EFFECT OF CRM PERCEPTION AND SERVICE QUALITY SATISFACTION ON CUSTOMER LOYALTY IN BANKING SECTOR

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ABSTRACT

This paper addresses the critical imperative for banking institutions, particularly in India, to cultivate enduring relationships with customers with a focus on Customer Relationship Management (CRM) and its effect on service quality satisfaction and customer loyalty. The research employs Partial Least Square Structural Equation Modeling (PLS-SEM) to analyze the relationship between CRM perception and customer loyalty with customer satisfaction from service quality acting as a mediator. The findings reveal significant positive path coefficients, affirming that a positive perception of CRM practices influences customer satisfaction from service quality as well as customer loyalty. Additionally, the research establishes a significant and positive impact of customer satisfaction on customer loyalty, and identifies a complementary partial mediation effect suggesting that customer satisfaction from service quality mediates between CRM perception and customer loyalty relationship. These findings provide a robust framework for understanding the dynamics shaping customer-bank relationship, allowing banking firms to strategically enhance customer satisfaction and loyalty. The study emphasizes the ongoing need for banks to adapt and refine their CRM practices to align with the evolving needs of customers, ultimately adding value to all stakeholders involved in the financial landscape.

Key Words: Customer Relationship Management, Customer Relationship Management Perception, Customer Satisfaction, Customer Loyalty, Banking

I. INTRODUCTION

Building a lifelong relationship with its customers is imperative for any business to survive and succeed in today's market. It is particularly important for service organizations such as banks. The changes in financial markets, customer needs, preferences and expectations, the use of modern technologies, and intense competition have necessitated the usage of Customer Relationship Management (CRM) in banks. This rising competition has put pressure on banks to retain old customers. There is a constant increase in customer expectations, and it is becoming increasingly difficult for banks to meet these expectations. If the performance of banks does not meet the desired expectations, then the very survival of the banks would be difficult.

In the highly competitive banking environment, banks in India need to stress on providing quality service and must understand the requirements and perceptions of customers in order to find out what they expect from the banking service and what they have received and, in the process, identify the gap that needs to be filled to ensure satisfaction and loyalty of customers.

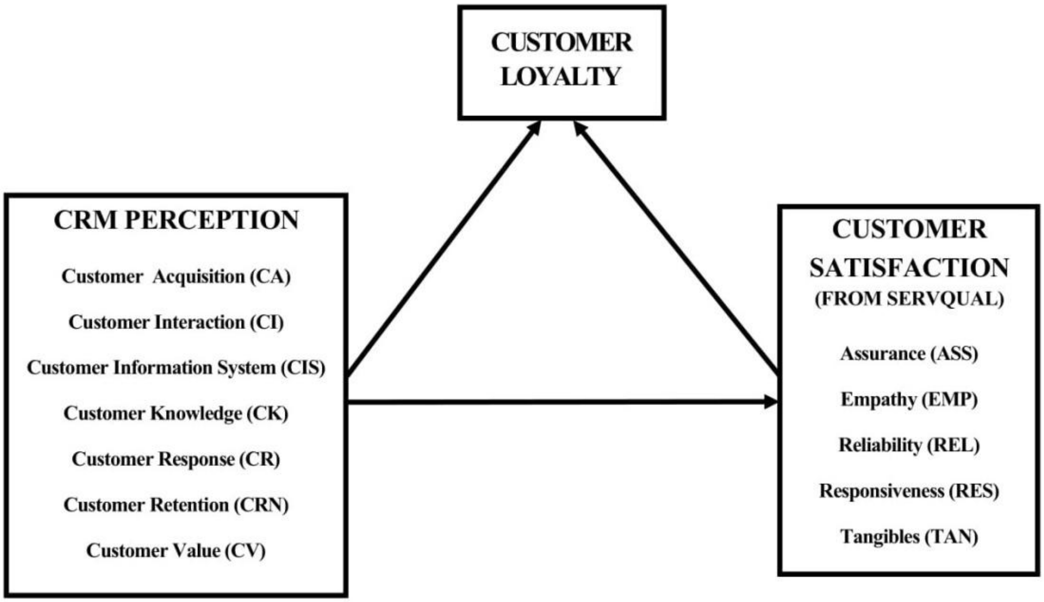
Banks must identify whether their customers have a positive perception of CRM practices and satisfaction from the service quality being offered by them and understand their effect on loyalty. The present paper intends to assess the effect of CRM Perception (CRMP) among the customers on Service Quality Satisfaction and Customer Loyalty, with Customer Satisfaction from Service Quality (CSSQL) as the mediator. The findings will help to focus and build upon key areas that transform customers into satisfied as well as loyal clients and contribute to the improvement of the bank's relationship with its customers, which in turn is expected to add value to all stakeholders.

