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Exploring the Impact of Cloud Service Quality on Customer Loyalty towards Cloud Service Providers: A Stimulus Organism Response (SOR) Approach

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ABSTRACT
Cloud computing, a versatile computing service offering processing power and data storage, presents numerous advantages including flexible payment models, expedited marketing processes, adaptable costs and capacities, cost-effective disaster recovery solutions, and enhanced global collaboration efficiency. Despite its merits, assessing cloud computing service adoption remains a challenge, especially concerning long-term factors like customer loyalty. This study endeavors to identify the determinants of user loyalty towards cloud services and assesses the predictive strength of the model. Employing a quantitative approach, the research integrates the SERVQUAL framework and the stimulus organism response (SOR) model, incorporating cloud service quality variables. Data collection, utilizing Google Forms and purposive sampling, targeted cloud service users aged 18 to 60. Analysis of responses from 286 participants was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS 4. The findings reveal the acceptance of 10 hypotheses, indicating significant influence of cloud service quality variables agility, service responsiveness, reliability, scalability, security, and assurance of service on user loyalty. Additionally, customer loyalty is influenced by factors including perceived brand image, customer satisfaction, and electronic word of mouth. The PLS-SEM model tested using PLSPredict that showed good strength for overall prediction variables. This study contributes to a deeper understanding of user loyalty dynamics within the context of cloud computing services, offering insights for service providers and researchers alike.

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1. INTRODUCTION

The global technological landscape is undergoing a profound transformation, driven by the convergence of digital, biological, and physical realms, marking the advent of Industry 4.0 (Scanlon, 2022). At the forefront of this transformation is cloud computing, powered by innovations such as artificial intelligence, machine learning, and high-speed internet connectivity. Cloud computing has emerged as a cornerstone of Industry 4.0, offering unparalleled opportunities for organizations to revolutionize their operations and services.

Facilitating this transformation is the rapid evolution of cloud computing services over the past decade. These services provide a plenty of benefits compared to traditional on-premise approaches, ranging from reduced capital expenditure to faster time-to-market and more efficient global collaboration (Senarathna et al., 2018). As organizations worldwide embrace the cloud, the landscape of computing services is reshaped, offering infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS) models tailored to diverse organizational needs (Mell & Grance, 2011).

Indonesia, amidst its burgeoning internet growth and expanding population, stands as a testament to the global adoption of cloud computing. With a notable increase in cloud computing expenditure over the years, Indonesia's potential in the cloud market is on the rise. The country boasts a burgeoning number of data centers, attracting major global players like Google, Microsoft Azure, and Amazon, alongside a thriving ecosystem of local cloud service providers (Annur, 2023; Karnadi, 2021; Setyowati, 2020; Vu et al., 2020).

However, amidst this proliferation of cloud services, users encounter challenges in adopting new technologies, particularly concerning data security, configuration selection, and trust in service providers (Alshahrani et al., 2022; Amron et al., 2019). Addressing these challenges necessitates continuous innovation and a nuanced understanding of user behavior and preferences.

While existing research has explored the adoption of cloud computing technology, there remains a gap in understanding advanced usage behavior and its impact on customer loyalty and satisfaction, particularly within the Indonesian context. This study aims to bridge this gap by analyzing the influence of cloud computing service quality on customer loyalty and satisfaction among cloud service providers in Indonesia.

Employing the Stimulus-Organism-Response (SOR) framework, this research integrates additional constructs such as electronic word of mouth (EWOM) and perceived brand image to provide a comprehensive understanding of the factors influencing service quality, customer satisfaction, and loyalty (Agarwal & Dhingra, 2023; Alam & Noor, 2020; Purwanto et al., 2020; Tan et al., 2017). By delving into these dynamics, this study seeks to offer valuable insights for IT practitioners and organizations navigating the cloud computing landscape in Indonesia, thus contributing to the broader discourse on technology adoption and usage behavior.

This study explores factors influencing customer loyalty on use of cloud computing. Four research question are outlined below:

RQ1. What factors influence customer loyalty to cloud computing in Indonesia?

RQ2. What is the extent of the influence of cloud computing service quality variables on customer loyalty to cloud computing in Indonesia?

RQ3. What is the impact of cloud computing service quality in Indonesia with mediating factors (customer satisfaction, perceived brand image, and electronic word of mouth) on customer loyalty?

