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Examining The Impact of E-Service Quality and E-Recovery Service Quality in Digital Public Services in Indonesia

Yovian Yovian, Novandra Rhezza Pratama
Universitas Indonesia, Depok, Indonesia
yovian@ui.ac.id, novandra@ui.ac.id

ABSTRACT

Digital government services are increasingly delivered through applications that interact directly with users and offer the potential to enhance public service efficiency. This study investigates the impact of e-service quality and e-recovery service quality on customer experience, satisfaction, and loyalty within the context of digital public services. Constructs such as efficiency, fulfilment, security, and availability represent e-service quality, while compensation, responsiveness, and contact reflect e-recovery service quality. The relationships between these constructs and the dimensions of customer experience, satisfaction, and loyalty were examined using Partial Least Squares Structural Equation Modeling (PLS-SEM). Data were collected through a questionnaire distributed to users of digital services at the Legal Metrology Standardization Regional IV Office, Ministry of Trade of the Republic of Indonesia. A total of 273 valid responses were analyzed from customers who had used the digital service within the past year. The findings reveal that both e-service quality and e-recovery service quality significantly influence customer experience, satisfaction, and loyalty. This study offers new insights into how customer loyalty is shaped in the context of government-provided digital services.

Keywords: E-Service Quality, Digital Public Services, Government Services,

INTRODUCTION

The Indonesian government has been implementing Bureaucratic Reform since 2009, guided by Presidential Regulation No. 81 of 2010, to enhance public service quality and accessibility (Akaka Vargo S. L. & Schau H. J., 2015; Malech Garabedian E. & Hsieh M. W., 2022; Mallya Gadre M. A. Varadharajan S. & Vasanthan K. S., 2025; Milone U., 2018). This reform focuses on three key outcomes: strengthening organizational capacity and accountability, establishing a clean government free from corruption, and improving public services. The digitalization of public services has become a crucial aspect of this transformation, aligning with the principles of *Dynamic Governance*, which emphasize efficiency, adaptability, and continuous learning in response to rapid technological advancements (Jain Aagja J. & Bagdare S., 2017).

The increasing adoption of digital applications in public administration aims to improve service efficiency, transparency, and accessibility (Kanthachai, 2015). Digital transformation reduces processing times and costs while ensuring greater accountability through digitized documentation (Li & Liu G. H., 2022; Li Shen L. Deng Z. & Huang Z., 2023; Li Z. Portillo X. Arora R. Yang M. Mintzer E. . & Church G. M., 2024; Liu Yang B. & Zhou X., 2020). These advancements are essential in addressing the growing public demand for transparency, responsiveness, and efficiency in government services. However, challenges remain, particularly in Eastern Indonesia, where infrastructure limitations hinder the accessibility and quality of services such as calibration. Government institutions must enhance competitiveness while meeting non-tax state revenue targets and maintaining service standards. The presence of private competitors adds further challenges, as they often offer more flexible and innovative services (Ginn Amaya A. K. Alexander I. E. Edelstein M. L. & Abedi M. R., 2018; Wang et al., 2019).