II. RESEARCH FRAMEWORK AND HYPOTHESES

A rigorous review of extant literature has been undertaken for this research to derive the various dimensions of CRM practices and Service Quality. Both these factors are considered important in determining the loyalty of customers [1] [2].
CRM Perception of the retail bank customers comprises 7 distinct constructs of Customer Acquisition (CA), Customer Interaction (CI), Customer Information System (CIS), Customer Knowledge (CK), Customer Response (CR), Customer Retention (CRN), and Customer Value (CV) derived from the extant literature [3] [4]. The Customer Satisfaction from Service Quality construct, which serves as the mediator in the structural model, has five dimensions, namely - Assurance (ASS), Empathy (EMP), Reliability (REL), Responsiveness (RES), and Tangibles (TAN) derived from the SERVQUAL model [5].

This study presents a comprehensive analysis of the dimensions affecting the loyalty of banking customers. It integrates the factors studied by different researchers into the Lower Order Constructs (LOC), which further make the Higher Order Constructs (HOC) of CRMP and CSSQL. Figure 1 depicts the conceptual framework hypothesized for this research. The PLS-SEM method has been utilized to build and test the structural equation model. The hypotheses for the study have been detailed below.
H1: CRM perception of customers has a significant positive effect on customer satisfaction from service quality of banks.

H2: CRM perception of customers has a significant positive effect on customer loyalty in banks.
H3: Customer satisfaction from service quality has a significant positive effect on customer loyalty in banks.
H4: Customer satisfaction from service quality has a significant mediation effect on the relationship between CRM perception and customer loyalty in banks.



Source: Developed by the Researcher

Figure 1 Conceptual Model

III. SAMPLING AND DATA COLLECTION

The study's population comprises the retail banking customers of select banks in the Kamrup (Metro) district of the state of Assam. Kamrup Metropolitan is a district in the Assam State of India. The Kamrup Metropolitan district has 5 Revenue Circles and a total of 12 public banks and 13 private banks [6]. Out of these, the banks were selected proportionately for the study from both the public and private sectors. Multistage sampling was used to select specific branches of the banks to be included in the sample, and a purposive sample was then drawn from these branches. The sample, therefore, comprised of retail customers having savings accounts in the selected bank branches of Kamrup Metropolitan District of Assam. Power analysis was conducted to calculate the study's sample size using G*Power software [7]. A minimum sample size of 262 was required to achieve 0.95 power with a 0.05 significance level and an assumed effect size of 0.05. However, a large sample size of 398 consumers was drawn, which was sufficient for the analysis.

The final survey instrument comprised 8 questions related to demographics, including age, marital status, gender, education, income, occupation, the name of the primary bank of the customer, and length of association with the primary bank. These were followed by statements to be measured on a 5-point Likert scale. The final instrument consisted of 31 statements measuring customer perception regarding the seven dimensions of the customer relationship management variable, 22 items for measuring the five dimensions of service quality, and 4 items for measuring customer loyalty. The items related to CRM dimensions have been adapted from various sources in the literature [3] [4] [8] [9]. On the other hand, the items for service quality dimensions have been adapted from the well-established SERVQUAL scale [5] [10]. Customer loyalty items have been adapted from the research of Zeithaml, Berry, & Parasuraman (1996) [11].

IV. DATA ANALYSIS METHODOLOGY

For analyzing the relationship between CRMP and CL, with CSSQL as the mediator, this study employs PLS-SEM, incorporating the variables of Customer Acquisition (CA), Customer Interaction (CI), Customer Information System (CIS), Customer Knowledge (CK), Customer Response (CR), Customer Retention (CRN), and Customer Value (CV) as the LOCs which reflect the HOC of CRM Perception (CRMP) in the model. Customer Satisfaction from Service Quality (CSSQL) is conceived as a reflective-formative HOC with Assurance (ASS), Empathy (EMP), Reliability (REL), Responsiveness (RES), and Tangibles (TAN) as the LOCs.