RQ4. What is the strength of the model in predicting the factors influencing customer loyalty to cloud computing services?

2. RESEARCH FRAMEWORK

Reynolds et al. (1974) pioneered loyalty research, defining it as repeated consumer purchases. Battor and Battour (2013) highlighted loyal users' importance for business profitability. Loyalty is measured through behaviors like repeat purchases and advocating for a company, as highlighted by Çoban (2012) and Suh and Ahn (2012) . In the Stimulus-Organism-Response (SOR) theory, stimuli trigger emotional states. Alam and Noor (2020) found that service quality positively influences loyalty. Similarly, Tan et al. (2017) observed a positive link between service quality and loyalty.

H1: Cloud Service Quality (CSQ) positively affects Customer Loyalty (CL).

Creating customer satisfaction is paramount for any company, as it influences purchase intention and reflects users' emotional reactions to their interactions with a product or service. Studies by (Lo, 2014) and Sajjad (2014) emphasize that satisfaction is shaped by pleasant user experiences, performance expectations, proof of user experience, and user interest. Battor and Battour (2013) identified a link between user satisfaction and increased purchase intention, while Agarwal and Dhingra (2023) found that satisfaction in cloud services hinges on the perceived quality of service. Prior research, such as that by Smith and Swinehart (2001), has consistently shown a strong association between service quality and customer satisfaction. In the Stimulus-Organism-Response (SOR) theory, satisfaction serves as the emotional state of concern. Defined as the extent to which cloud computing services meet user expectations (Agarwal & Dhingra, 2023), satisfaction is influenced by service quality, as demonstrated in studies on online purchasing delivery services Uzir et al. (2021) and cloud computing services (Agarwal & Dhingra, 2023).

H2: Cloud Service Quality (CSQ) positively affects Customer Satisfaction (CS).

The research conducted by Barsky and Nash (2002) underscores the integral role of consumer emotions in the service process, indicating their influence on both customer satisfaction and loyalty. Informed by the service environment, consumer behavior experiences shape users' perceptions and emotions regarding the services received (Deng et al., 2013). A body of literature supports the notion that customer satisfaction positively correlates with customer loyalty (Agarwal & Dhingra, 2023; Zhong & Chen, 2023). According to the Stimulus-Organism-Response (SOR) model, the organism, representing individuals' emotional states, can influence the response. Thus, this study posits that user satisfaction can impact user loyalty, as indicated by recent research across various contexts such as food ordering applications (Dirsehan & Cankat, 2021), and mediation of experience on loyalty (Molinillo et al., 2022). Agarwal and Dhingra (2023) investigation into cloud services also supports this idea, demonstrating how satisfaction positively predicts loyalty to cloud services.

H3: Customer Satisfaction (CS) positively affects Customer Loyalty (LOY).

Brand image encompasses users' impressions, trust, and knowledge of a company, playing a pivotal role in stimulating customer satisfaction and fostering loyal relationships in business (Jara & Cliquet, 2012). Recent research by Fu et al. (2018) confirms a positive relationship between service quality, satisfaction, and loyalty, with corporate image exerting influence on satisfaction and loyalty. Within the Stimulus-Organism-Response (SOR) theory, Alam and Noor (2020) demonstrate that service quality positively impacts brand image, which in turn influences loyalty in retail store applications. Moreover, perceived brand image serves as a moderator, elucidating the impact of service quality and customer satisfaction on customer loyalty (Nyadzayo & Khajehzadeh, 2016). Given these findings, perceived brand image emerges as a crucial aspect for further exploration.

H4: Cloud Service Quality (CSQ) positively influences Perceived Brand Image (PBI).

H5: Perceived Brand Image (PBI) positively influences Customer Satisfaction (CS).

H6: Perceived Brand Image (PBI) positively influences Customer Loyalty (LOY).

Electronic word of mouth (EWOM), also known as online word of mouth, refers to online communication typically between non-selling communicators and receivers regarding a brand, product, or service, and its quality (Krishnamurthy & Kumar, 2018). In recent times, EWOM has gained prominence as individuals spend significant amounts of time exchanging ideas and opinions online (Chan et al., 2022). This trend particularly influences millennials, who are known to swiftly adjust their brand loyalty based on online reviews (Purwanto et al., 2020).