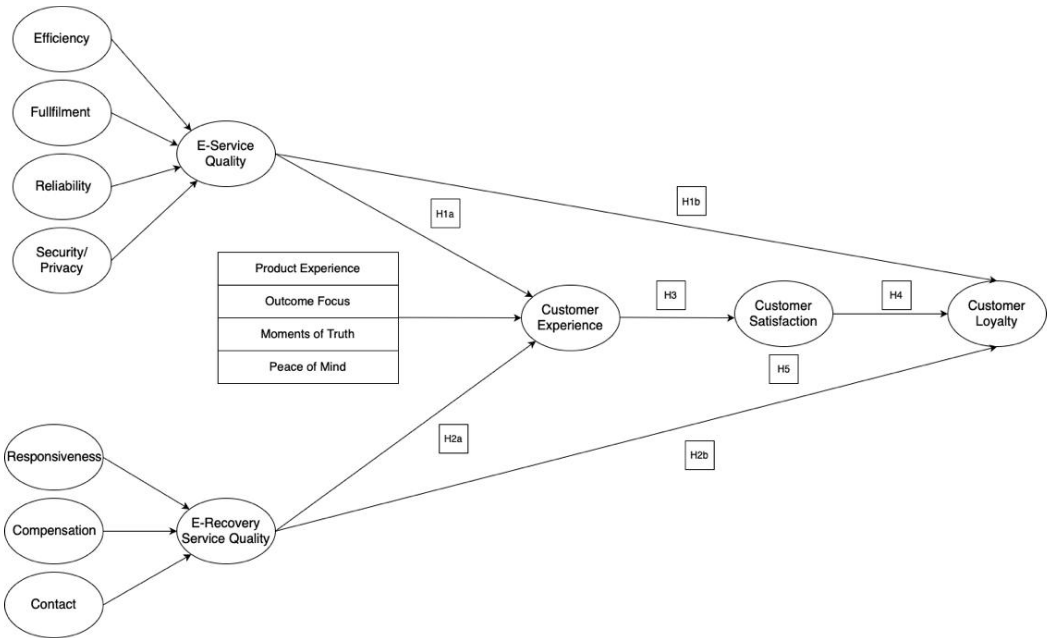
Within the framework of digital service improvement, *e-service quality* (*e-servqual*) and *e-recovery service quality* (*e-recovery servqual*) are critical for enhancing customer experience, satisfaction, and loyalty. *E-servqual* reflects how digital platforms facilitate transactions and service delivery, while *e-recovery servqual* measures the effectiveness of issue resolution and compensation for service failures ((Ghifari M, 2021); Zeithaml et al., 2010). Customer loyalty in public services is defined as the sustained use of government digital services, influenced by service quality, responsiveness, and customer trust (Lovelock & Wirtz, 2011; Kotler & Keller, 2016).

Despite extensive research on *e-servqual* and *e-recovery servqual* in private sectors such as banking and e-commerce, limited studies have explored their integrated impact on government digital services (Giacca S., 2012; Salauddin et al., 2024). This research aims to bridge this gap by analyzing the combined influence of *e-servqual* and *e-recovery servqual* on customer experience, satisfaction, and loyalty within Indonesia's public sector. The study is expected to contribute to both academic discourse and practical policy recommendations, helping government institutions enhance digital service quality.

The research will examine digital public services at the Regional IV Office of Legal Metrology Standardization, which operates under the Directorate of Metrology, Ministry of Trade. This study will gather data from customers across 144 regencies and cities in the eastern region of Indonesia, covering *Sulawesi*, *Maluku*, and *Papua*, from November 2024 to February 2025. The findings are expected to offer valuable insights for enhancing digital public services and addressing the challenges associated with digital transformation in Indonesia's government sector.

METHOD

This study investigates how government digital services impact customer experience, satisfaction, and loyalty. Customer satisfaction acts as a mediator, consistent with Hsu and Lin (2023), who identify it as a key driver of loyalty. As users interact with digital applications, their loyalty shifts based on their experience and satisfaction. Expanding on Hsu and Lin's framework, this study develops a theoretical model to examine how digital applications influence these factors, ultimately fostering loyalty. The model integrates input and output variables using a second-order formative construct matrix, including *e-service quality*, *e-service recovery quality*, and customer experience. Efficiency, fulfillment, security/privacy, and system availability are the four first-order reflective constructs used to evaluate the quality of *e-services* (Hsu & Lin J. C. C., 2023). Compensation, responsiveness, and interaction quality are all assessed by *e-service recovery quality*. Following Klaus & Maklan S. (2013), customer experience was substituted for conversational quality in order to expand the model's application. Carvajal-Trujillo et al. (2022) emphasize that improving customer experience enhances satisfaction and strengthens loyalty. Digital service providers should focus on affective experience management by ensuring comfort, enjoyment, intuitive navigation, and entertainment. Applications should incorporate user-friendly designs, interactive content, and exclusive features such as personalized color schemes, augmented or virtual reality, and gamification elements (Carvajal-Trujillo et al., 2022). These enhancements increase engagement, making digital interactions more compelling and reinforcing customer loyalty. Below is the proposed framework and research model.



