Prithvi Academic Journal
[A Peer-Reviewed, Open Access Multidisciplinary Journal]
Indexed in NepJOL with JPPS Star Ranking
ISSN 2631-200X (Print); ISSN 2631-3252 (Online)
URL: https//ejournals.pncampus.edu.np/ejournals/paj/

Centre for Research & Innovation
Prithvi Narayan Campus
Tribhuvan University
Pokhara, Nepal
https://prnc.tu.edu.np/

RESEARCH ARTICLE

Examining the Role of e-CRM in Boosting Customer Satisfaction in Financial Institutions in Nepal: A Two-Stage PLS-SEM and ANN Approach

Bibek Karmacharya
School of Business, Pokhara University, Nepal

Article History : *Submitted 15 December 2024; Reviewed 23 March 2025; Accepted 19 April 2025*
Corresponding Author :*Bibek Karmacharya*, ***Email:*** *bibekkarme@gmail.com*
DOI: *https://doi.org/10.3126/paj.v8i1.78891*

Scan To Access eCopy

ABSTRACT

e-CRM has become a critical tool for enhancing customer satisfaction, particularly in financial institutions navigating the challenges of digital transformation. This study investigates the impact of key e-CRM components—Trust and Security, Personalization, Technology Infrastructure, Customer Data Management, Service Quality and Customer Engagement—on customer satisfaction. A causal-comparative research design was adopted, with data collected from 360 customers of financial institutions in Pokhara and analyzed using SEM-PLS and ANN methodologies. SEM-PLS results identified Trust and Security and Personalization as significant predictors, while ANN confirmed their high predictive importance, with Trust and Security achieving a normalized importance of 99.14 percent. The study concludes that building trust and delivering personalized services are paramount for enhancing customer satisfaction, while foundational e-CRM elements play a supportive role. Financial institutions should prioritize robust security and personalization strategies to optimize customer satisfaction and leverage advanced analytics like ANN for deeper insights. These findings provide a roadmap for financial institutions to develop customer-centric e-CRM strategies, contributing to both academic literature and practical applications.

KEYWORDS: e-CRM, customer satisfaction, financial institutions, SEM-PLS, ANN analysis

INTRODUCTION

The financial services sector is evolving rapidly, making customer satisfaction a critical factor in determining institutional success. As competition intensifies and consumer expectations continue to rise, financial institutions are prioritizing innovative strategies to maintain customer loyalty and sustain long-term relationships. One of the most significant advancements in this regard is the implementation of electronic Customer Relationship

Management (e-CRM), which has become an essential tool for enhancing customer satisfaction. By integrating advanced technological solutions, e-CRM optimizes customer interactions, streamlines service delivery processes and personalizes offerings to create a more engaging and seamless customer experience. With the ongoing digital transformation of financial services, e-CRM plays a pivotal role in reshaping traditional banking models into more efficient, customer-centric and personalized service frameworks (Kumar et al., 2021).

Customer satisfaction, which refers to the extent to which customer needs and expectations are met through service delivery, is a crucial driver of customer retention and overall institutional success in the financial industry (Dwivedi et al., 2024; Rust & Zahorik, 1993). As modern consumers increasingly demand greater convenience, accessibility and tailored services, financial institutions must implement comprehensive e-CRM systems that go beyond mere data management. These systems should facilitate improved customer engagement, enhance service quality and foster trust, all of which are essential for long-term customer relationships. However, the effectiveness of e-CRM in enhancing customer satisfaction depends on several interconnected factors, including the quality of customer data management, the degree of personalization, the reliability of service delivery, the robustness of technological infrastructure and the presence of trust-building mechanisms (Liu et al., 2006).

Despite the growing body of literature on e-CRM, research specifically examining its role within financial institutions remains limited. Most studies tend to explore customer satisfaction from a broad perspective, often overlooking the unique dynamics and specialized components of e-CRM in financial services (Peppard, 2000). This gap in the literature highlights the need for a more comprehensive investigation into how different dimensions of e-CRM contribute to customer satisfaction in this sector. Addressing this gap, the present study seeks to examine the influence of e-CRM on customer satisfaction by focusing on key elements such as Customer Data Management, Customer Engagement, Personalization, Service Quality, Technology Infrastructure and Trust and Security.

A deeper exploration of these factors will not only provide financial institutions with valuable insights for improving customer satisfaction but also contribute to the theoretical understanding of e-CRM's role in the financial services industry. The study's findings are expected to offer practical recommendations for financial practitioners seeking to enhance customer satisfaction through effective CRM strategies. Additionally, by conducting a thorough analysis of the various dimensions of e-CRM and their impact on customer satisfaction, this research aims to make both theoretical and practical contributions to the ongoing discourse on customer relationship management within the financial sector (Rashwan et al., 2020).

LITERATURE REVIEW

Customer satisfaction (CS) has long been recognized as an important factor in the success and permanency of financial institutions. In today's digitally transformed financial services world, institutions increasingly rely on electronic customer Relationship Management (e-CRM) technologies to optimize client interactions, service delivery and satisfaction. e-CRM, by connecting technological improvements, offers a strategic approach to customer relationship management, with the goal of improving engagement, trust and overall customer experience. This part examines the important elements of e-CRM and their impact on customer satisfaction in the context of financial institutions, culminating in the establishment of the study's hypotheses.

Customer Data Management (CDM) and Customer Satisfaction

Customer Data Management (CDM) is one of the fundamental pillars of e-CRM, focusing on the effective collection, storage and analysis of customer data to inform personalized service offerings. Studies have highlighted that the efficient use of customer data can significantly enhance customer satisfaction by providing personalized experiences and improving the relevance of services (Kilinc, 2024; Mithas et al., 2005). Proper CDM practices enable financial institutions to understand individual customer preferences, leading to better-targeted products and services, which in turn promote stronger customer satisfaction. However, the influence of CDM on customer satisfaction is dependent on factors such as data security, privacy concerns and the perceived transparency with which customer data is handled (Kumar et al., 2021). Poor data management practices or violation of customer trust can reduce from satisfaction levels. Therefore, it is *hypothesized that:*

H1: There is significant positive impact of Customer Data Management on Customer Satisfaction.

Customer Engagement (CE) and Customer Satisfaction

Customer Engagement (CE) plays a key role in determining customer satisfaction within e-CRM frameworks. CE involves creating strong, meaningful connections with customers through personalized interactions across various touchpoints. When customers are actively engaged with a financial institution, their satisfaction levels tend to increase due to the perceived value of the institution's efforts in meeting their needs (Al-Dmour et al., 2019). Engagement mechanisms such as personalized communication, proactive problem-solving and loyalty programs have been shown to drive customer satisfaction by enhancing the overall experience (Monferrer et al., 2019). However, the impact of engagement on satisfaction may vary based on factors such as the nature of the engagement and the consistency of customer interactions. Based on these insights, it is hypothesized that:

H2: There is significant positive impact of Customer Engagement on Customer Satisfaction.

