INTERNATIONAL DEVELOPMENT PLANNING REVIEW
ISSN:1474-6743 | E-ISSN:1478-3401

FORECASTING CUSTOMER LIFETIME VALUE IN THE BANKING INDUSTRY

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Abstract
This research investigates the predictive factors influencing customer lifetime value within the banking sector, specifically targeting loan users at the Commercial Bank of Ethiopia in Hossana Town. It evaluates strategies employed by banks, predicts customer lifetime value through financial metrics, and analyzes socio-demographic factors influencing customer behavior. The research design utilizes primary data from in-depth interviews with branch managers and secondary data from loan account statements. The analysis uses multiple regression techniques to forecast and explore relationships between independent variables and customer lifetime value. Results show a positive correlation between age, income, occupation, interest rate, and customer tenure. These findings indicate the importance of demographic and economic factors in customer relationships. Recommendations emphasize implementing targeted marketing, strengthening customer relationship management, and leveraging feedback mechanisms to improve service offerings. By adopting these strategies, banks should better align their operations with customer needs, maximizing lifetime value and developing long-term profitability.

Keywords: Customer Lifetime Value, Banking Industry, Socio-Demographic factors, Financial factors.

1. Introduction

Understanding and projecting customer lifetime value (CLV) has emerged as a critical marketing method in today's aggressively competitive business world, which is marked by consumers' ever-changing behavior and technologically advanced market environments (Kumar, & Reinartz, 2018). Financial institutions use various strategies like personalized marketing, loyalty programs, and enhanced customer support to build strong customer relationships, but their effectiveness varies depending on the banking environment and customers (Reinartz, & Kumar, 2002). To establish a sustainable competitive advantage, financial institutions must be able to keep profitable customers in the aggressively competitive banking sector (Reinartz, W. J., & Kumar, 2003).

Customer lifetime value is a critical metric that banks may use to understand better and manage their relationships with customers (Gupta, S., & Lehmann, 2006). Customer Lifetime Value is crucial for assessing long-term profitability in the banking industry, as banks seek to attract new customers and optimize existing ones amid increasing competition and evolving customer expectations (Kumar, V., & Reinartz,2016). Customer lifetime value (CLV) is a numerical representation of a company's net cash flows generated by customers, used by businesses like banks, retail stores, and telecommunications to identify customer differences and create tailored marketing strategies (Gupta, S., & Lehmann, 2003).

Customer lifetime value is a crucial metric for assessing the success of marketing strategies, indicating the net profit a business anticipates from each customer throughout its relationship. (Kumar et al., 2018). The net present value of the future cash flows attributable to a customer's association with a business is the Customer's Lifetime Value (Berger, P. D., & Nasr, 1998). In the banking sector, customer lifetime value is a crucial indicator of the long-term profitability of customer relationships (Gupta et al., 2006). CLV in banking aids financial organizations in customer segmentation, marketing strategy optimization, and informed decisions regarding customer acquisition and retention (Hwang & Suh, 2004).

Accurate CLV forecasting can aid banks in resource allocation, targeted marketing strategies, and customer profitability enhancement (Kumar, V., & Reinartz, 2016). Many banks struggle with accurate CLV forecasting due to the increasing complexity of customer behavior and the availability of large customer datasets (Ascarza et al., 2018). Predictable approaches frequently depend on transactional data, which may not fully capture the subtleties of customer behavior and engagement (Lemmens, A., & Croux, 2006). Advanced predictive analytics, incorporating various financial metrics, can enhance CLV forecasts and assist banks in tailoring their services and offerings to better serve their customers (Gupta et al., 2006). Because of the complexity of customer contacts and the dynamic nature of financial markets, many banks still find it difficult to precisely estimate CLV, even with the potential benefits (Malthouse, E. C., & Blattberg, 2005).

Digital banking and other financial technology advances have brought about significant changes to the banking industry. As a result of these modifications, there is a wealth of data that, with careful analysis, can provide perceptive knowledge about the preferences and actions of customers (Lemon, K. N., & Verhoef, 2016). Leveraging this massive amount of data, predictive analytics which uses machine learning algorithms has become a powerful technique for estimating CLV (Schmittlein & Peterson, 1994).

Studies reveal that customer behavior and preferences are highly influenced by variables including age, income, education, and geography (Homburg et al., 2009). Digital banking and financial technology advancements have significantly transformed the banking industry, generating vast data that can provide valuable insights into customer preferences and actions.

Financial institutions must better understand and manage their customer interactions in light of the growing competition in the banking sector and shifting consumer (Risselada et al., 2010).