To analyze the Structural Model of the study, the Disjoint 2-Stage Approach was employed [12]. The Measurement Model Assessment for Stage I was conducted independently for the First Order Constructs, excluding the HOCs from the PLS-SEM. Stage I latent variable scores of the LOCs were incorporated during Stage II as indicators of the HOC. Subsequently, both the models—measurement as well as structural—were assessed. SmartPLS 4 software was used for analyzing the complete model of PLS-SEM, comprising both lower-order and higher-order constructs.

V. ANALYSIS RESULTS

V.1 Stage I: Measurement Model Assessment for LOCs

Tables 1 and 2 summarize the assessment of Measurement Model results, including Convergent Validity, Discriminant Validity, and Reliability of the reflective LOCs and also for the dependent variable (CL), which is also reflective.

For evaluating the measurement model, Composite Reliability (rho_C) and Cronbach's Alpha are calculated to check the internal consistency reliability, with values above 0.60

deemed acceptable [13] [14]. Rho_A (pA) [15] is used to estimate the exact reliability of a construct and should be above 0.7.

To evaluate reflective constructs, convergent validity is assessed through Average Variance Extracted (AVE). AVE represents the mean of the squared factor loadings for a construct. A value of 0.5 and higher is deemed acceptable, indicating that the construct accounts for at least 50 percent of the indicators' variance. Table 1 exhibits the convergent validity and reliability measures for the constructs as well above the recommended thresholds.

Table 1 Reliability and Convergent Validity of Constructs

Construct	Factor Loading	Cronbach's Alpha	rho_A	Composite Reliability (rho_C)	Average Variance Extracted (AVE)
Customer Acquisition (CA) CA1 CA2 CA3 CA4	0.885 0.633 0.656 0.703	0.698	0.774	0.814	0.527
Customer Interaction (CI) CI1 CI2 CI3 CI4 CI5	0.679 0.767 0.726 0.649 0.720	0.757	0.763	0.834	0.503
Customer Information System (CIS) CIS1 CIS2 CIS3 CIS4 CIS5	0.788 0.796 0.729 0.776 0.746	0.827	0.834	0.877	0.589
Customer Knowledge (CK) CK1 CK2 CK3 CK4	0.765 0.806 0.641 0.705	0.708	0.714	0.821	0.536

Customer Response (CR) CR1 CR2 CR3 CR4 CR5	0.749 0.763 0.758 0.618 0.763	0.782	0.788	0.852	0.536
Customer Retention (CRN) CRN1 CRN2 CRN3 CRN4	0.680 0.679 0.731 0.800	0.698	0.706	0.814	0.524
Customer Value (CV) CV1 CV2 CV3 CV4	0.790 0.659 0.709 0.810	0.733	0.756	0.832	0.554
Customer Loyalty (CL) CL1 CL2 CL3 CL4	0.737 0.752 0.798 0.828	0.787	0.793	0.861	0.608
Assurance (ASS) ASS1 ASS2 ASS3 ASS4	0.775 0.773 0.702 0.792	0.762	0.778	0.846	0.580
Empathy (EMP) EMP1 EMP2 EMP3 EMP4 EMP5	0.810 0.796 0.715 0.793 0.545	0.785	0.799	0.855	0.546
Reliability (REL) REL1 REL2 REL3 REL4 REL5	0.655 0.729 0.735 0.712 0.783	0.773	0.781	0.846	0.524

Responsiveness (RES) RES1 RES2 RES3 RES4	0.603 0.828 0.843 0.868	0.796	0.820	0.869	0.628
Tangibles (TAN) TAN1 TAN2 TAN3 TAN4	0.756 0.616 0.708 0.767	0.688	0.705	0.805	0.510

Source: Statistical Analysis on Survey Data

Table 1 also depicts that all the retained indicators have factor loadings above 0.708, which is the recommended threshold [14], except for a few indicators that have a loading of above 0.5 but below 0.7. An indicator having a loading above 0.4 can be retained if the AVE of the latent variable exceeds 0.5 [16], and therefore those indicators have been retained.