Personalization and Customer Satisfaction

Personalization in e-CRM refers to the customization of products, services and communication based on individual customer preferences and behaviors. Research consistently reveals that personalization improves customer satisfaction by making customers feel valued and understood (Mittal & Lassar, 1996; Kumar et al., 2021). Personalized services provide to specific needs and desires, increasing the perceived value of the services offered, which ultimately leads to higher satisfaction levels. However, it is essential to balance personalization with concerns related to customer privacy, as overly intrusive personalization may result in dissatisfaction (Xu et al., 2011; Chen & Duan, 2022). Given the positive relationship between personalization and satisfaction, it is hypothesized that:

H3: There is significant positive impact of Personalization on Customer Satisfaction.

Service Quality (SQ) and Customer Satisfaction

Service Quality (SQ) is another critical dimension of e-CRM that directly influences customer satisfaction in the financial services industry. Financial institutions that deliver high-quality services, characterized by reliability, responsiveness, empathy and consistency, tend to experience higher customer satisfaction levels (LeBlanc & Nguyen, 1988; Supriyanto et al., 2021). Service quality is often perceived as a reflection of the institution's commitment to meeting customer needs, which in turn promote greater trust and loyalty. Studies have consistently shown that financial institutions that prioritize service excellence are better positioned to increase customer satisfaction. Therefore, it is hypothesized that:

H4: There is significant positive impact of Service Quality on Customer Satisfaction.

Technology Infrastructure (TI) and Customer Satisfaction

Technology Infrastructure (TI) is a fundamental factor of e-CRM, as it supports the delivery of digital services, data management and customer interactions. Financial institutions can provide smooth, effective and easily available services that improve consumer satisfaction when they have a solid technology base (Khudair & Ali Hussein, 2022). The infrastructure supports critical e-CRM functions such as automated customer support, mobile banking and online transaction systems, which improve convenience and service accessibility. However, the impact of technology infrastructure on customer satisfaction is dependent upon factors such as system reliability, ease of use and customer trust in digital platforms (Peng & Yang, 2024). Thus, the hypothesis is proposed:

H5: There is significant positive impact of Technology Infrastructure on Customer Satisfaction.

Trust and Security (TS) and Customer Satisfaction

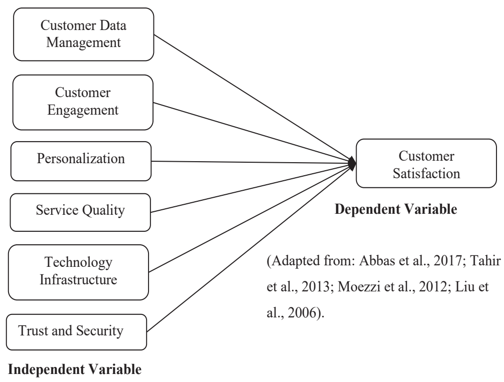
Trust and Security (TS) are key components of e-CRM in financial institutions, where customers expect their personal and financial data to be secure. Trust has been identified as a key determinant of customer satisfaction, particularly in the context of digital interactions (Kundu & Datta, 2015; Iqbal et al., 2023). When financial institutions implement strong security measures and effectively communicate their commitment to data protection, customers are more likely to feel satisfied and confident in their interactions. The perceived security of digital platforms directly influences the level of customer trust, which in turn affects satisfaction (Almaiah et al., 2023). Given the critical nature of trust and security in financial services, it is hypothesized that:

H6: There is significant positive impact of Trust and Security on Customer Satisfaction.

This study examines how electronic Customer Relationship Management (e-CRM) enhances customer satisfaction in Nepal's financial institutions, testing six hypotheses: the positive impacts of Customer Data Management (H1), Customer Engagement (H2), Personalization (H3), Service Quality (H4), Technology Infrastructure (H5), and Trust and Security (H6). Figure 1 presents the conceptual framework guiding this investigation.

Figure 1

Conceptual Framework Examining the Role of e-CRM in Boosting Customer Satisfaction in Financial Institutions in Nepal



RESEARCH METHODOLOGY

This study adopts a causal-comparative research design to examine the impact of e-CRM practices on customer satisfaction in financial sector of Pokhara. The design enables investigation of cause-effect relationships between key independent variables (Customer Data Management, Engagement, Personalization, Service Quality, Technology Infrastructure and Trust/Security) and customer satisfaction without experimental manipulation, making it ideal for real-world business contexts. The theoretical framework draws on validated e-CRM models from established literature (Abbas et al., 2017; Tahir et al., 2013; Moezzi et al., 2012; Liu et al., 2006).

A convenience sampling approach was employed to survey 360 customers across multiple financial institutions in Pokhara. While this non-probability method has limitations, it was chosen for its practicality in accessing respondents familiar with e-CRM systems, with demographic diversity maintained to enhance representativeness. The sample size and screening for e-CRM experience help mitigate potential bias, aligning with methodologies used in similar studies (Abbas et al., 2017; Liu et al., 2006). Data was collected through structured questionnaires using validated measurement scales from prior research.

Analysis employed a sophisticated dual-method approach combining Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 3.0 and Artificial Neural Networks (ANN) in SPSS 26.0. PLS-SEM was selected for its ability to handle complex relationships between multiple variables, accommodate non-normal data and provide strong predictive validity - particularly valuable given the study's sample size and business research context (Hair et al., 2017). ANN complemented this by detecting non-linear patterns and complex interactions that traditional methods might miss, enhancing the robustness of findings through machine learning capabilities. This comprehensive methodology integrating causal-comparative design, carefully implemented convenience sampling and advanced PLS-SEM/ANN analysis - ensures both explanatory depth and predictive strength in examining e-CRM's role in customer satisfaction. The approach addresses common methodological challenges in business research while building on established theoretical foundations, yielding insights valuable for both academic understanding and practical application in financial services. Ethical considerations including voluntary participation, anonymity and data confidentiality were strictly maintained throughout the research process.

RESULTS

The demographic distribution of the 360 respondents is presented in Table 1, showcasing a diverse population in terms of gender, age, education, income, association with financial institutions, frequency of service usage and primary device used.