Accurately anticipating CLV is still difficult, nevertheless, particularly in light of the growing complexity of consumer behavior and the accessibility of big customer datasets (Ascarza et al., 2018). Many banks struggle with forecasting CLV and customer attrition, hindering their ability to improve financial performance and enhance customer relationships despite the significance of these indicators (Berger, P. D., & Nasr, 1998; Reinartz, W. J., & Kumar, 2003). Accurately modeling customer behavior over time is the main obstacle to predicting customer lifetime value in the banking sector. Traditional methods frequently fail due to their reliance on historical data and oversimplified predictions about future behavior (Venkatesan, R., & Kumar, 2004). Consequently, banks can either overvalue or underestimate their customers, which would result in an inefficient use of resources and a loss of potential for expansion (Gupta, S., & Lehmann, 2003). To tackle these problems, complex predictive models that combine several data sources and make use of cutting-edge analytical methods are desperately needed. According to Malthouse, & Blattberg (2005) Banks can generate sustainable growth by optimizing marketing activities, strengthening customer relationship management techniques, and enhancing CLV prediction models to represent consumer interactions accurately (Hwang et al., 2004).

The banking industry faces challenges in assessing and optimizing customer lifetime value (CLV) for long-term growth and profitability, often overlooking sociodemographic factors that significantly impact customer behavior and retention (Kumar, V., & Reinartz, 2016). Furthermore, banks usually use conventional techniques to anticipate CLV, which might not adequately account for the intricacies of customer relationships and their long-term worth (Lemmens, A., & Croux, 2006). Insufficient comprehension results in inadequate marketing strategies and resource distribution, which eventually impact client contentment and allegiance (Gupta et al.,2006).
Therefore, banks must thoroughly review their methods for increasing CLV, use complete financial data metrics to forecast CLV, and examine the socio-demographic variables influencing CLV. By addressing these problems, banks will gain practical understandings that will enhance customer engagement, maximize marketing expenditures, and promote long-term profitability. The study's general objective is to forecast customer lifetime value in the banking industry.

2. Review of Related Literature

2.1 The customer's lifetime value

Customer Lifetime Value is the net present value of the future cash flows attributed to the customer relationship (Rust et al., 2004). Customer lifetime value is the present value of the future profit streams attributed to the customer relationship (Reinartz & Kumar, 2003). In Gupta, S., & Lehmann, (2003) the CLV is defined as the present value of all future profits generated from a customer. In Pearson (1996) CLV is defined as the net present value of the stream of contributions to profit that result from customer transactions and contacts with the company. In Jain D (2002) the customer lifetime value is the net profit or loss to the firm from a customer over the entire life of transactions of that customer with the firm. Customer lifetime value is the present value of the future cash flows attributed to the customer relationship (Gupta et al., 2004).

2.2 Customer Lifetime Value Prediction

Accurately predicting CLV is essential for businesses to optimize their marketing strategies and allocate resources effectively (Fader & Hardie, 2010). Several researchers have explored various approaches to CLV prediction. Regression-based models have been widely used, where customer characteristics and past behavior are used to predict future customer value (Venkatesan & Kumar, 2004).
Customer lifetime value modeling can be categorized into past and future behavior models. RFM is the most widely used model in marketing for decades, with unique parameters related to the model's characteristics (Gupta et al.,2006). Future-past customer behavior models determine customer activation duration and calculate net present values using parameters like retention rate, marketing cost, cash flow ratio, and reduction rate, often incorporating customer demographics, purchase history, and marketing activities (Gupta et al., 2006). Machine learning techniques have also gained attention in CLV prediction. Researchers have employed methods like decision trees, random forests, and neural networks to capture the complex relationships between customer attributes and their future value (Malthouse & Blattberg, 2005; Neslin et al.,2006). These models have shown improved predictive performance compared to traditional regression-based approaches (Glady et al., 2009). Furthermore, researchers have explored the integration of customer behavior data with external data sources, such as social media and online reviews, to enhance CLV prediction (Kumar & Reinartz, 2013; Ascarza et al., 2018). Recent deep learning advancements are being used to predict customer loyalty (CLV) by modeling the temporal dynamics of customer behavior and understanding nonlinear relationships between customer attributes (Fader & Hardie, 2010).

CLV prediction has made progress, but challenges persist in incorporating customer heterogeneity, handling missing data, and addressing dynamic customer behavior (Ascarza et al.,2018). Additionally, the interpretability and explainability of CLV prediction models are important considerations for practical applications (Martens & Provost, 2014). CLV models help identify customer focus, estimate lifetime value, and analyze firm actions' effects on customer lifetime value. Observation of customer behavior is crucial, with technological advancements enabling better tracking of customer behaviors (Jakson, 1994).

2.3 Customer Segmentation

Segmentation allows banks to direct their marketing efforts more efficiently. By tailoring messages and offers to specific segments, banks can increase conversion rates and return on investment (ROI) (Smith, 1956). Understanding customer segments enables banks to provide personalized services that enhance the overall customer experience. Research by Reinartz, W. J., & Kumar (2016) highlights that personalized interactions lead to higher customer satisfaction and loyalty. Segmentation also aids in risk management by identifying high-risk customers based on behavioral patterns. According to Ahn et al.(2018), banks can develop targeted strategies to mitigate risks associated with specific segments, improving overall financial stability.