Source: *Author's Processed Findings, 2024*

Customer satisfaction depends on how enjoyable an application is, with user responses shaped by their experience with frequently used digital services. These experiences span various sectors, such as fashion, food, sports, and electronics, influencing overall perceptions (Molinillo et al., 2022). This study explores whether prior experience is necessary for customer loyalty (Klaus & Maklan, 2013) and whether satisfaction must precede loyalty. To ensure a robust framework, the research model adopts a second-order approach for independent variables, maintaining the input-output structure as recommended by Hsu and Lin (2023).

Hypothesis Development

This study examines the influence of customer experience and satisfaction with government digital service applications on customer loyalty. Prior research has highlighted that e-service quality significantly shapes customer satisfaction, contributing to the rapid adoption of digital services (Hsu & Lin, 2023). Zehir and Baykal (2016) further found that both service quality and recovery quality directly affect loyalty intentions in e-business contexts. Based on these insights, the following hypotheses are proposed:

- **H1a**: E-Service Quality significantly influences Customer Experience

- **H1b**: E-Service Quality significantly influences Customer Loyalty
- **H2a**: E-Recovery Service Quality significantly influences Customer Experience
- **H2b**: E-Recovery Service Quality significantly influences Customer Loyalty

Satisfaction is also posited to positively influence loyalty in digital services. The Expectation Confirmation Model (ECM) supports this, emphasizing that user satisfaction is a key predictor of continued usage (Limayem & Cheung, 2008; Lee & Kwon, 2011; Kim (2010); Lin & Bennett, 2014; Hew Lee V. H. Ooi K. B. & Wei J. (2016); (Chiu Lin T. J. & Lonka K., 2021). This aligns with findings that satisfied users are more likely to remain loyal (Araujo (2018); (Johari Zaman H. B. & Nohuddin P. N. E., 2019). Hence:

- **H3**: Customer Experience significantly influences Customer Satisfaction

Emotional engagement also plays a critical role. Affective experiences have been found to strongly impact user satisfaction, particularly in online and mobile application contexts (Martin et al., 2008; Barari & Furrer O. (2018); Souden et al., 2019; (Alnawas & Aburub F., 2016). Satisfaction, in turn, is a major determinant of loyalty. Research shows that satisfied customers exhibit greater purchase intentions, advocacy behavior, and resistance to competitors (Brakus et al., 2009; Lin & Bennett, 2014; Rose et al., 2012; Kim, 2010; Pandey & Chawla, 2018; Iyer Davari A. & Mukherjee A. (2018); Thakur, 2018). Therefore:

- **H4**: Customer Satisfaction significantly influences Customer Loyalty

Lastly, following Baron and Kenny's (1986) mediation framework and supported by earlier studies (Caruana, 2002; Mosahab et al., 2010; Yunus Ibrahim M. & Amir F. (2018), this study hypothesizes that satisfaction mediates the relationship between service quality and loyalty:

H5: Customer Satisfaction mediates the relationship between Customer Experience and Customer Loyalty

RESULTS AND DISCUSSION

High-quality data are essential for ensuring research validity. In this study, data were collected through self-administered questionnaires targeting eligible respondents aligned with the research objectives (Malhotra, 2019). The instrument was designed to elicit complete and accurate responses using a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The population included all users of digital public services at the Regional IV Office, while the sample comprised those who had accessed these services during the study period. Based on Roscoe's (1975) and Bentler and Chou's (1987) sampling recommendations, a minimum of 215 responses was required for 43 indicators. After screening, 273 valid responses were retained.

The descriptive analysis indicated that all variables and their indicators possess a minimum value of 1, a maximum value of 5, and an average score of 4. This suggests that most respondents tend to agree with the questionnaire statements. The validity test assesses whether measurement indicators accurately represent the research concept, while the reliability test evaluates the consistency of the measurement tool across different assessments (Malhotra, 2019). This study assessed validity by component analysis utilizing IBM SPSS 26, with the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO-MSA) as the evaluation metric. A KMO value of at least 0.5 is required, and Bartlett's Test of Sphericity must be significant at less than 0.05 (Malhotra, 2019). Reliability testing was performed by evaluating the Cronbach's alpha for each variable's indicators, which must achieve a minimum threshold of 0.6 (Malhotra, 2019). Table 1 displays the processed data results for the validity and reliability assessments conducted in this study.