Table 1

Demographic Profile

Demographic profile	Sub categories	Frequency	Percent
Gender	Male	260	72.2
	Female	100	27.8
Age	Between 18-25 years	54	15
	Between 25-35 years	111	30.8
	Between 35-45 years	56	15.6
	Between 45-55 years	113	31.4
	Above 55 years	26	7.2
Education	SLC/SEE	4	1.1
	Plus two	50	13.9
	Bachelors	176	48.9
	Masters	130	36.1

Income	Below Rs 25000	46	12.8
	Between Rs 25000-50000	180	50
	Between Rs 50000-75000	74	20.6
	Between Rs 75000-100000	58	16.1
	Above Rs 100000	2	0.6
Association	Less than 1 year	78	21.7
	Between 1-3 years	180	50
	Between 3-6 years	52	14.4
	Between 6-10 years	48	13.3
	Above 10 years	2	0.6
Frequency usage	Daily	136	37.8
	Weekly	148	41.1
	Monthly	34	9.4
	Rarely	42	11.7
Primary device	Smartphone	142	39.4
	Tablet	117	32.5
	Laptop/PC	42	11.7
	Others	59	16.4
Total		360	100

Table 1 regarding gender, the majority of respondents were male (72.2 percent), while females constituted 27.8 percent. The age distribution revealed that most participants fell between 25–35 years (30.8 percent) and 45–55 years (31.4 percent), followed by 35–45 years (15.6 percent), 18–25 years (15 percent) and above 55 years (7.2 percent). This indicates a wide representation across different age groups, with a concentration in the economically active segments. In terms of educational background, nearly half (48.9 percent) held a bachelor's degree, 36.1 percent a master's degree, 13.9 percent completed their Plus Two level and 1.1 percent had SLC/SEE qualifications. Regarding income, the majority earned between Rs. 25,000–50,000 (50 percent), followed by 20.6 percent earning Rs. 50,000–75,000 and 16.1 percent earning Rs. 75,000–100,000, with only a small proportion earning above Rs. 100,000 (0.6 percent) or below Rs. 25,000 (12.8 percent). Participants' association with financial institutions mainly ranged between 1–3 years (50 percent), followed by less than one year (21.7 percent), 3–6 years (14.4 percent) and 6–10 years (13.3 percent), with very few having associations exceeding 10 years (0.6 percent). The frequency of usage revealed that a significant proportion of respondents used financial services weekly (41.1 percent) or daily (37.8 percent), while 9.4 percent accessed them monthly and 11.7 percent reported rare usage. Finally, the primary device used for financial services showed that smartphones were the most common (39.4 percent), followed by tablets (32.5 percent), other devices (16.4 percent) and laptops/PCs (11.7 percent).

Common Method Bias

The study employed Harman's single-factor test, a standard diagnostic approach for detecting common method bias (CMB), to investigate the possibility of CMB because both predictor and outcome variables were collected using a single instrument (Podsakoff et al., 2024). According to the statistical study, a single component accounts for just 34.666 percent of the variation, which is far lower than the widely accepted 50 percent criteria. According to Podsakoff et al. (2024), the chance of common technique bias is reduced when one component accounts for less than 50 percent of the variation. This finding validates the validity of the study's instrument by demonstrating that CMB does not pose a significant concern.

Table 2

Measurement Model for eCRM

Constructs	Indicator	Factor Loading	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Customer Data Management	CDM1	0.606	0.742	0.83	0.508
	CDM2	0.760			
	CDM3	0.578			
	CDM4	0.730			
	CDM5	0.823			
Customer Engagement	CE1	0.713	0.791	0.856	0.545
	CE2	0.701			
	CE3	0.801			
	CE4	0.779			
	CE5	0.69			
Customer Satisfaction	CS1	0.781	0.853	0.894	0.629
	CS2	0.788			
	CS3	0.810			
	CS4	0.810			
	CS5	0.776			
Personalization	P1	0.662	0.777	0.847	0.528
	P2	0.642			
	P3	0.820			
	P4	0.754			
	P5	0.741			
Service Quality	SQ1	0.625	0.778	0.848	0.529
	SQ2	0.783			
	SQ3	0.681			
	SQ4	0.748			
	SQ5	0.786			

Assessment of Measurement Model

Table 2 provides a comprehensive evaluation of the measurement model for the constructs underpinning eCRM, including Customer Data Management, Customer Engagement, Customer Satisfaction, Personalization, Service Quality, Technology Infrastructure and Trust and Security. The model assessment encompasses factor loadings, Cronbach's Alpha, Composite Reliability (CR) and Average Variance Extracted (AVE) to ascertain the reliability and validity of the constructs.

Technology Infrastructure	TI1	0.635	0.754	0.836	0.505
	TI2	0.715			
	TI3	0.719			
	TI4	0.764			
	TI5	0.714			
Trust and Security	TS1	0.762	0.845	0.89	0.619
	TS2	0.648			
	TS3	0.861			
	TS4	0.815			
	TS5	0.830			

Table 2 factor loadings across all indicators range from 0.578 to 0.861, with the majority exceeding the recommended threshold of 0.70, reflecting strong indicator reliability. Cronbach's Alpha values for each construct are well above the benchmark of 0.70, demonstrating internal consistency. Similarly, CR values exceed the threshold of 0.7 across constructs, ensuring composite reliability. The AVE values for all constructs are greater than 0.50, meeting the criteria for convergent validity by confirming that the constructs explain a substantial proportion of the variance in their indicators. These findings validate the robustness of the measurement model and affirm its suitability for analyzing the dimensions of eCRM in the study, providing a reliable foundation for subsequent structural model assessments. The figure for measurement model for eCRM is presented as below:

Figure 2

Measurement Model for eCRM

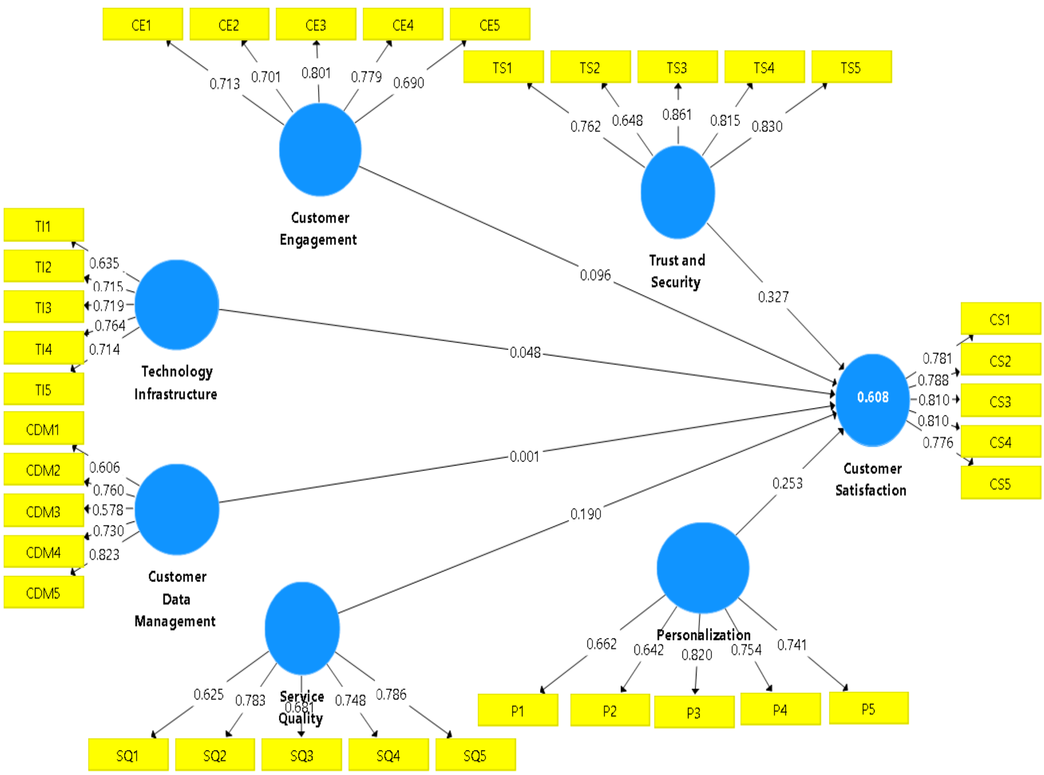


Table 3

Fornell Larcker Criteria

	CDM	CE	CS	P	SQ	TI	TS
CDM	0.706						
CE	0.558	0.738					
CS	0.521	0.655	0.793				
P	0.539	0.684	0.666	0.727			
SQ	0.629	0.718	0.643	0.612	0.727		
TI	0.632	0.517	0.508	0.477	0.541	0.711	
TS	0.551	0.686	0.7	0.635	0.619	0.57	0.787

Table 4

Heterotrait Monotrait Ratio

	CDM	CE	CS	P	SQ	TI	TS
CDM							
CE	0.713						
CS	0.637	0.786					
P	0.696	0.847	0.79				
SQ	0.845	0.811	0.77	0.773			
TI	0.832	0.672	0.624	0.602	0.703		
TS	0.679	0.827	0.799	0.762	0.759	0.704	

Note. CDM: Customer Data Management, CE: Customer Engagement, CS: Customer Satisfaction, P: Personalization, SQ: Service Quality, TI: Technology Infrastructure, TS: Trust and Security

Tables 3 and 4 present the assessment of discriminant validity for the eCRM constructs, utilizing the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio, respectively. In Table 3, the diagonal values, representing the square roots of the Average Variance Extracted (AVE), exceed the inter-construct correlations, confirming discriminant validity as per the Fornell-Larcker criterion. The square root of the AVE for Customer Data Management (CDM) is 0.706, higher than its correlations with Customer Engagement (0.558) and Customer Satisfaction (0.521). Similarly, the square root of the AVE for Customer Satisfaction (CS) is 0.793, which is greater than its correlations with all other constructs. Table 4 demonstrates that all HTMT ratios are below the established threshold of 0.85, ensuring that discriminant validity is upheld. The HTMT ratio between Customer Engagement (CE) and Customer Satisfaction (CS) is 0.786 and the highest HTMT ratio observed is 0.845, between Customer Data Management (CDM) and Service Quality (SQ). These results confirm that the constructs are distinct and measure unique dimensions of eCRM.

Assessment of Structural Model

Table 5 presents the results of hypothesis testing, examining the direct effects of various eCRM dimensions on Customer Satisfaction.

Table 5

Hypothesis Testing

Hypothesis	Path	β	T	p
H1	Customer Data Management -> Customer Satisfaction	0.001	0.018	0.986
H2	Customer Engagement -> Customer Satisfaction	0.096	1.571	0.116
H3	Personalization -> Customer Satisfaction	0.253	3.75	0
H4	Service Quality -> Customer Satisfaction	0.19	3.346	0.001
H5	Technology Infrastructure -> Customer Satisfaction	0.048	0.999	0.318
H6	Trust and Security -> Customer Satisfaction	0.327	6.15	0

The analysis indicates that Customer Data Management (H1) has no significant impact on Customer Satisfaction (β = 0.001, t = 0.018, p = 0.986). Similarly, Customer Engagement (H2) does not exhibit a significant effect (β = 0.096, t = 1.571, p = 0.116) and Technology Infrastructure (H5) also shows no significant influence (β = 0.048, t = 0.999, p = 0.318). Conversely, significant positive effects are observed for Personalization (H3) (β = 0.253, t = 3.750, p < 0.001), Service Quality (H4) (β = 0.190, t = 3.346, p = 0.001) and Trust and Security (H6) (β = 0.327, t = 6.150, p < 0.001). These findings highlight that Personalization, Service Quality and Trust and Security are key drivers of Customer Satisfaction, while the effects of Customer Data Management, Customer Engagement and Technology Infrastructure are not statistically significant in this context. The figure for path analysis is presented as below:

Figure 3

Structural Model of eCRM

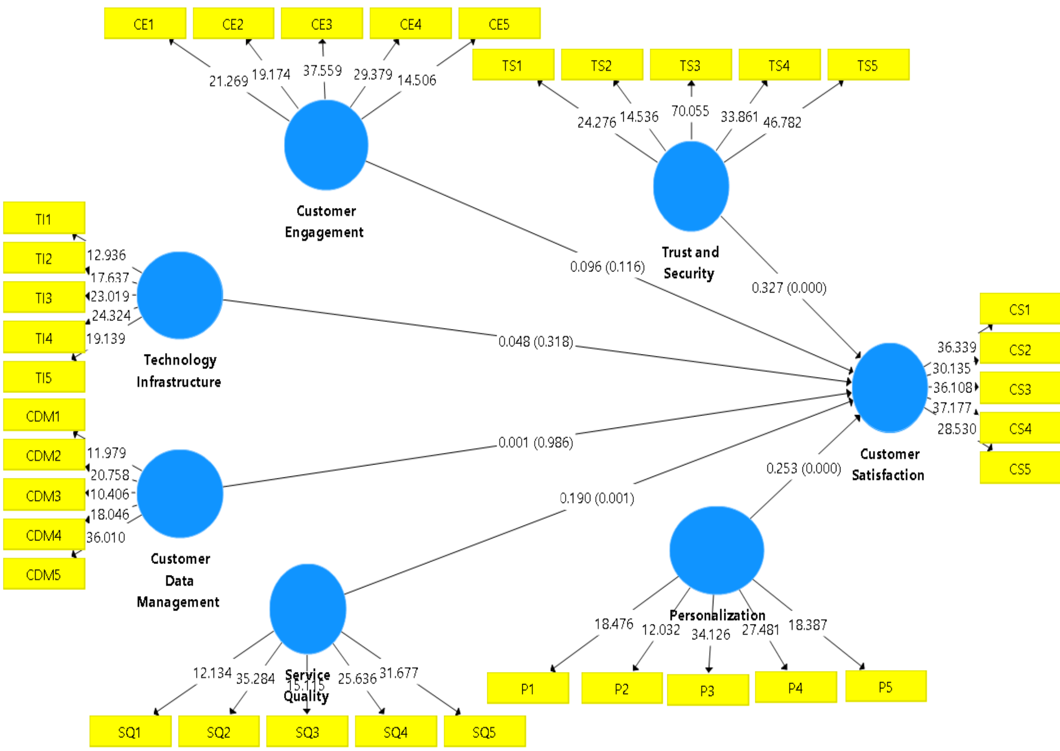


Table 6

Predictive Relevance and VIF

Constructs	F square	VIF	R square	Q square
Customer Data Management	0	2.143		
Customer Engagement	0.008	2.866		
Personalization	0.075	2.188		
Service Quality	0.036	2.562		
Technology Infrastructure	0.003	1.912		
Trust and Security	0.116	2.351		
Customer Satisfaction			0.608	0.369

Table 6 evaluates the predictive relevance and multicollinearity of the constructs in the model. The R-Square value for Customer Satisfaction is 0.608, indicating that 60.8 percent of the variance in Customer Satisfaction is explained by the independent constructs. The Q-Square value of 0.369 confirms the model's predictive relevance, as it is greater than zero. The F-Square values demonstrate the individual contributions of each construct to Customer Satisfaction. Trust and Security has the highest effect size (F-Square = 0.116), followed by Personalization (F-Square = 0.075) and Service Quality (F-Square = 0.036), while Customer Engagement (F-Square = 0.008), Technology Infrastructure (F-Square = 0.003) and Customer Data Management (F-Square = 0.000) exhibit negligible effects. Variance Inflation Factor (VIF) values for all constructs range between 1.912 and 2.866, remaining well below the threshold of 5, indicating no issues of multicollinearity. These results confirm that the model is robust, with significant predictive power and reliable constructs contributing to Customer Satisfaction.

Artificial Neural Network (ANN)

PLS-SEM has been widely adopted for analyzing linear relationships among latent constructs; however, its inability to capture complex non-linear patterns represents a significant limitation (Hair et al., 2022). Given this constraint, the study employs an Artificial Neural Network (ANN) approach, which effectively models intricate, non-linear relationships without requiring strict distributional assumptions (Leong et al., 2020). Figure 4 presents the ANN architecture developed to predict customer satisfaction using the significant predictors identified through prior PLS-SEM analysis.

Figure 4

Artificial Neural Network Diagram

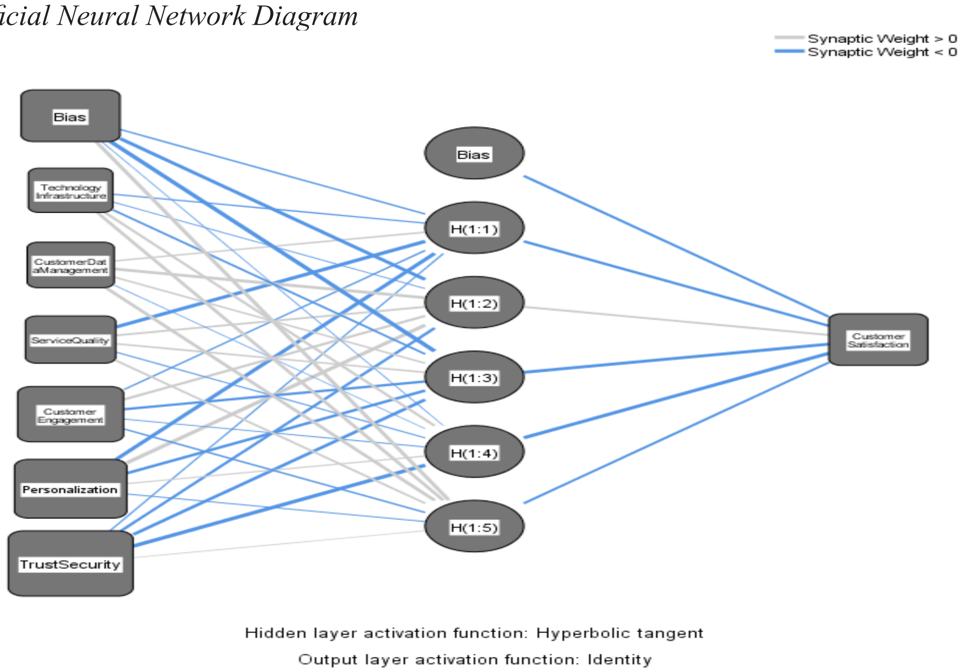
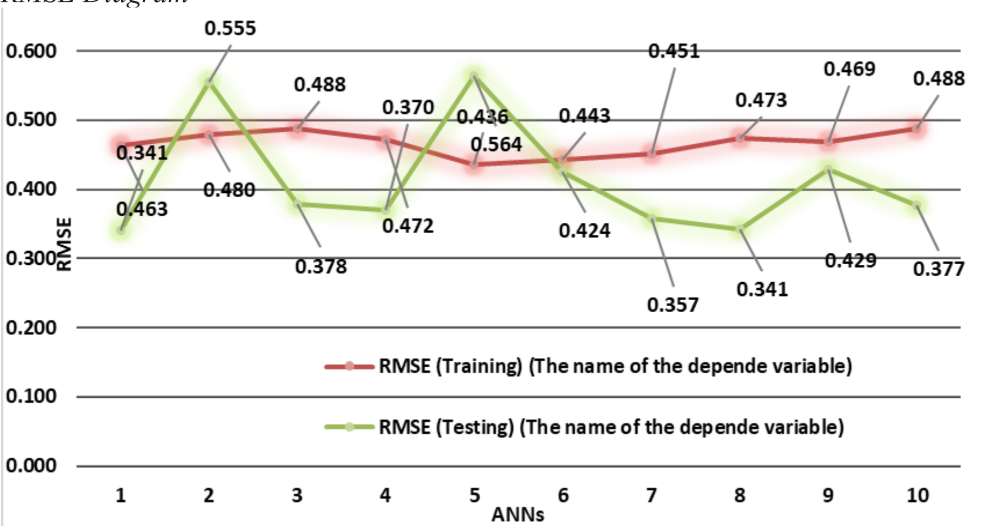