Demographic Segmentation: Demographic segmentation remains foundational in banking. It involves categorizing customers based on age, gender, income, and education level. Research by Aaker, & Jacobson (2001) indicates that demographic factors are useful for identifying potential customer needs and preferences.

Behavioral Segmentation: Behavioral segmentation focuses on customer behaviors, such as transaction patterns, product usage, and responsiveness to marketing efforts. According to (Lemon et al.(2002), this approach allows banks to tailor their offerings based on how customers interact with their services, leading to more effective marketing strategies.

Psychographic Segmentation: Psychographic segmentation considers customers' lifestyles, values, and attitudes. As noted by Dolnicar & Grün (2008), understanding customers' psychographics can help banks develop targeted marketing campaigns that resonate with specific customer segments, enhancing engagement and loyalty.

Data-Driven Segmentation: Big data and advanced analytics have revolutionized customer segmentation in banking, enabling banks to analyze vast data and identify distinct customer segments. According to Bhaduri, G., & Stanforth (2018), data-driven segmentation allows for more precise targeting and personalization of services.

2.4 Factors Influencing CLV

2.4.1 Customer Lifetime Value and Sociodemographic Factors in the Banking Industry

Customer Lifetime Value (CLV) is a crucial metric in banking, enabling financial institutions to make informed decisions about customer acquisition, retention, and resource allocation (Berger, P. D., & Nasr, 1998). Sociodemographic factors, such as age, income, education, and marital status, have been found to significantly impact customer behavior and, consequently, CLV in the banking industry (Venkatesan, R., & Kumar 2004). Age is a key determinant of CLV in banking, with older customers having higher CLV due to longer relationships, higher account balances, and stable financial behavior (Reinartz, W. J., & Kumar, 2000). In contrast, younger customers may have lower CLV due to their lower account balances and higher likelihood of switching to other banks. Higher-income levels in the banking industry lead to higher account balances, increased banking service usage, and higher profitability for the bank (Glady et al., 2009). Marital status significantly influences CLV in the banking industry, as married customers have higher financial needs and longer-lasting bank relationships, leading to higher CLV (Hwang et al., 2019). Sociodemographic factors are crucial for understanding and predicting CLV in banking, but further research is needed to understand their nuances and practical implications for marketing strategies (Martens, D., & Provost, 2014). Research indicates that demographic factors such as age, gender, income, and education level significantly influence CLV. For instance, Gupta et al. (2006) found that younger customers tend to have a higher CLV due to their longer potential engagement with brands. Psychographic factors, including customer values and lifestyle, also play a significant role in determining CLV (Kumar, V., & Shah, 2004).

2.5 Customer Satisfaction and Loyalty

One important factor that determines CLV is customer joy Anderson, E. W., & Mittal, (2000) propose that elevated levels of satisfaction result in heightened loyalty, hence augmenting CLV. Loyal consumers are more likely to recommend others and make repeat purchases, which boosts overall sales.

Purchase Frequency and Recency

An essential measure of CLV is the frequency and recentness of consumer purchases. According to Blattberg et al. (2000) research, customers who make larger purchases have a considerable impact on CLV. Furthermore, the recentness of the purchases shows how engaged the client is; those who have made purchases recently are more likely to make more, which will raise their CLV.

Customer Engagement

Customer lifetime value (CLV) is increasingly measured by engagement metrics like social media interactions and loyalty program participation, with higher engagement levels indicating higher customer retention (Lemon et al., 2002).

Marketing Strategies

CLV is directly impacted by how well marketing initiatives work. Targeted marketing efforts that appeal to particular client segments can improve customer retention and raise CLV, claim (Venkatesan, R., & Kumar, 2004).

2.6 Customer Relationship Management (CRM)

Customer relationship Management (CRM) is defined as the management of a mutually beneficial relationship from the perspective of the seller LaPlaca (2004), which benefits all those in the relationship Mitussis, D (2006), or other words, the enterprise approach aimed at understanding and influencing customer behavior to improve customer acquisition, customer retention, customer loyalty, and customer profitability (Swift, 2001). Future CRM strategies are likely to emphasize customer advocacy, where organizations actively engage customers as brand ambassadors. This shift aligns with the growing importance of social proof and peer recommendations in influencing purchasing decisions (Kumar, 2013). To identify, acquire, and retain valuable customers, firms must shift from a short-term transactional focus to building long-term relationships through personal contact or media (Peelen, 2005). An essential characteristic of a relationship, engagement, requires that partners invest in the relationship (Hoekstra, J. C., & Huizingh, 1999). For example, sellers invest in relationships because they expect these efforts will increase customers‟ contributions to sales and profits, and therefore increase the value of the customer to the firm (Palmatier, 2008). Customers invest time and effort in identifying potential firms and establishing relationships, which can range from simple choices to detailed discussions and may involve additional costs for travel or rewards (Bendapudi, N., & Berry,1997). According to Buttle (2009), CRM, originating in the 1980s, has evolved through phases like operational, analytical, and collaborative, reflecting technological advancements and organizational shifts toward customer-centric strategies.