Table 1. Validity and Reliability Test

Variable	Validity		Reliability
	KMO	Bartlett's Test of sphericity	Cronbach's Alpha
E-Servqual	0,942	0,000	0,911
E-Recovery Servqual	0,915	0,000	0,942
Customer Experience	0,968	0,000	0,975
Customer Satisfaction	0,845	0,000	0,911
Customer Loyalty	0,848	0,000	0,917

Source: *Results Processed by the Researcher Based on IBM SPSS Output*

All variables in this study meet validity and reliability criteria. The KMO score surpasses 0.5, and Bartlett's Test of Sphericity is below 0.05, so affirming validity. Reliability is ensured as all Cronbach's Alpha values exceed 0.6.

Data analysis employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS software. PLS-SEM was chosen for its suitability with small samples, non-normal data, and formative constructs (Hair Jr. Sarstedt M. Hopkins L. & Kuppelwieser V. G., 2014). Unlike CB-SEM, which is confirmatory, PLS-SEM focuses on prediction and can handle complex models with multicollinearity. The model includes a second-order construct, combining reflective first-order and formative second-order dimensions. The measurement model (outer model) evaluates indicator reliability and validity, while the structural model (inner model) assesses relationships between latent variables. Convergent validity was tested through factor loadings, with values of 0.50 to 0.69 deemed acceptable (Hair et al., 2014). Outer loading results are presented in the following table.

Table 2. Convergent Validity Test Using Outer Loading

	Outer Loading		Outer Loading
CL1 <- Customer Loyalty	0.916	MT4 <- Moments of Truth	0.892
CL2 <- Customer Loyalty	0.874	OF1 <- Outcome Focus	0.888
CL3 <- Customer Loyalty	0.881	OF2 <- Outcome Focus	0.900
CL4 <- Customer Loyalty	0.907	OF3 <- Outcome Focus	0.884
COM1 <- Compensation	0.929	OF4 <- Outcome Focus	0.893

COM2 <- Compensation	0.930	PE1 <- Product Experience	0.925
CON1 <- Contact	0.927	PE2 <- Product Experience	0.894
CON2 <- Contact	0.931	PE3 <- Product Experience	0.884
CS1 <- Customer Satisfaction	0.912	PM1 <- Peace of Mind	0.888
CS2 <- Customer Satisfaction	0.871	PM2 <- Peace of Mind	0.882
CS3 <- Customer Satisfaction	0.876	PM3 <- Peace of Mind	0.897
CS4 <- Customer Satisfaction	0.894	REL1 <- Reliability	0.876
EFI1 <- Efficiency	0.912	REL2 <- Reliability	0.891
EFI2 <- Efficiency	0.893	REL3 <- Reliability	0.876
EFI3 <- Efficiency	0.879	REL4 <- Reliability	0.880
FUL1 <- Fulfillment	0.913	RES1 <- Responsiveness	0.941
FUL2 <- Fulfillment	0.878	RES2 <- Responsiveness	0.934
FUL3 <- Fulfillment	0.900	SEC1 <- Security Privacy	0.848
FUL4 <- Fulfillment	0.915	SEC2 <- Security Privacy	0.695
MT1 <- Moments of Truth	0.883	SEC3 <- Security Privacy	0.864
MT2 <- Moments of Truth	0.886	SEC4 <- Security Privacy	0.814
MT3 <- Moments of Truth	0.887		

***Source**: Output generated by the SMART-PLS application, 2025*

The results indicate that all items exhibit outer loading values above 0.50, confirming reliable and consistent measurement of latent variables. This supports the convergent validity of the constructs. Discriminant validity, which ensures that each construct is empirically distinct, is also assessed. High discriminant validity reflects the construct's ability to capture a unique concept. Construct validity is further confirmed through the Average Variance Extracted (AVE), with all values meeting the recommended threshold of 0.50 (Hair et al., 2017).