Table 7
RMSE Value

Training			Testing			
N	SSE	RMSE	N	SSE	RMSE	Total Samples
320	68.532	0.4628	40	4.653	0.3411	360
325	74.772	0.4797	35	10.8	0.5555	360
324	77.16	0.4880	36	5.144	0.3780	360
321	71.535	0.4721	39	5.327	0.3696	360
315	59.867	0.4360	45	14.306	0.5638	360
326	63.859	0.4426	34	6.126	0.4245	360
320	64.949	0.4505	40	5.111	0.3575	360
324	72.564	0.4732	36	4.195	0.3414	360
316	69.496	0.4690	44	8.114	0.4294	360
323	77.042	0.4884	37	5.254	0.3768	360
Mean	84.049	0.5110	Mean	8.2433	0.4592	
S.D.	6.3091	0.0192	S.D.	2.3525	0.0689	

Figure 5
RMSE Diagram



The Artificial Neural Network (ANN) diagram (Figure 4) illustrates the architecture utilized to model significant factors, with input neurons derived from SEM-PLS path analysis. The ANN employed a feed-forward-backward-propagation (FFBP) algorithm to adjust weights through backward error propagation, facilitating accurate learning during training. Multilayer perceptrons with sigmoid activation functions were used to capture complex linear and non-linear relationships within the data. A ten-fold cross-validation process was implemented to enhance generalizability and prevent overfitting. RMSE values were computed for both training and testing datasets across ten different ANN iterations (ANN I to ANN X). As shown in Table 7, the training RMSE values ranged from 0.4360 to 0.4884, with a mean of 0.4628, while the testing RMSE values ranged from 0.3411 to 0.5638, with a mean of 0.4592. These results indicate strong model performance, with low error rates in both phases. The RMSE diagram (Figure 5) further illustrates the distribution of errors, highlighting the robustness of the ANN model and its ability to consistently generalize to unseen data.

Table 8

Sensitivity Analysis

Neural Network	Technology Infrastructure	Customer Data Management	Service Quality	Customer Engagement	Personalization	Trust Security
NN(I)	0.306	0.167	0.467	0.234	0.997	1
NN(II)	0.134	0.101	0.546	0.248	0.362	1
NN(III)	0.226	0.274	0.338	0.636	0.761	1
NN(IV)	0.364	0.203	0.541	0.784	1	0.914
NN(V)	0.358	0.356	0.663	0.823	0.708	1
NN(VI)	0.554	0.424	0.547	0.585	0.538	1
NN(VII)	0.129	0.38	0.647	0.856	0.68	1
NN(VIII)	0.306	0.167	0.467	0.234	0.997	1
NN(IX)	0.134	0.101	0.546	0.248	0.362	1
NN(X)	0.226	0.274	0.338	0.636	0.761	1
Percentage (percent)	27.37%	24.47%	51%	52.84%	71.66%	99.14%

The sensitivity analysis (Table 8) was conducted to evaluate the predictive importance of each input variable in the ANN model. The study revealed that Trust Security emerged as the most influential factor, with a normalized importance value of 99.14 percent, followed by Personalization, which demonstrated a strong impact with a normalized value of 71.66 percent. Customer Engagement and Service Quality also exhibited significant predictive power, with normalized importance values of 52.84 percent and 51.00 percent, respectively. In contrast, Technology Infrastructure and Customer Data Management showed lower predictive importance, with normalized values of 27.37 percent and 24.47 percent, respectively, indicating their relatively limited role in the model. The sensitivity analysis underscores the critical role of Trust Security and Personalization in driving the model's predictions, while other variables, though less influential, contribute meaningfully to the overall prediction. This analysis provides valuable insights into the varying impact of different factors, helping prioritize efforts to enhance outcomes in the context of the study.

Table 9

Comparison of PLS-SEM and ANN Results Predicting Customer Satisfaction

Predictor	PLS-SEM β	SEM Rank	ANN Importance (percent)	ANN Rank
Trust and Security	.327***	1	99.14	1
Personalization	.253***	2	71.66	2
Service Quality	.190**	3	51.00	4
Customer Engagement	.096	4	52.84	3

Technology Infrastructure	.048	5	27.37	5
Customer Data Management	.001	6	24.47	6

Note. β = standardized path coefficient; ANN = Artificial Neural Network; Importance = Normalized relative importance.
*** p < .001. ** p < .01.

The comparative analysis reveals both convergence and divergence between PLS-SEM and ANN results. Both methods consistently identified Trust and Security as the most influential predictor (PLS-SEM: β = .327, rank 1; ANN: 99.14 percent, rank 1) and Personalization as the second strongest factor. However, notable differences emerged for other constructs: Customer Engagement showed minimal impact in PLS-SEM (β =.096, nonsignificant) but moderate predictive importance in ANN (52.84 percent, rank 3), suggesting its influence operates through non-linear relationships undetectable by PLS-SEM. Similarly, Service Quality maintained stronger linear effects (β =.190, rank 3) than its non-linear predictive importance (51.00 percent, rank 4). Technology Infrastructure and Customer Data Management demonstrated limited predictive power in both approaches. These findings highlight ANN's value in uncovering complex, non-additive relationships that traditional SEM cannot capture, while PLS-SEM remains effective for testing theoretical linear pathways. The complementary use of both methods provides a more comprehensive understanding of the factors driving customer satisfaction.

DISCUSSION

This study investigated the relationship between electronic customer relationship management (e-CRM) dimensions and customer satisfaction in financial institutions. The findings affirm the critical importance of trust, security and personalization as significant drivers of customer satisfaction, corroborating earlier studies that emphasize these factors' pivotal role (Kundu & Datta, 2015; Mittal & Lassar, 1996; Almaiah et al., 2023). The integration of Structural Equation Modeling (SEM-PLS) and Artificial Neural Networks (ANN) highlighted the robustness of e-CRM components in predicting customer satisfaction, consistent with recent methodological approaches in digital service research (Peng & Yang, 2024). Trust and security emerged as the most influential factors, with normalized importance of 99.14 percent, aligning with findings by Kumar, Mokha and Pattnaik (2021) and Almaiah et al. (2023), who demonstrated that trust significantly enhances customer satisfaction within e-CRM frameworks. Personalization, with a normalized importance of 71.66 percent, reinforced previous conclusions that tailored interactions improve service quality and customer loyalty (Mittal & Lassar, 1996; Xu et al., 2011; Chen & Duan, 2022).