Table 2 HTMT Table for Discriminant Validity of Constructs

	ASS	CA	CI	CIS	CK	CL	CR	CRN	CV	EMP	REL	RES
CA	0.487											
CI	0.540	0.870										
CIS	0.434	0.611	0.585									
CK	0.458	0.780	0.831	0.657								
CL	0.471	0.514	0.420	0.259	0.407							
CR	0.504	0.800	0.781	0.521	0.775	0.479						
CRN	0.526	0.729	0.832	0.713	0.842	0.408	0.749					
CV	0.332	0.731	0.746	0.523	0.810	0.377	0.766	0.859				
EMP	0.839	0.602	0.473	0.422	0.572	0.556	0.610	0.632	0.560			
REL	0.818	0.605	0.629	0.494	0.639	0.477	0.590	0.691	0.633	0.841		
RES	0.711	0.505	0.461	0.488	0.582	0.430	0.604	0.656	0.577	0.840	0.852	
TAN	0.701	0.618	0.424	0.582	0.610	0.630	0.631	0.552	0.585	0.854	0.833	0.704

Source: Statistical Analysis on Survey Data

The Heterotrait-Monotrait (HTMT) ratio is a robust criterion for assessing discriminant validity [17]. HTMT values less than 0.85 for constructs that are distinct conceptually and below 0.9 for conceptually similar ones prove that they have discriminant validity. As observed from Table 2, all HTMT values are below 0.9, with most of them being below 0.85; therefore, the discriminant validity is confirmed for all the constructs with this criterion also.

V.2 Stage II (A): Measurement Model Assessment for HOCs

The Stage II results have to be examined according to the HOC measurement model and structural model. The HOC of CRMP is of Reflective-Reflective type, while the HOC for CSSQL is of Reflective-Formative type in the study's model.

V.2.1 Measurement Model Assessment of CRM Perception (CRMP) - Reflective

i) Convergent Validity and Reliability of CRM Perception HOC

For assessing constructs that are reflective, firstly the convergent validity and reliability of the HOC have to be evaluated. Table 3 exhibits the output of the convergent validity and reliability tests conducted for the HOC of CRMP. It can be seen from Table 3 that the HOC of CRM Perception of Customers (CRMP) satisfies the established benchmarks for convergent validity and internal consistency reliability. Composite Reliability (rho_C), rho_A, and Cronbach's Alpha exceed 0.7, while AVE exceeds 0.5 [18].

Table 3 Reliability and Convergent Validity of CRM Perception HOC

Higher Order Construct	Outer Loadings		Cronbach's Alpha	rho_A	Composite Reliability (rho_C)	Average Variance Extracted (AVE)
CRM Perception	Customer Acquisition Customer Interaction Customer Information System Customer Knowledge Customer Response Customer Retention Customer Value	0.785 0.818 0.673 0.828 0.796 0.830 0.805	0.900	0.903	0.922	0.628

Source: Statistical Analysis on Survey Data

ii) Discriminant Validity of CRM Perception HOC

Similar to the LOCs, the discriminant validity of the HOCs was examined by the HTMT criterion. Table 4 indicates that the HTMT Ratio is below 0.85, establishing the discriminant validity of the CRMP construct with respect to other constructs [17] [19].

Table 4 HTMT Table for Discriminant Validity of HOC

Heterotrait-Monotrait Ratio (HTMT)	
CRM Perception <-> Customer Loyalty	0.477

Note: HTMT not calculated for CSSQL as it is a formative construct
Source: Statistical Analysis on Survey Data

V.2.2 Measurement Model Assessment of Customer Satisfaction (CSSQL) - Formative

Customer Satisfaction from Service Quality (CSSQL) is a formative HOC and, by definition, formative constructs are free of reliability errors [16]. For establishing the validity of HOC CSSQL, the study adopted the method enumerated by Sarstedt, Hair, Cheah, et al. (2019) [12].

The measurement model assessment for the formative HOCs involves a three-step procedure. Firstly, redundancy analysis is done to examine the construct's convergent validity. Secondly, collinearity analysis is conducted to ensure that there are no multicollinearity issues among the LOCs forming the HOC. Lastly, the relevance of the relation between the HOC and the respective LOCs and their significance are estimated.

i) Redundancy Analysis

Redundancy analysis is employed to evaluate the HOC's convergent validity in the measurement model assessment for formative constructs [20]. This process involves estimating the relationship between the HOC and a single-item alternative measurement of the concept being measured by the HOC. A global single-item is utilized to know the respondents' overall assessment of the concept as a benchmark construct. The path coefficient between the global item and the HOC should be 0.7 or higher for establishing a construct's convergent validity [20] [21].