Table 3. Discriminant Validity Test Through Average Variance Extracted Criteria

	Average variance extracted (AVE)		**Average variance extracted (AVE)**
Compensation	0.865	Fulfillment	0.813
Contact	0.863	Moments of Truth	0.787
Customer Experience	0.757	Outcome Focus	0.795
Customer Loyalty	0.800	Peace of Mind	0.790
Customer Satisfaction	0.790	Product Experience	0.812
E-Recovery Service Quality	0.774	Reliability	0.776
E-Service Quality	0.565	Responsiveness	0.879
Efficiency	0.801	Security Privacy	0.653

***Source**: Output generated by the SMART-PLS application, 2025*

Discriminant validity was examined using the Average Variance Extracted (AVE), with all constructs exceeding the 0.5 threshold, indicating adequate indicator representation of their latent constructs. The Fornell-Larcker criterion further confirmed that each construct's AVE square root surpasses its inter-construct correlations, fulfilling the condition for discriminant validity (Hair et al., 2017). These findings, summarized in the table below, validate the distinctiveness of each construct.

Table 4. Results of the Discriminant Validity Test According to Fornell & Larcker Criteria

	Customer Experience	Customer Loyalty	Customer Satisfaction	E-Recovery Service Quality	E-Service Quality
Customer Experience	0.970				
Customer Loyalty	0.912	0.895			
Customer Satisfaction	0.961	0.843	0.889		
E-Recovery Service Quality	0.913	0.852	0.849	0.880	
E-Service Quality	0.910	0.854	0.862	0.869	0.952

Source: *Output generated by the SMART-PLS application, 2025*

The Fornell-Larcker results confirm that each indicator has the highest value within its associated construct, supporting strong discriminant validity and the absence of collinearity. Cross-loading analysis further validates this, as each indicator loads more strongly on its intended construct than on others. These loadings reflect the degree of association between indicators and constructs, with validity established when indicators relate more closely to their own construct than to others.

Table 5. Discriminant Validity Test Through Cross Loading Criteria

	Customer Experience	Customer Loyalty	Customer Satisfaction	E-Recovery Service Quality	E-Service Quality
CL1	0.889	0.916	0.868	0.874	0.880
CL2	0.843	0.874	0.830	0.835	0.840
CL3	0.856	0.881	0.831	0.853	0.847
CL4	0.853	0.907	0.843	0.843	0.847
COM1	0.835	0.808	0.813	0.869	0.829
COM2	0.847	0.827	0.826	0.874	0.848
CON1	0.858	0.849	0.849	0.869	0.866
CON2	0.853	0.818	0.818	0.896	0.860
CS1	0.882	0.877	0.912	0.855	0.871
CS2	0.832	0.820	0.871	0.830	0.840
CS3	0.859	0.823	0.876	0.845	0.859
CS4	0.842	0.829	0.894	0.843	0.849
EFI1	0.878	0.857	0.853	0.863	0.894
EFI2	0.853	0.827	0.834	0.841	0.872
EFI3	0.837	0.801	0.832	0.834	0.853
FUL1	0.846	0.816	0.837	0.840	0.882
FUL2	0.860	0.842	0.847	0.861	0.873
FUL3	0.873	0.846	0.859	0.857	0.888