Customer engagement and service quality were also significant predictors, supporting the notion that an engaging and high-quality service environment cultivates satisfaction and loyalty (Monferrer et al., 2019; Al-Dmour et al., 2019; Supriyanto et al., 2021). The ANN results, with low RMSE values across training (mean RMSE = 0.4628) and testing phases (mean RMSE = 0.4592), confirm the reliability of the model in addressing complex and non-linear relationships, a methodological strength supported by Hair et al. (2017) and Peng and Yang (2024). Interestingly, technology infrastructure and customer data management showed lower predictive importance, a finding consistent with prior research indicating that while these factors provide operational support (Kilinc, 2024), they are secondary to customer-facing elements in driving satisfaction (Peppard, 2000; Liu et al., 2006). These results suggest that focusing on trust, security and personalization should be prioritized for e-CRM strategies in financial institutions, as these factors yield the greatest impact on customer satisfaction (Iqbal et al., 2023).

The study's alignment with extant literature validates the comprehensive model developed, while the integration of ANN provides a novel methodological approach to understanding e-CRM dynamics (Peng & Yang, 2024). Future research can expand by exploring the mediating role of e-CRM on customer loyalty or retention and integrating cross-cultural comparisons to enhance generalizability (Rust & Zahorik, 1993; Abbas et al., 2017). The current findings contribute to the growing body of knowledge on digital customer relationship management, particularly in the financial services sector where trust and personalized experiences are paramount (Kumar et al., 2021; Almaiah et al., 2023).

CONCLUSION

The study highlighted the significant impact of key e-CRM components on customer satisfaction in financial organizations. While Trust, Security and Personalization emerged as the most influential aspects, the findings highlight the necessity of a complete strategy to e-CRM, which includes features such as Service Quality and Customer Engagement to improve customer experience. The minor roles of Technology Infrastructure and Customer Data Management emphasize the need for financial institutions to recast these components as facilitators rather than differentiators in their e-CRM strategy. The findings underscore the importance of financial institutions promoting confidence through improved security measures and providing individualized services that are suited to the demands of customers. Furthermore, maintaining good service quality and encouraging meaningful customer participation are critical for retaining customer happiness. The combined use of SEM-PLS and ANN techniques has resulted in a thorough understanding of the linear and non-linear dynamics of e-CRM, providing a solid foundation for future research and implementation.

IMPLICATIONS

The study has several theoretical and practical implications. From a theoretical standpoint, the combination of SEM-PLS and ANN offers a fresh method for investigating the intricate interactions between e-CRM components and customer satisfaction. The findings support and build on existing research by emphasizing the critical roles of trust, security and personalization, as well as providing a complex viewpoint on the supporting roles of service quality and customer involvement. The findings have practical implications for financial institutions. First, strong security standards and cultivating client trust are critical, as trust is still a cornerstone of effective e-CRM systems. Second, investing in advanced personalization technology can boost consumer satisfaction, loyalty and long-term involvement. Third, while core aspects such as technology infrastructure and customer data management are vital, financial institutions must use them to provide value-added services. Furthermore, the study highlights the potential of artificial neural networks (ANN) as a tool for financial institutions to better correctly anticipate consumer happiness, providing insights into non-linear interactions that traditional methods may ignore. Future research should look into including other characteristics, such as customer loyalty or retention, to create a more comprehensive framework for e-CRM performance in financial institutions.

AUTHOR CONTRIBUTIONS

Bibek Karmacharya conceived the study, developed the framework and hypotheses, conducted data collection and analysis. He interpreted results and authored the manuscript, guiding critical methodological decisions.

ACKNOWLEDGMENTS

The researcher would like to express their gratitude to the anonymous reviewers for their efforts to improve the quality of this paper.

REFERENCES

Abbas, A., Chachar, A. A., & Bilal, A. (2017). Impact of customer relationship management dimensions on customer outcomes: Evidence from Pakistan. *International Research Journal of Arts and Humanities, 45*(45), 261-274.

Al-Dmour, H. H., Ali, W. K., & Al-Dmour, R. H. (2019). The relationship between customer engagement, satisfaction and loyalty. *International Journal of Customer Relationship Marketing and Management, 10*(2), 35-60. https://doi.org/10.4018/ijcrmm.2019040103

Almaiah, M. A., Al-Otaibi, S., Shishakly, R., Hassan, L., Lutfi, A., Alrawad, M., Qatawneh, M., & Alghanam, O. A. (2023). Investigating the role of perceived risk, perceived security and perceived trust on smart m-banking application using SEM. *Sustainability, 15*(13), 9908. https://doi.org/10.3390/su15139908

Chen, C., & Duan, Y. (2022). Impact of personalization and privacy concerns on information disclosure and pricing. *Journal of Retailing and Consumer Services, 69*, 103099. https://doi.org/10.1016/j.jretconser.2022.103099

Dwivedi, R. K., Lohmor Choudhary, S., Dixit, R. S., Sahiba, Z., & Naik, S. (2024). The customer loyalty vs. customer retention: The impact of customer relationship management on customer satisfaction. *Web Intelligence*, 22(3), 425–442. https://doi.org/10.3233/web-230098

Hair, J. F., Jr., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: Updated guidelines on which method to use. *International Journal of Multivariate Data Analysis, 1*(2), 107. https://doi.org/10.1504/ijmda.2017.10008574

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage. https://doi.org/10.1007/978-3-030-80519-7

Iqbal, M., Tanveer, A., Ul Haq, H. B., Baig, M. D., & Kosar, A. (2023). Enhancing customer satisfaction in e-commerce: The role of service quality and brand trust. *Forum for Economic and Financial Studies, 1*(1), 287. https://doi.org/10.59400/fefs.v1i1.287

Khudair, R., & Ali Hussein, I. (2022). The role of financial technology in achieving customer satisfaction: A field study in a sample of Iraqi banks. *Millennium Journal of Economic and Administrative Sciences, 3*(4), 1-16. https://doi.org/10.47340/mjeas.v3i4.2.2022

Kilinc, T. (2024). How does the customer experience benefit from better customer data? *Applied Marketing Analytics: The Peer-Reviewed Journal, 10*(3), 216. https://doi.org/10.69554/nmqi7891