The redundancy analysis was conducted for the HOC of CSSQL. A global item for assessing satisfaction related to the service quality of banks was incorporated in the questionnaire. The analysis revealed the coefficient of redundancy analysis value of 0.798, exceeding the limit of 0.7, which establishes the convergent validity of the formative HOC of CSSQL.

ii) Collinearity Analysis

Collinearity among the items forming the construct is evaluated because, in the measurement model for HOCs, the Latent Variable Scores of the LOCs serve as the items. For this, the Variance Inflation Factor (VIF) is calculated for the LOCs, and the values below 5 indicate the absence of any serious collinearity problems among the LOCs; therefore, the HOC is considered to be valid. The analysis yields all the outer VIF values to be below the benchmark of 3. This rules out any collinearity issues, thereby establishing the Higher Order CSSQL construct's validity [18].

iii) Assessment of Significance and Relevance of Outer Weights

Lastly, the formative HOC's assessment involves evaluating the significance and relevance of the model's outer weights, establishing the LOC's validity in measuring the HOC. The outer weights estimated for the model, along with their significance, are given in Table 5.

Table 5 Outer Weights for CSSQL (HOC) Measurement Model

	Outer Weight	T Statistics	Sig.
Assurance -> Customer Satisfaction (CSSQL)	0.129*	1.604	0.054
Empathy -> Customer Satisfaction (CSSQL)	0.187**	0.231	0.046
Reliability -> Customer Satisfaction (CSSQL)	0.289***	2.368	0.005
Responsiveness -> Customer Satisfaction (CSSQL)	0.142*	2.939	0.083
Tangibles -> Customer Satisfaction (CSSQL)	0.433***	2.213	0.007

*Note: ***, **, and * show significance at 1%, 5%, and 10%, respectively.*
Source: Statistical Analysis on Survey Data

Significant outer weights can be observed from the table, but Assurance and Responsiveness are significant at 10% only. Assessing the relevance of the weights, it was found that Tangibles contribute the most towards the CSSQL, and when the customers are satisfied, it leads to a positive effect on the overall customer satisfaction from service quality (CSSQL). Tangibles is followed by Reliability and Empathy as the most important contributors to the overall CSSQL.

Assurance and Responsiveness weights were found significant at 10% but not 5%, and hence, as the next step to determine whether they should be retained as an indicator, the absolute contribution was checked by assessing the size and significance of their outer loadings. The outer loadings of Assurance and Responsiveness were found to be above 0.5 and significant; therefore, all the 5 indicators of CSSQL were retained.

V.3 Stage II (B): Structural Model Assessment

The structural model was analyzed after obtaining satisfactory results from the measurement model evaluation. Key criteria such as path coefficients' size and significance, effect size (f^2), and the coefficient of determination (R^2) were examined. The model's predictive accuracy was estimated by checking the Q^2 values derived from PLSPredict.

Multicollinearity Assessment

The structural model output includes regression coefficients for the relationships between latent variables. Thus, multicollinearity was assessed to ensure regression results were not biased due to collinearity issues. VIF values were calculated by performing a partial regression using the latent variable scores of the exogenous constructs. Since all inner VIFs were below 5, significant collinearity issues were ruled out [22].

Explanatory Power and Model Fit

Next, the R^2 values indicating how much of the variation in the dependent variable is defined by the independent constructs were examined for the model. R^2 is used as an indicator of its explanatory efficacy.

Table 6 Explanatory Power & Model Fit

Explanatory Power: R2		
	R2	R2 Adjusted
Customer Satisfaction (CSSQL)	0.426	0.425
Customer Loyalty (CL)	0.562	0.558

Effect Size: f2		
	CL	CSSQL
CRM Perception (CRMP)	0.122	0.743
Customer Satisfaction (CSSQL)	0.315	
Model Fit		
SRMR	0.067	

Source: Statistical Analysis on Survey Data

Table 6 shows that the R^2 and Adjusted R^2 values for CSSQL are above 0.4, which indicates a reasonably satisfactory explanatory power of the model. The R^2 and Adjusted R^2 for Customer Loyalty towards the banks are more than 0.5, which shows the model's moderately high explanatory power, with the independent variables accounting for the variations in the dependent variables up to more than 50%. This implies the model's reasonably satisfactory explanatory power for all the dependent variables as per the standards followed in social sciences dealing with human behavior [14].