FUL4	0.864	0.848	0.844	0.851	0.884
MT1	0.863	0.843	0.836	0.833	0.848
MT2	0.864	0.825	0.835	0.843	0.866
MT3	0.861	0.820	0.828	0.837	0.843
MT4	0.872	0.838	0.835	0.843	0.866
OF1	0.875	0.839	0.841	0.852	0.849
OF2	0.879	0.848	0.852	0.855	0.856
OF3	0.884	0.845	0.851	0.855	0.867
OF4	0.868	0.822	0.840	0.844	0.849
PE1	0.898	0.864	0.839	0.874	0.879
PE2	0.867	0.844	0.829	0.854	0.847
PE3	0.870	0.827	0.839	0.854	0.850
PM1	0.857	0.836	0.824	0.842	0.834
PM2	0.856	0.823	0.821	0.820	0.833
PM3	0.867	0.846	0.837	0.846	0.853
REL1	0.855	0.837	0.847	0.849	0.860
REL2	0.880	0.871	0.854	0.868	0.889
REL3	0.847	0.824	0.816	0.836	0.850
REL4	0.841	0.821	0.831	0.820	0.861
RES1	0.881	0.867	0.856	0.907	0.863
RES2	0.861	0.853	0.845	0.864	0.847
SEC1	-0.132	-0.110	-0.140	-0.128	-0.162
SEC2	-0.069	-0.047	-0.070	-0.081	-0.086
SEC3	-0.125	-0.113	-0.107	-0.123	-0.166
SEC4	-0.089	-0.088	-0.105	-0.092	-0.142

Source: *Output generated by the SMART-PLS application, 2025*

The cross-loading results show that each indicator loads highest on its respective construct, confirming adequate discriminant validity and indicating that the indicators accurately reflect their intended variables. Furthermore, strong correlations between each indicator and its associated construct were observed. To evaluate the structural model's reliability, inner model analysis was conducted, covering collinearity assessment, coefficient of determination (R^2), predictive relevance, and significance testing for both direct and indirect effects (Malhotra, 2019). Collinearity was examined using the inner VIF values, with all indicators scoring below the 5.0 threshold, indicating no multicollinearity and supporting the model's stability. The coefficient of determination was evaluated using the adjusted R^2, where values below 0.50 indicate weak explanatory power, 0.50–0.75 suggest moderate strength, and above 0.75 reflect a strong relationship between endogenous and exogenous variables (Hair, 2014). The results of this analysis are presented in the next section.

Table 6. Determination Coefficient Test

	R-square	**R-square adjusted**
Customer Experience	0.970	0.970
Customer Loyalty	0.927	0.926
Customer Satisfaction	0.923	0.923

Source: *Output generated by the SMART-PLS application, 2025*

The coefficient of determination (R^2) indicates that E-Service Quality and E-Recovery Quality explain 97.0% of the variance in Customer Experience, reflecting a strong predictive relationship. Likewise, R^2 values for other endogenous constructs exceed 0.75, suggesting a high level of explanatory power. This confirms that the independent variables have substantial influence on the dependent variables. The F-square (f^2) test was also conducted to assess each predictor's contribution by observing changes in R^2 when a variable is removed. Following Hair et al. (2014), effect sizes are classified as small ($f^2 > 0.02$), medium ($f^2 > 0.15$), or large ($f^2 > 0.35$), with values below 0.02 indicating negligible effect. The detailed results are presented below.

Table 7. *F-Square Test*

	Customer Experience	**Customer Loyalty**	**Customer Satisfaction**
Customer Experience			12.065
Customer Loyalty			
Customer Satisfaction		0.056	
E-Recovery Service Quality	0.285	0.109	
E-Service Quality	0.788	0.077	

Source: *Output generated by the SMART-PLS application, 2025*

The f^2 analysis reveals that all exogenous variables exert a meaningful effect, with values exceeding the 0.02 threshold. The smallest f^2 value is 0.056, which still reflects a notable influence on the endogenous construct. Furthermore, the Goodness of Fit (GoF) index, as introduced by Tenenhaus et al. (2004), evaluates both measurement and structural model quality. Calculated as the square root of the product between average communality and average R-squared, GoF values of 0.10, 0.25, and 0.36 indicate small, medium, and large effect sizes, respectively.

Table 8. ***Goodness of Fit Test***

	R-square	**AVE**
Customer Experience	0.970	0.757
Customer Loyalty	0.927	0.800
Customer Satisfaction	0.923	0.790
Average	0.940	0.782
GOF	0.858	

Source: *Output generated by the SMART-PLS application, 2025*

The model yielded a Goodness of Fit (GoF) value of 0.858, which meets the criteria for a large effect size, indicating a strong explanatory power of the empirical data. Predictive relevance was then assessed using the blindfolding procedure through the Q^2 test. A Q^2 value greater than 0 confirms the model's predictive capability. According to Hair et al. (2014), Q^2 values of 0.02, 0.15, and 0.35 reflect small, medium, and large predictive relevance, respectively. The Q^2 values obtained from the model are presented in the following section.