H7: Cloud Service Quality (CSQ) positively influences Electronic Word of Mouth (EWOM).

H8: Perceived Brand Image (PBI) positively influences Electronic Word of Mouth (EWOM).

H9: Customer Satisfaction (CS) positively influences Electronic Word of Mouth (EWOM).

H10: Electronic Word of Mouth (EWOM) positively influences Customer Loyalty (LOY).

Previous research, such as that conducted by Kiran (2010), has found that satisfaction can elucidate the influence of perceived quality of web-based library services on loyalty. Similarly, Bakti and Sumaedi (2013) applied SERVQUAL dimensions to demonstrate that service quality indirectly affects loyalty through customer satisfaction in the context of public application services, a model also adopted by Agarwal and Dhingra (2023) in the realm of cloud services. However, few studies have explored other mediating variables that could interact with service quality to influence loyalty. Drawing inspiration from Rashed (2020), this study seeks to clarify the mediating effects of brand image, satisfaction, and electronic word of mouth on cloud service quality towards customer loyalty.

H11: Perceived Brand Image (PBI) mediates the relationship between Cloud Service Quality (CSQ) and Customer Loyalty (LOY).

H12: Customer Satisfaction (CS) mediates the relationship between Cloud Service Quality (CSQ) and Customer Loyalty (LOY).

H13: Electronic Word of Mouth (EWOM) mediates the relationship between Cloud Service Quality (CSQ) and Customer Loyalty (LOY).

H14: Perceived Brand Image (PBI) and Customer Satisfaction (CS) mediate the relationship between Cloud Service Quality (CSQ) and Customer Loyalty (LOY).

H15: Perceived Brand Image (PBI) and Electronic Word of Mouth (EWOM) mediate the relationship between Cloud Service Quality (CSQ) and Customer Loyalty (LOY).

H16: Customer Satisfaction (CS) and Electronic Word of Mouth (EWOM) mediate the relationship between Cloud Service Quality (CSQ) and Customer Loyalty (LOY).

H17: Perceived Brand Image (PBI), Customer Satisfaction (CS), and Electronic Word of Mouth (EWOM) mediate the relationship between Cloud Service Quality (CSQ) and Customer Loyalty (LOY).

3. RESEARCH METHODS

3.1 Sampling

This study adopts purposive sampling, a non-probability sampling technique, based on specific criteria to collect relevant information not easily accessible through other means (Taherdoost, 2016). Data collection occurred over a two-week period, spanning from January 4th, 2023, to February 18th, 2024. During this timeframe, the aim was to gather a minimum of 250 respondents (Hair et al., 2018), with meeting predetermined criteria, namely individuals aged 18 years and above who are users of cloud computing services. Ultimately, 286 respondents completed online questionnaires, with subsequent data screening resulting in 266 datasets deemed suitable for further analysis.

3.2 Research Instrument

The research instrument consists of two parts written in Indonesian. The initial section focuses on gathering demographic information about the respondents, covering aspects like gender, age, education level, and occupation, along with inquiries about the cloud computing provider used and its frequency of use. The latter section comprises statements related to indicators of cloud service quality dimensions (CSQ), including agility (AG), assurance of service (AS), reliability (RL), scalability (SB), security (SC), service responsiveness (SR), and usability (US). Additionally, it addresses variables such as perceived brand image (PBI), customer satisfaction (CS), electronic word of mouth (EWOM), and customer loyalty (LOY). Furthermore, the study utilizes a 5-point Likert scale, offering respondents five options for each question, ranging from strongly disagree (assigned a value of 1) to strongly agree (assigned a value of 5).

3.3 Data Analysis

The study utilized partial least squares–structural equation modelling (PLS-SEM) for data analysis. PLS-SEM was selected due to its widespread acceptance in the quantitative research community for evaluating the connections between independent and dependent variables in research models (Abumalloh et al., 2020). This method employs a regression-based approach, focusing on reducing residual variance in the dependent variable. The PLS-SEM analysis in this study encompasses two assessments: the outer model and the inner model. This research is organized to employ a high-order model, with the evaluation of cloud service quality dimensions forming the initial model (Sarstedt et al., 2021). The latent variables derived from this evaluation will then be integrated into the subsequent analysis as components of a second-order model.