The f^2 value was computed to evaluate how much effect a specific predictor construct has on the endogenous constructs. Typically, an f^2 value of 0.02 is deemed small, 0.15 is considered medium, and 0.35 is recognized as large [23] [24]. Table 6 depicts that the effect size of CRMP on CSSQL is above 0.7, which is regarded as large; the effect size of CRMP on CL is 0.122, which is considered medium, and that of CSSQL on CL is moderately large, being close to 0.35.

PLS-SEM Model Fit is determined by the Standardized Root Mean Square Residual (SRMR) calculation for the model, and this value for the present research is 0.067. It is less than the recommended threshold of 0.08 [25], thus exhibiting that the model is a good fit.

Path Coefficients

To test for the above hypotheses, SmartPLS 4 software was used to run the SEM Model, as exhibited in Figure 2. Table 7 shows the path coefficients, while Figure 2 displays the bootstrapping results, including the path coefficients for the structural model. Figure 2 and Table 7 exhibit that all the direct and indirect path coefficients are found to be statistically significant. This indicates that CRMP has a positive significant effect on both CSSQL and CL. CSSQL has a positive and significant impact on CL and is a mediator between CRMP and CL.

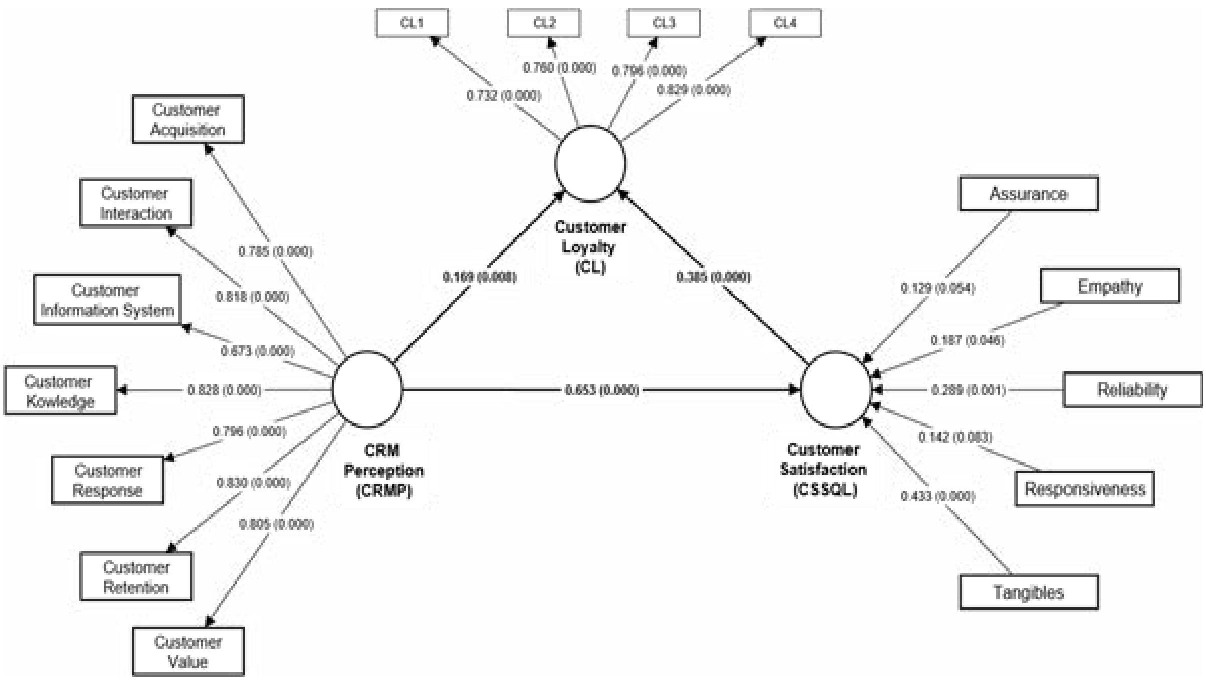
Table 7 Path Coefficients of Structural Model