Table 9. *Q-Square Test*

	SSO	SSE	Q² (=1-SSE/SSO)
Customer Experience	3822.000	963.368	0.748
Customer Loyalty	1092.000	293.423	0.731
Customer Satisfaction	1092.000	306.178	0.720
E-Recovery Service Quality	1638.000	386.063	0.764
E-Service Quality	4095.000	1815.109	0.557

***Source**: Output generated by the SMART-PLS application, 2025*

The analysis indicates that all variables have Q-Square values above 0.35, demonstrating strong predictive relevance of the model. This suggests that the exogenous variables effectively forecast the endogenous variables.

According to Hartono (2008), hypothesis testing relies on comparing t-statistics against critical values and examining p-values from the total effects table. The significance of the direct effect (path coefficient) between an exogenous and an endogenous variable is assessed at a one-tailed 0.05 significance level. A hypothesis is supported if the t-statistic is equal to or exceeds 1.64 and the p-value is below 0.05. The interpretation criteria are as follows:

- A positive path coefficient indicates a direct positive relationship, where increases in the exogenous variable lead to increases in the endogenous variable.
- A negative path coefficient implies an inverse relationship, where increases in the exogenous variable result in decreases in the endogenous variable.
- Significance is determined by p-values, with values less than 0.05 indicating a significant effect, and values above 0.05 indicating a lack of significance.

Table 10. Results of Path Coefficient Significance (Direct Effect)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Hypothesis
E-Service Quality -> Customer Experience	0.620	0.617	0.058	10.746	0.000	H1a
E-Service Quality -> Customer Loyalty	0.362	0.360	0.089	4.084	0.000	H1b
E-Recovery Service Quality -> Customer Experience	0.373	0.375	0.057	6.506	0.000	H2a
E-Recovery Service Quality -> Customer Loyalty	0.372	0.374	0.075	4.984	0.000	H2b
Customer Experience -> Customer Satisfaction	0.961	0.961	0.006	167.060	0.000	H3
Customer Satisfaction -> Customer Loyalty	0.241	0.242	0.062	3.881	0.000	H4

Customer Experience -> Customer Satisfaction -> Customer Loyalty	0.232	0.232	0.060	3.872	0.000	H5

***Source*:** *Output generated by the SMART-PLS application, 2025*

The table above indicates that all endogenous variables have a direct influence on the exogenous variables, as evidenced by a t-statistic value exceeding 1.64 and a significance level below 0.05. The highest t-statistic value is observed in the relationship between customer experience and customer satisfaction, reaching 167.060.

DISCUSSION

According to the hypothesis analysis performed by the researcher, based on the data processing outcomes:

H1a: E-Service Quality significantly influences Customer Experience

The results show that electronic service quality in government digital services has a significant and positive influence on customer experience, with a path coefficient of 0.620, a t-statistic of 10.746, and a p-value below 0.05. This suggests that higher service quality leads to more favorable user experiences. The finding aligns with Sukendia and Harianto (2021), who emphasized that enhanced e-service features directly contribute to improved user perceptions. An optimized digital service system reflects institutional responsiveness to citizen needs and plays a critical role in shaping positive, engaging experiences. Parasuraman, Zeithaml Bitner M. J. & Gremler D. D. (2010) as well as Alanezi et al. (2012) support this by asserting that evaluating digital service quality is essential for meeting public expectations in technology-driven environments.

H1b: E-Service Quality significantly influences Customer Loyalty

The analysis confirms that electronic service quality significantly influences customer loyalty, with a path coefficient of 0.362, a t-statistic of 4.084, and a p-value below 0.05. This implies that improvements in service performance can encourage users to continue using government digital services. This result supports Zehir & Narcıkara E. (2016), who found that service quality and responsiveness positively shape loyalty intentions. In digital governance, loyalty manifests through repeated system use and user commitment. Thus, strengthening service attributes such as reliability, security, and personalization can enhance user retention. Kassim and Ismail (2009) further emphasize that loyalty is shaped by consistent satisfaction and trust in digital environments.