4. RESULTS AND DISCUSSION

4.1 Demographic Analysis

Out of the 266 respondents who completed the questionnaire, 213 individuals, constituting 80% of the total, identified as male, while 53 respondents, making up 20% of the total, identified as female. Thus, this study was predominantly composed of male respondents, echoing the typical gender distribution observed in IT-related fields, where males tend to be more prevalent. This gender skew mirrors the findings of Kovaleva et al. (2023), which suggest that female participation in the IT industry remains limited due to various inhibiting factors. Although efforts to promote gender diversity persist, the current demographic makeup of the study sample reflects industry norms.

Regarding age distribution, most respondents fell within the 18 to 22-year-old bracket, totaling 150 individuals out of the 266. This age range predominantly comprises college students or recent graduates, belonging to Generation Z, who are often targeted for large-scale internet surveys due to their extensive use of computers and the internet.

Most respondents in this study, totaling 184 out of 266, attained their highest education at the bachelor's degree. Subsequently, 54 respondents stated that their highest educational attainment was secondary school. Furthermore, 16 respondents mentioned holding an associate’s degree, while 12 respondents reported having a master's degree. This breakdown sheds light on the educational profiles of the study participants. The demographic profile of respondent is shown in Table 1.

Table 1. Demographic Profile of Respondents

Respondent profile	Total	Percentage
Gender		
Male	213	80%
Female	53	20%
Age		
18 - 22 years	150	56%
23 - 27 years	90	34%
28 - 32 years	11	4%
33 - 37 years	4	2%
38 - 45 years	7	3%

Respondent profile	Total	Percentage
45 - 60 years	4	2%
Educational stage		
Secondary School	54	20%
Associate's Degree	16	6%
Bachelor's Degree	184	69%
Master's Degree	12	5%

4.2 Measurement Model Test Results (Outer Model)

The measurement model, also known as the outer model test, initiates with the evaluation of convergent validity. As per Hair Jr et al. (2021), an indicator is considered valid if its outer loading surpasses the minimum threshold of 0.7. Table 2 and 3 display the results of the convergent validity analysis for all indicators/items on first and second order model. It indicates that all 38 indicators examined in this study exhibit validity, as their outer loading values exceed 0.7.

Table 2. Convergent Validity Outputs of the First-Order Construct

Indicator	Outer Loading	Information
AG2	0.720	Valid
AG3	0.717	Valid
AG4	0.741	Valid
AS1	0.760	Valid
AS2	0.791	Valid
AS3	0.797	Valid
CS1	0.743	Valid
CS2	0.710	Valid
CS4	0.746	Valid
CS5	0.719	Valid
CS7	0.746	Valid
EWOM1	0.748	Valid
EWOM2	0.754	Valid
EWOM3	0.742	Valid
EWOM4	0.818	Valid
LOY1	0.800	Valid
LOY2	0.738	Valid
LOY3	0.729	Valid
LOY4	0.721	Valid
PBI1	0.844	Valid
PBI2	0.822	Valid
PBI3	0.781	Valid
RL1	0.772	Valid
RL3	0.765	Valid
RL5	0.731	Valid
SB2	0.815	Valid

SB3	0.865	Valid
SB4	0.813	Valid
SC2	0.750	Valid
SC3	0.735	Valid
SC5	0.759	Valid
SR1	0.761	Valid
SR2	0.832	Valid
SR3	0.733	Valid
SR4	0.770	Valid
US1	0.844	Valid
US2	0.840	Valid
US3	0.790	Valid

Table 3. Convergent Validity Outputs of the Second-Order Construct

Indicator	Outer Loading	Information
CS1	0.742	Valid
CS2	0.709	Valid
CS4	0.747	Valid
CS5	0.719	Valid
CS7	0.748	Valid
EWOM1	0.747	Valid
EWOM2	0.755	Valid
EWOM3	0.742	Valid
EWOM4	0.818	Valid
LOY1	0.800	Valid
LOY2	0.737	Valid
LOY3	0.730	Valid
LOY4	0.720	Valid
AG	0.780	Valid
AS	0.756	Valid
RL	0.754	Valid
SB	0.741	Valid
SC	0.743	Valid
SR	0.747	Valid
PBI1	0.844	Valid
PBI2	0.824	Valid
PBI3	0.778	Valid

The next convergent validity test for each of these variables will employ the AVE criteria, with each variable having a minimum value of 0.5 so that each variable can be considered valid (Hair Jr et al., 2021). The result of the convergent validity test indicates that the AVE values for all nine variables are more than 0.5. The subsequent test examination involves test discriminant validity utilizing the Fornell-Larcker criterion, which states that the square of each variable AVE must be greater than its highest correlation with other variables. The results in Table 3 demonstrate that all variables satisfy this criterion, with their square root AVE values exceeding correlations with other variables, confirming their validity.

