be.
- The direct effect of the *Usefulness* variable on the *Satisfaction* Dimension variable is 0.191, which indicates that the higher the *Usefulness* variable, the more significant the *Satisfaction* variable will be.
- The direct effect of the *Self Regulation* variable on the *Satisfaction* variable is 0.154, which indicates that the higher the *Self Regulation* variable, the more significant the *Satisfaction* variable will be.

These findings confirm that both instructor-related and content-related factors play a pivotal role in shaping perceived usefulness and satisfaction in digital learning environments, aligning with prior studies in the field of online learning and information systems quality.

Indirect Effects

Indirect effects show how a variable affects certain variables through other variables. Just like the direct effect value, the indirect effect value ranges from -1 to +1. The closer the value is to +1, the stronger the relationship between the two constructs. The relationship that is closer to -1 indicates that the relationship is negative [43], [44]. The results of the indirect effect of this research iteration model are as follows Table 13.

Table 13. Indirect Effects Results

	Indirect Effects
Self Regulation x Y1. Usefulness -> Y2. Satisfaction	-0.061

The indirect path between *Self Regulation* and *Satisfaction* through *Usefulness* has a coefficient of -0.061, indicating a significant but negative mediation effect. This suggests that while self-regulated learners are generally more satisfied, they may perceive the LMS as less useful due to their critical evaluation standards. Such findings highlight the complex nature of learner self-regulation acting both as a motivator for satisfaction

and as a factor that increases performance expectations, which may reduce perceived usefulness when system capabilities do not meet user standards.

PLS-Predict

Predictive relevance assesses how well the model predicts observed values for indicators of endogenous constructs. The Q^2 predict value, along with *Root Mean Square Error (RMSE)* and *Mean Absolute Error (MAE)*, provides an indicator of the model's out-of-sample predictive performance. According to Hair et al., Q^2 values greater than 0.2 indicate sufficient predictive accuracy, values above 0.3 indicate good accuracy, and values exceeding 0.5 indicate high predictive accuracy.

Table 14. Results PLS-Predict Value

	Q^2 predict	RMSE	MAE
Y1.Usefulness	0.535	0.694	0.551
Y2. Satisfaction	0.764	0.495	0.373

The Q^2 values of *Usefulness* (0.535) and *Satisfaction* (0.764) exceed 0.5, confirming high predictive accuracy. This demonstrates that the model effectively predicts the variance of endogenous constructs, indicating robust predictive relevance in the PLS-SEM context.

Table 15. RMSE & MAE Comparison Results (PLS vs LM Model)

	Q^2 predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
Y1.10	0.320	0.577	0.446	0.596	0.426
Y1.11	0.349	0.519	0.391	0.563	0.419
Y1.12	0.309	0.552	0.427	0.567	0.410
Y1.3	0.343	0.500	0.388	0.515	0.395
Y1.4	0.341	0.485	0.380	0.509	0.395
Y1.5	0.321	0.519	0.393	0.535	0.398
Y1.7	0.355	0.564	0.447	0.581	0.426
Y1.8	0.328	0.511	0.396	0.530	0.394
Y1.9	0.400	0.521	0.414	0.561	0.420
Y2.1	0.595	0.421	0.339	0.463	0.362
Y2.10	0.530	0.432	0.348	0.473	0.360
Y2.11	0.503	0.469	0.381	0.482	0.378
Y2.12	0.503	0.456	0.364	0.491	0.368
Y2.13	0.456	0.475	0.373	0.528	0.399
Y2.14	0.549	0.437	0.346	0.473	0.357
Y2.2	0.632	0.430	0.339	0.462	0.344
Y2.3	0.564	0.450	0.356	0.511	0.385
Y2.4	0.482	0.477	0.377	0.522	0.410
Y2.5	0.515	0.471	0.365	0.521	0.395
Y2.6	0.490	0.469	0.361	0.491	0.364
Y2.8	0.487	0.480	0.378	0.531	0.408
Y2.9	0.457	0.486	0.377	0.530	0.388

All indicator measurement items show a higher predicted Q^2 value for the PLS model than the LM model shown in green, so the PLS model has predictive power. The RMSE and MAE values of the PLS model only have 5 measurement items with lower values than the LM RMSE and MAE models, indicating the model has very good *predictive power*. Only 5 PLS SEM indicator items have lower RMSE and MAE values than the linear regression model (LM), indicating the PLS SEM model has high predictive power. The results of this study indicate that the Structural Equation Modeling - Partial Least Squares (PLS-SEM) model has better predictive power than the linear regression model (LM). This can be seen from all indicator items in this study which show a higher Q^2 Predict value in the PLS model than the LM model, as marked in green in the test results. This confirms that the PLS-SEM model is able to provide more accurate predictions in the context of this study, especially for measuring the acceptance of LMS (both SIPDA and Google Classroom) by students.