H2a: E-Recovery Service Quality significantly influences Customer Experience

The statistical results demonstrate that the quality of electronic service recovery significantly affects customer experience, with a path coefficient of 0.373, a t-statistic of 6.506, and a p-value under 0.05. This indicates that effective recovery mechanisms, such as timely issue resolution and empathetic communication, contribute meaningfully to a positive user experience. This finding is consistent with Holloway and Beatty (2003), who showed that service recovery influences satisfaction following service failures. Similarly, Lin and Hsieh (2011) found that digital recovery efforts reflect fairness and provider responsiveness, which help reinforce trust and improve perceptions of service quality.

H2b: E-Recovery Service Quality significantly influences Customer Loyalty

The findings indicate that e-recovery service quality has a significant influence on customer loyalty, with a path coefficient of 0.372, a t-statistic of 4.984, and a p-value below 0.05. This shows that effective recovery strategies—such as transparent procedures, personalized responses, and timely resolutions—can restore user trust and strengthen continued use of digital platforms. This supports the work of Hsu and Lin (2023), who highlighted that recovery quality is a strong determinant of loyalty. Davidow (2003) also emphasized that successful recovery not only addresses dissatisfaction but also promotes long-term relationship building.

H3: Customer Experience significantly influences Customer Satisfaction

The analysis confirms a strong and significant influence of customer experience on customer satisfaction, with a path coefficient of 0.961, a t-statistic of 167.060, and a p-value below 0.05. This indicates that positive experiences with digital public services lead to substantially higher satisfaction levels. The result supports Manyanga et al. (2022), who stated that user experience plays a pivotal role in shaping satisfaction, particularly in digital service contexts. Users reported appreciation for the ease of use, speed of access, and ability to resolve issues remotely, which contribute to overall satisfaction with government digital services.

H4: Customer Satisfaction significantly influences Customer Loyalty

The analysis shows that customer satisfaction has a significant impact on customer loyalty, with a path coefficient of 0.241, a t-statistic of 3.881, and a p-value below 0.05. This suggests that satisfied users are more likely to continue using digital public service platforms. The finding is consistent with Manyanga et al. (2022) and Hsu and Lin (2023), who found that satisfaction fosters long-term commitment and user loyalty. Public agencies must therefore prioritize key satisfaction drivers such as reliability, responsiveness, and user-oriented design to enhance retention and trust.

H5: Customer Satisfaction mediates the relationship between Customer Experience and Customer Loyalty

The results support the hypothesis that customer satisfaction mediates the relationship between customer experience and customer loyalty, with a path coefficient of 0.232, a t-statistic of 3.872, and a p-value under 0.05. This means that better user experiences enhance satisfaction, which in turn strengthens loyalty. Choi et al. (2019) highlighted the importance of emotional connection in forming lasting service relationships, especially in digital settings. The mediating role of satisfaction suggests that governments should adopt a comprehensive approach that integrates experience design, satisfaction monitoring, and data-informed service refinement to foster sustainable loyalty.

CONCLUSION

This study establishes that both *e-service quality* and *e-recovery service quality* are critical determinants of customer experience, satisfaction, and loyalty in digital government services. Rather than serving as supplementary elements, these dimensions of service quality function as foundational drivers of sustained user engagement and public trust. The findings demonstrate that consistent enhancement of service delivery and recovery mechanisms significantly improves user satisfaction and long-term loyalty, thereby strengthening the overall performance and credibility of digital public services. By analyzing the interconnected effects of *e-servqual* and *e-recovery servqual* on key behavioral outcomes, this research not only informs public service strategies but also contributes meaningfully to academic discourse. It provides empirical insights into how digital service quality influences user perceptions and engagement, offering a strategic framework for policymakers and scholars to advance digital transformation in the public sector.

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