Table 4. Discriminant Validity (Fornell and Larcker Criterion) of the First-Order Construct

	AG	AS	CS	EWOM	LOY	PBI	RL	SB	SC	SR	US
AG	0.726										
AS	0.519	0.783									
CS	0.542	0.523	0.733								
EWOM	0.496	0.419	0.620	0.766							
LOY	0.487	0.518	0.631	0.569	0.748						
PBI	0.465	0.485	0.645	0.562	0.595	0.816					
RL	0.513	0.448	0.512	0.415	0.491	0.414	0.756				
SB	0.531	0.410	0.534	0.424	0.456	0.477	0.566	0.831			
SC	0.517	0.471	0.546	0.413	0.421	0.367	0.466	0.439	0.748		
SR	0.433	0.551	0.601	0.467	0.440	0.530	0.438	0.416	0.505	0.775	
US	0.403	0.446	0.485	0.411	0.415	0.423	0.357	0.328	0.458	0.465	0.825

Table 5. Discriminant Validity (Fornell and Larcker Criterion) of the Second-Order Construct

	CS	CSQ	EWOM	LOY	PBI
CS	0.733				
CSQ	0.721	0.754			
EWOM	0.620	0.584	0.766		
LOY	0.631	0.623	0.569	0.747	
PBI	0.646	0.609	0.562	0.595	0.816

The reliability is also assessed through two criteria: Cronbach's alpha and composite reliability, which must be greater than 0.7 (Hair Jr et al., 2021). This study cites Ekolu and Quainoo (2019), indicating that while Cronbach's alpha between 0.5 - 0.7 is generally deemed acceptable with sufficient reliability, it should be supplemented by a composite reliability value exceeding 0.7. The reliability test show demonstrates that all variables utilized in this study are reliable as indicated in Table 6 and 7.

Table 6. Reliability of the First-Order Construct

Variable	Cronbach's Alpha	Composite Reliability	Information
Agility (AG)	0.551	0.551	Moderate
Assurance of Service (AS)	0.684	0.684	Moderate
Customer Satisfaction (CS)	0.785	0.786	High
Cloud Service Quality (CSQ)	0.920	0.923	Excellent
Electronic Word of Mouth (EWOM)	0.765	0.770	High
Customer Loyalty (LOY)	0.736	0.741	High
Perceived Brand Image (PBI)	0.749	0.754	High
Reliability (RL)	0.625	0.626	Moderate
Scalability (SB)	0.776	0.779	High
Security (SC)	0.607	0.607	Moderate
Service Responsiveness (SR)	0.777	0.781	High

Table 7. Reliability of the Second-Order Construct

Variable	Cronbach's Alpha	Composite Reliability	Information
Customer Satisfaction (CS)	0.785	0.786	High
Cloud Service Quality (CSQ)	0.848	0.849	High
Electronic Word of Mouth (EWOM)	0.765	0.770	High
Customer Loyalty (LOY)	0.736	0.741	High
Perceived Brand Image (PBI)	0.749	0.755	High

4.3 Structural Model Test Result (Inner Model)

This test encompasses model fit testing, path coefficient analysis, determination coefficient (R2), effect size (f2), and predictive relevance (Q2). Model fit tests are conducted to evaluate the suitability of the research model and to mitigate or prevent specification errors, ensuring compatibility with the sample data. The criteria for fit model testing in this study include the standardized root mean square residual (SRMR), exact fit test (Euclidean and Geodesic values), and normed fit index (NFI). The result of the fit model test indicates that the research model is deemed satisfactory as it satisfies the specified criteria, as depicted in Table 8.