In addition, although the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values only show five measurement items that have lower values in the PLS model than LM, these results still indicate that the PLS model has high predictive power. This can be interpreted that the PLS model is more sensitive in

predicting the relationship between latent variables in this study, especially for complex constructs such as self-regulation and satisfaction. This finding is in line with the recommendations of Shmueli et al., which state that PLS-SEM is superior in predictive studies and is suitable for models that focus on prediction rather than just confirming theory [49].

In relation to previous studies, these results support studies that use the DeLone and McLean evaluation model (ISSM Model) that utilize PLS-SEM to analyze the quality of information systems, such as research by Al-Fraihat et al and Tam & Oliveira, both show that PLS-SEM is able to map complex relationships between variables such as information quality, system quality, user satisfaction, and net benefits with strong predictive results [42], [31]. However, these findings also differ from some studies focusing on the ISSM model that are more concerned with the overall goodness of fit of the model and prefer covariance-based SEM (CB-SEM) or ordinary linear regression models for theory validation, such as studies by Petter et al., argued that in the context of ISSM, what matters more is the theoretical fit of the model than its predictive ability, especially when the data has a good distribution and the sample size is large [50].

Thus, the results of this study further confirm that the selection of analytical models in LMS or other information system acceptance studies should be tailored to the research objectives. If the main objective is prediction and exploration of relationships between variables as in this study, then PLS-SEM is more appropriate. However, for research that purely focuses on testing ISSM theory structurally and theoretically, CB-SEM or LM can still be considered. The practical implications of the optimism scale developed in this study are significant for the field of education. The optimism construct, which measures students' confidence, perseverance, and positive expectations toward learning, provides a valuable diagnostic tool for educators and academic institutions. By assessing optimism levels, instructors can identify students who require motivational or emotional support in adapting to online learning environments such as SIPDA and Google Classroom. Practically, the integration of optimism assessment into LMS-based learning analytics can help universities design targeted interventions that strengthen student engagement, persistence, and satisfaction, thereby improving learning outcomes in digital education contexts.

Despite its contributions, this study has several limitations that should be acknowledged. The research sample was limited to one department—Accounting—under the Faculty of Economics, Universitas Negeri Medan, which may restrict the generalizability of the findings across other academic disciplines. Future research should extend the model to other departments within the faculty, such as Management, Development Economics, and Business Education, to explore whether the relationships among instructor quality, information content, self-regulation, and optimism produce consistent results. Additionally, subsequent studies could employ longitudinal or experimental designs to assess changes in optimism and satisfaction over time and examine how specific LMS design features influence these psychological variables.

This study provides both theoretical and practical insights by validating the predictive strength of the PLS-SEM model and highlighting the relevance of optimism as a psychological factor in digital learning success. The findings underscore the importance of integrating cognitive, pedagogical, and affective dimensions in the evaluation of LMS effectiveness and provide a strong foundation for future interdisciplinary research on educational technology and student well-being.

4. CONCLUSION

The findings of this study indicate that Instructor Quality, Information Content Quality, and Self-Regulation significantly influence students' perceived Usefulness and Satisfaction in using the SIPDA Learning Management System (LMS). High-quality instruction and relevant, accessible content enhance students' engagement, while self-regulation strengthens satisfaction both directly and indirectly through perceived usefulness. These results confirm that the effectiveness of online learning depends on both external instructional support and internal learning autonomy. To improve LMS-based learning such as SIPDA and Google Classroom, universities should enhance instructor competence, ensure the clarity and relevance of course materials, and provide responsive technical and academic assistance. Encouraging students to build self-discipline, combined with interactive content and continuous feedback, will promote deeper learning and sustained engagement within digital learning environments.

The study's primary contribution lies in the development of an explanatory style-based optimism scale contextualized for Indonesian higher education, integrating psychological dimensions into the Information System Success Model (ISSM). This framework demonstrates that LMS platforms function not merely as administrative tools but as catalysts for deep learning, critical thinking, and academic resilience. Future research can broaden this framework by including other departments within the Faculty of Economics at Universitas Negeri Medan to validate the model's applicability across disciplines. Expanding longitudinally and incorporating factors such as digital literacy, institutional support, and motivation will further deepen understanding of LMS effectiveness. Ultimately, measuring optimism is vital to enhancing students'

psychological well-being, helping educators cultivate adaptive learning attitudes, emotional resilience, and a more positive digital academic environment.

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