Path	Coefficient	T statistics	P values	Confidence Interval (Bias Corrected)	
				5%	95%
CRM Perception -> Customer Satisfaction	0.653**	19.471	0.000	0.588	0.701
CRM Perception -> Customer Loyalty	0.169**	2.415	0.008	0.055	0.286
Customer Satisfaction -> Customer Loyalty	0.385**	5.653	0.000	0.258	0.482
CRM Perception -> Customer Satisfaction -> Customer Loyalty	0.251*	5.479	0.025	0.169	0.319

*** & * imply significant at 1% and 5% respectively*

Source: Statistical Analysis on Survey Data

Results of the PLS Bootstrapping run with 5000 subsamples show a significant positive path coefficient of CRM Perception (CRMP) to Customer Satisfaction from Service Quality (CSSQL), thus supporting the hypothesis H1. This indicates that CRMP positively influences CSSQL. Additionally, the coefficient of CRMP to CL is also significant, thus providing support for the hypothesis H2, indicating that CRMP has a significant and positive effect on CL. The coefficient of CSSQL to CL is also found to be positive and significant at 1%, providing support for the hypothesis H3, implying that CSSQL positively affects CL. Finally, the mediating effect of CSSQL exhibited by the specific indirect effect from CRMP to CSSQL to CL is also significant at 5%. Since these effects—both direct and indirect—are significant and positive, this represents complementary partial mediation [26]. Thus, all the structural model hypotheses are supported.



Source: Statistical Analysis on Survey Data

Figure 2 Bootstrapping Results for the Structural Model

Predictive Power Assessment

For this study, the PLS model predictive accuracy was examined using the PLSpredict procedure run with SmartPLS 4 [27]. The procedure of PLSpredict functions using the k-fold cross-validation method. In this research, the recommended k=10 setting was used, dividing the data into 10 sub-folds, and this process was repeated 10 times [28].

Table 8 PLSpredict Results

Latent Variable	Q^2 predict	Measured Variable	Q^2 predict
Customer Satisfaction	0.410	Assurance	0.212
		Empathy	0.296
		Reliability	0.356
		Responsiveness	0.296
		Tangibles	0.296
Customer Loyalty	0.167	CL1	0.172
		CL2	0.034
		CL3	0.100
		CL4	0.072

Source: Statistical Analysis on Survey Data

For the predictive power assessment of the model through PLSpredict results, the Q^2 values of both the latent variables and manifest variables were examined. Table 8 presents the Q^2 values for the PLS model, which were assessed to confirm that the predictions made by the PLS model in the study outperform those of a simple linear model [27]. Table 8 illustrates that all the Q^2 values derived from PLSpredict results exceed zero, suggesting that the study's model has better predictive power compared to a simple benchmark model. For a PLS path model, typically Q^2 values above 0 are deemed small, 0.25 is considered medium, and 0.50 is regarded as having a large predictive relevance level [22]. Table 8 shows that the Customer Satisfaction Q^2 value is more than 0.4, which means a moderately high predictive power for Customer Satisfaction in the model. Meanwhile, the Q^2 value for Customer Loyalty is 0.167, indicating a relatively medium level of predictive power for that construct. As all the Q^2 values for the measured variables are also above 0, with most of them above or near 0.25, this shows satisfactory predictive accuracy with regard to out-of-sample predictions for the model.

VI. CONCLUSION

This paper is an attempt to build a model integrating CRM perception and service quality satisfaction among customers, with the dependent variable of customer loyalty. The study used the PLS-SEM model analysis to estimate the effect of CRM perception on the loyalty of customers, with customer satisfaction from service quality as the mediator.

The effect of CRM perception on customer satisfaction from service quality, as well as customer loyalty, was found to be positive and significant. This implies that banks need to make conscious efforts to improve their CRM strategies and make them more effective to enhance customer satisfaction from service quality, as well as customer loyalty.

The results also show customer satisfaction from service quality as a positive and significant partial mediator between CRM perception and customer loyalty. This reinforces that efforts to close the gap in service quality and improve customer satisfaction from service quality are of paramount importance for banks to achieve customer loyalty.

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