Table 8. Model Fit Outputs

Criterion	Limit Value	Model Value	Information
SRMR	Should be < 0.08	0.062	Good fit
Chi-square/df	Should be < 3	2.465	Good fit
d_ULS	Should be < 95	0.985	Good fit
d_G	Should be < 95	0.350	Good fit
NFI	Between 0 and 1	0.788	Marginal fit

The coefficient of determination test evaluates the accuracy of predicting the impact of independent variables on dependent variables. R2 values range from 0 to 1, with higher values indicating better measurement accuracy. According to (Hair Jr et al., 2021), R2 values fall into three categories: < 0.25 indicates weak, 0.25 - 0.75 indicates moderate, and > 0.75 indicates strong. Given that this research pertains to consumer behavior, an R2 value of 0.20 is considered sufficiently high. The results of the coefficient of determination test are presented in Table 7.

Table 9. Coefficient of Determination Outputs

Variabel	R Square	Information
Customer Satisfaction (CS)	0.588	High
Electronic Word of Mouth (EWOM)	0.450	High
Customer Loyalty (LOY)	0.510	High
Perceived Brand Image (PBI)	0.371	High

The effect size test (f2) tests the predictive impact of specific variables on others within the model. According to Hair et al. (2018), if the value of f2 falls between 0.02-0.15, it indicates a small impact; between 0.15-0.35 suggests a moderate impact; and if it exceeds 0.35, it signifies a large impact. Conversely, if the f2 value is less than 0.02, it suggests no impact on the model structure. The results of the effect size test indicate that: a) seven hypotheses or correlations demonstrate a small impact, including CS-EWOM, CS-LOY, CSQ-EWOM, CSQ-LOY, EWOM-LOY, PBI-EOWM, and PBI-LOY; b) one hypothesis exhibit a moderate effect, which is PBI-CS; c) and two hypotheses show large impact: CSQ-CS and CSQ-PBI.

The predictive relevance test (Q2) evaluates the degree to which independent variables (predictors) can predict the dependent variable. Hair Jr et al. (2021), a model exhibits predictive relevance if the Q2 value exceeds 0. This test calculates the Q2 value using the blindfolding method. The results of the predictive relevance test indicate that all dependent variables have Q2 values greater than 0, affirming that the model in this study possesses predictive relevance for estimating independent variables within the model.

In this study, the model was also tested using PLSpredict provided by SmartPLS 4. The PLS-SEM model was compared with linear regression (LM) to assess the predictive strength of the model. The research employed a value of k = 10 and iterated 10 times as recommended (Shmueli et al., 2019). Based on the PLSpredict testing results, it was found that in comparing PLS-SEM_RMSE with LM_RMSE, the PLS-SEM model exhibited smaller error predictions across all variables compared to LM_RMSE. This indicates that the PLS-SEM model has higher predictive accuracy. Meanwhile, in terms of PLS-SEM_MAE and LM_MAE, the PLS-SEM model demonstrated smaller error predictions for some variables compared to LM_MAE, suggesting that the PLS-SEM model has a high level of prediction based on the MAE results. Overall, this indicates that the PLS-SEM model has higher and more reliable prediction levels for dependent variables in this study.

Table 10. PLSpredict Assessment Outputs

Variable	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
CS1	0.546	0.443	0.555	0.450
CS2	0.683	0.551	0.690	0.556
CS4	0.570	0.469	0.572	0.466
CS5	0.573	0.475	0.581	0.483
CS7	0.577	0.473	0.585	0.472
EWOM1	0.660	0.523	0.665	0.526
EWOM2	0.678	0.516	0.695	0.529
EWOM3	0.777	0.624	0.791	0.637
EWOM4	0.690	0.541	0.700	0.556
LOY1	0.665	0.537	0.679	0.544
LOY2	0.640	0.521	0.654	0.525
LOY3	0.695	0.541	0.703	0.545
LOY4	0.630	0.510	0.640	0.520
PBI1	0.553	0.448	0.556	0.445
PBI2	0.643	0.525	0.645	0.522
PBI3	0.647	0.524	0.654	0.525

The path coefficient analysis, which involves hypothesis testing, aims to assess the significance and strength of relationships between variables and to test hypotheses. Path coefficients typically range from -1 to +1. The bootstrapping procedure is employed to determine the significance of the coefficient (t-value) and the strength of the relationship (p-value), as well as to test the hypotheses. Bootstrapping is conducted using a two-tailed test with a critical value of 1.96 (at a significance level of 5%). If the t-value exceeds the critical value, the coefficient is considered significant, and if the p-value is less than 0.05, the hypothesis can be accepted (Hair Jr et al., 2021). The results of the path coefficient test are detailed in Table 11.