Kumar, P., Mokha, A. K., & Pattnaik, S. C. (2021). Electronic customer relationship management (E-CRM), customer experience and customer satisfaction: Evidence from the banking industry. *Benchmarking: An International Journal, 29*(2), 551-572. https://doi.org/10.1108/bij-10-2020-0528

Kundu, S., & Datta, S. K. (2015). Impact of trust on the relationship of e-service quality and customer satisfaction. *EuroMed Journal of Business, 10*(1), 21-46. https://doi.org/10.1108/emjb-10-2013-0053

LeBlanc, G., & Nguyen, N. (1988). Customers' perceptions of service quality in financial institutions. *International Journal of Bank Marketing, 6*(4), 7-18. https://doi.org/10.1108/eb010834

Leong, L. Y., Hew, T. S., Tan, G. W. H., & Ooi, K. B. (2020). Predicting mobile wallet resistance: A two-staged structural equation modeling-artificial neural network approach. *International Journal of Information Management*, 51, 102047. https://doi.org/10.1016/j.ijinfomgt.2019.102047

Liu, Y., Zhou, C.-F., & Chen, Y.-W. (2006). Determinants of E-CRM in influencing customer satisfaction. In *PRICAI 2006: Trends in Artificial Intelligence* (pp. 767-776). Springer. https://doi.org/10.1007/11801603_81

Mithas, S., Krishnan, M. S., & Fornell, C. (2005). Why do customer relationship management applications affect customer satisfaction? *Journal of Marketing, 69*(4), 201-209. https://doi.org/10.1509/jmkg.2005.69.4.201

Mittal, B., & Lassar, W. M. (1996). The role of personalization in service encounters. *Journal of Retailing, 72*(1), 95-109. https://doi.org/10.1016/s0022-4359(96)90007-x

Moezzi, H., Nawaser, K., Shakhsian, F., & Khani, D. (2012). Customer relationship management (e-CRM): New approach to customer's satisfaction. *African Journal of Business Management, 6*(5), 2048-2055.

Monferrer, D., Moliner, M., & Estrada, M. (2019). Increasing customer loyalty through customer engagement in the retail banking industry. *Spanish Journal of Marketing - ESIC, 23*(2), 161-181. https://doi.org/10.1108/sjme-07-2019-0042

Peppard, J. (2000). Customer relationship management (CRM) in financial services. *European Management Journal, 18*(3), 312-327. https://doi.org/10.1016/s0263-2373(00)00013-x

Peng, B., & Yang, J. (2024). The trust of electronic service quality in customer patronage willingness: The regulatory effect of adopting advanced technology. *IEEE Transactions on Engineering Management, 71*, 3580-3598. https://doi.org/10.1109/tem.2023.3346926

Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method bias: It's bad, it's complex, it's widespread and it's not easy to fix. *Annual Review of Organizational Psychology and Organizational Behavior, 11*(1), 17-61. https://doi.org/10.1146/annurev-orgpsych-110721-040030

Rashwan, H. H. M., Mansi, A. L. M., & Hassan, H. E. (2020). Exploring electronic-loyalty antecedents in Egyptian commercial banks; Electronic customer relationship management and banking electronic satisfaction. *Journal of Business and Retail Management Research, 14*(2), 62-73. https://doi.org/10.24052/jbrmr/v14is02/art-06

Rust, R. T., & Zahorik, A. J. (1993). Customer satisfaction, customer retention and market share. *Journal of Retailing, 69*(2), 193-215. https://doi.org/10.1016/0022-4359(93)90003-2

Supriyanto, A., Wiyono, B. B., & Burhanuddin, B. (2021). Effects of service quality and customer satisfaction on loyalty of bank customers. *Cogent Business & Management, 8*(1), 1937847. https://doi.org/10.1080/23311975.2021.1937847

Tahir, H., Waggett, C., & Hoffman, A. (2013). Antecedents of customer satisfaction: An E-CRM framework. *Journal of Business and Behavioral Sciences, 25*(2), 112-125.

Xu, H., Luo, X. (Robert), Carroll, J. M., & Rosson, M. B. (2011). The personalization privacy paradox: An exploratory study of decision-making process for location-aware marketing. *Decision Support Systems, 51*(1), 42-52. https://doi.org/10.1016/j.dss.2010.11.017

APPENDIX

Operationalization of Variables

Constructs	Indicator	Statements
Technology Infrastructure	TI1	Our financial institution has a robust technological infrastructure to support e-CRM.
	TI2	The online banking system of our institution is reliable and user-friendly.
	TI3	The institution frequently updates its technology to enhance customer experience.
	TI4	The security measures for online transactions are highly effective.
	TI5	The institution provides comprehensive technical support for online services.
Customer Data Management	CDM1	Our institution effectively collects and manages customer data.
	CDM2	The data management system allows for personalized customer service.
	CDM3	Customer information is regularly updated to ensure accuracy.
	CDM4	There are strict protocols in place for data privacy and security.
	CDM5	The institution uses customer data to anticipate and meet customer needs.
Service Quality	SQ1	The e-CRM system enhances the overall service quality provided to customers.
	SQ2	Our institution offers prompt and efficient online customer support.
	SQ3	The online services provided are consistent and reliable.
	SQ4	Customers find it easy to access and use our e-CRM services.
	SQ5	The institution handles online customer complaints swiftly and effectively.
Customer Engagement	CE1	The e-CRM platform encourages active customer participation and feedback.
	CE2	Customers feel valued and recognized through personalized online interactions.
	CE3	The institution regularly communicates with customers through digital channels.
	CE4	There are various online initiatives to engage and retain customers.
	CE5	Customer engagement strategies via e-CRM have strengthened customer loyalty.
Personalization	P1	The e-CRM system provides personalized recommendations based on customer preferences.
	P2	Customers receive personalized communication tailored to their needs.
	P3	The system adapts to individual customer behavior for a customized experience.
	P4	Personalized services have enhanced customer satisfaction.
	P5	The institution uses data analytics to personalize customer interactions.
Trust and Security	TS1	Customers trust the institution with their personal and financial information.
	TS2	The institution's security measures are perceived as reliable and robust.
	TS3	Customers feel safe conducting transactions through the online platform.
	TS4	Trust in the e-CRM system has increased customer loyalty.
	TS5	The institution transparently communicates its security policies to customers.
Customer Satisfaction	CS1	Overall, customers are satisfied with the online services provided by our institution.
	CS2	The e-CRM system has improved the customer experience significantly.
	CS3	Customers prefer using the online platform over traditional methods.
	CS4	The institution's e-CRM efforts meet customer expectations.
	CS5	Customer satisfaction levels have increased due to the e-CRM initiatives.