Table 11. Results of Path Coefficients, t statistics and p values

Hypothesis	Relationship	Original Sample (O)	t Statistics	p Values	Information
Direct effect					
HI	CSQ LOY	0.233	3.461	0.001	Accepted
H2	CSQ CS	0.522	9.917	0.000	Accepted
H3	CS LOY	0.213	3.299	0.001	Accepted
H4	CSQ PBI	0.609	16.549	0.000	Accepted
H5	PBI CS	0.328	5.640	0.000	Accepted
H6	PBI LOY	0.214	3.444	0.001	Accepted
H7	CSQ EWOM	0.219	3.033	0.002	Accepted
H8	PBI EWOM	0.223	3.662	0.000	Accepted
H9	CS EWOM	0.318	4.674	0.000	Accepted
H10	EWOM LOY	0.181	2.253	0.024	Accepted
Mediation effect					
H11	CSQ PBI LOY	0.130	3.346	0.001	Accepted
H12	CSQ CS LOY	0.111	3.239	0.001	Accepted
H13	CSQ EWOM LOY	0.040	1.610	0.107	Rejected
H14	CSQ PBI CS LOY	0.042	2.628	0.009	Accepted
H15	CSQ PBI EWOM LOY	0.025	1.635	0.102	Rejected
H16	CSQ CS EWOM LOY	0.030	1.812	0.070	Rejected
H17	CSQ PBI CS EWOM LOY	0.011	1.752	0.080	Rejected

Based on the test results, it was concluded that (**H1 was accepted**) and showed that cloud service quality has a significant influence on customer loyalty. This finding is consistent with previous research that information quality does not significantly influence satisfaction (Agarwal & Dhingra, 2023; Rahim, 2016). This may occur because service quality of cloud computing was very crucial for their application and business so it can be direct effect to loyalty.

Furthermore, it noticed that cloud service quality positively and significantly influences customer satisfaction (**H2 accepted**). The findings are in line prior research, which demonstrates that cloud service quality positively affects satisfaction (Agarwal & Dhingra, 2023; Chan et al., 2022). This indicated how important service quality for its customers is related to their satisfaction. Cloud service quality needs to be more understood by an IT company whether to improve or deliver to their customer.

In addition, a relationship that is positive and has no significant influence among customer satisfaction and customer loyalty then (**H3 accepted**). This finding aligns with previous research, which also suggests that customer satisfaction affected to customer loyalty (Agarwal & Dhingra, 2023; Al-dweeri et al., 2017; Chan et al., 2022; Iqbal et al., 2018; Rahim, 2016). Connectivity of customers to cloud computing services is important for IT companies. Loyal customers are not only tending to use cloud computing services but also reuse it for other reasons. Thus, customer satisfaction must be tightened and improved over time to maintain their market in the real world.

Based on the test results, it is concluded that cloud computing service quality positively and significantly influences perceived brand image (**H4 accepted**). This finding is consistent with prior research, that cloud computing service quality positively and significantly affects company brand image (Alam & Noor, 2020; Chan et al., 2022). Users are very sensitive if the service they use is not useful for their business. A good service quality will result in a good rating for its service and the company that served it. This being important for a company to enrich their brand to keep always being positive by maintaining their service served well to customers.

There is also positive and significant influence of perceived brand image on satisfaction then (**H5 accepted**). The overall evaluation of users on perceived brand image will deliver into a satisfying experience for users when using them. If the brand image of cloud computing exceeds user expectations, it can trigger feelings of satisfaction because there is alignment between user expectations and the perceived reality. This finding is relevant with previous research which indicated that perceived brand image affected satisfaction (Alam & Noor, 2020; Chan et al., 2022).

Moreover, the relationship between perceived brand image and customer loyalty was positive and significant (**H6 accepted**). This indicates that a good brand image of cloud computing creates positive expectations but also effectively ensures that the user experience meets their expectation to be loyal for this company and its services. This finding is aligned with previous research, which indicates that service quality positively influences confirmation (Alam & Noor, 2020; Chan et al., 2022; Tan et al., 2017).

Furthermore, from the statistic result indicated that there is positive and significant influence of cloud service quality and electronic word of mouth (**H7 accepted**). High-quality cloud services tend to create positive experiences for users, which can then encourage them to share their experiences with others through electronic platforms such as social media, online forums, or reviews. Users who are satisfied with the cloud service are more likely to be motivated to provide positive reviews and recommend the service to others. This is consistent with previous research, which suggests that cloud service quality and electronic word of mouth (Chan et al., 2022).

Positive and significant influences are also shown among perceived brand image and electronic word of mouth that was positively and significantly influenced (**H8 accepted**). Positive perceptions of a brand create trust and strong loyalty from users. When users have a positive perception of a brand, they are more motivated to share their positive experiences with others online. This can increase the brand's visibility on online platforms and create a domino effect, where positive reviews from one user can influence others to try the service. This finding is also in line with previous research, which suggests that perceived brand image influenced electronic word of mouth (Chan et al., 2022).

Next, positive and significant relationship was also proven between customer satisfaction on electronic word of mouth (**H9 accepted**). Satisfied customers tend to be more inclined to share their positive experiences with others, whether through social media, online reviews, or community platforms. This can be a powerful marketing strategy because testimonials from satisfied customers can influence the purchasing decisions of others and enhance the overall brand reputation as proven by previous research (Chan et al., 2022).

The relationship of electronic word of mouth was significantly affecting customer loyalty (**H10 accepted**). These findings in contrast with previous research indicating that perceived usefulness positively influences continuance intention (Chan et al., 2022). Electronic word of mouth plays an increasingly important role in influencing consumer behavior, including the decision to continue using a particular service. Reviews, testimonials, and recommendations from fellow users published online can influence customers' perceptions of the reliability, quality, and satisfaction with a cloud service. Customers tend to trust reviews from sources they consider reliable, such as reviews from friends or family, or reviews they find on trusted online platforms.

According to the test result, the p-values for relationship less than 0.05, meaning that cloud computing service quality indirectly affects customer loyalty positively through perceived brand image (**H11 accepted**), cloud computing service quality indirectly affects customer loyalty positively through customer satisfaction (**H12 accepted**), and cloud computing service quality indirectly affects customer loyalty positively through perceived brand image and customer satisfaction (**H14 accepted**). Meanwhile, based on the p-values above 0,05 indicating that cloud computing service quality does not indirectly influence customer loyalty through electronic word of mouth (**H13 rejected**), cloud computing service quality does not indirectly affect customer loyalty through perceived brand image and electronic word of mouth (**H15 rejected**), cloud computing service quality does not indirectly affect customer loyalty through customer satisfaction and electronic word of mouth (**H16 rejected**), and cloud computing service quality does not indirectly affect customer loyalty through perceived brand image, customer satisfaction, and electronic word of mouth (**H17 rejected**).

5. CONCLUSION

In conclusion, this study provides valuable insights into the factors influencing customer loyalty in cloud computing services, employing a quantitative approach, and utilizing the partial least squares-structural equation model (PLS-SEM) for analysis. The acceptance of all ten hypotheses underscores the significance of various factors, including cloud service quality (CSQ), perceived brand image (PBI), customer satisfaction (CS), and electronic word of mouth (EWOM), in shaping customer loyalty. While usability was not identified as a significant dimension of CSQ, other factors such as agility, assurance of service, reliability, scalability, security, and service responsiveness played crucial roles.

The analysis revealed that CSQ, influenced by six quality dimensions, exhibited a moderate effect on customer loyalty. Notably, CSQ emerged as the most influential factor, followed by PBI, CS, and EWOM. Moreover, PBI and CS acted as partial mediators in reinforcing the relationship between CSQ and customer loyalty. Overall, the PLS-SEM model demonstrated high predictive power, indicating its reliability in predicting variables related to customer loyalty in cloud computing services. These findings contribute to a better understanding of customer loyalty dynamics in the cloud computing industry, emphasizing the importance of factors such as CSQ, PBI, CS, and EWOM in fostering customer loyalty.

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