2.7 Customer Lifetime Value (CLV) Theories

CLV is an estimate of the net profit for the duration of a customer's future relationship. Understanding CLV is essential for banks to improve customer retention and resource allocation (Gupta, S., and Lehmann, 2005).

2.7.1 Recency, Frequency, Monetary (RFM) Analysis

RFM is a tool for marketing analysis that assesses a customer's worth by looking at their past purchases. By examining how recently and regularly a customer interacts with the bank as well as how much money they spend, banking can help identify high-value customers (Stone, M., & Woodcock, 1996).

2.7.2 Predictive Analytics

This entails analyzing past data and forecasting future results using statistical methods and machine learning. By examining client behavior patterns, predictive analytics in banking can estimate CLV (Shmueli, G., & Koppius, 2011).

2.7.3 Customer Segmentation

Banks can enhance customer lifetime value and customize marketing strategies by segmenting their client base based on shared attributes (Wedel, M., & Kamakura, 2000).

2.8 Empirical Studies on CLV in Banking

The Glady et al. (2009) this study utilized regression analysis and machine learning to predict CLV in retail banking, revealing that incorporating demographic and consumer transaction data significantly enhanced forecast precision. Verhoef, P. C., & Lemon (2013) the study utilized RFM analysis and behavioral data to improve CLV forecasting in a European bank, providing a deeper understanding of consumer value dynamics.

Studies by Shaikh (2016) The authors utilized survival analysis to predict client attrition and its impact on customer loyalty (CLV) in the banking sector, enabling banks to develop targeted initiatives. Lemon, K. N., & Verhoef (2002) The study highlights the importance of transactional data in predicting Consumer Liquidity (CLV) and suggests that predictive models can enhance the precision of CLV projections. To predict CLV, Böhm, M., (2020) Machine learning techniques like gradient boosting and random forests outperform conventional regression, revealing demographic variables like age, income, and education significantly influence consumer behavior and CLV. According to research by Kumar, V., & Reinartz (2016) according to their research, customized marketing tactics founded on demographic data can increase client value and retention. Verhoef, P. C (2010) The study reveals that higher customer involvement leads to increased loyalty and profitability, suggesting that banks should invest in CRM techniques to promote engagement decision trees and logistic regression. Hadden et al., (2018) created a churn prediction model, especially for the banking industry. According to their research, early intervention techniques could greatly lower customer attrition and raise total CLV. Reinartz, W., & Kumar (2002). The study highlighted the importance of retention tactics in enhancing customer loyalty and lifetime value, highlighting the effectiveness of proactive strategies like tailored communications and offers. The SERVQUAL model was developed by Parasuraman et al., (1988) The study reveals a direct correlation between customer satisfaction and perceived service quality, influencing the creation of value in the banking industry through business-customer interactions Vargo, S. L., & Lusch (2004) and Vargo, S. L., & Lusch (2004). According to their empirical research, banks may greatly increase CLV by involving the customer in the design and delivery of their services.

3. Research Methodology

3.1 Research Design

A research design is a comprehensive strategy that links theoretical research issues to relevant and feasible empirical studies (Creswell, 2014). The study utilized a predictive research design to predict customer lifetime value in the banking sector, utilizing statistical models and algorithms to analyze data and anticipate future outcomes (Shmueli, G., & Koppius, 2011).

3.2 Research Approach

The research approach is a systematic strategy used by researchers to integrate study components, ensuring effective problem-solving and providing a blueprint for data collection, measurement, and analysis (Creswell, 2014). The study was conducted by using a mixed research approach. Mixed methods analysis integrates different sides of both quantitative and qualitative methodologies (Edmonds, 2017). As explained by Admasu (2020) Combining qualitative and quantitative methods offers the opportunity to mitigate each technique's shortcomings while retaining the other's advantages. Thus, this study used a combination of qualitative methods.

3.3 Sources of Data

Sources of data are the origins from which data is obtained for research purposes. These sources are categorized into primary and secondary data sources, each offering unique advantages and considerations (Kumar, 2014). This study uses loan account statements and interviews with branch managers to assess creditworthiness and predict future loan performance for commercial bank loan users, providing a comprehensive dataset.

3.3 Target Population

According to Trochim (2006), This study focuses on loan users and managers from Commercial Bank of Ethiopia branches in Hossana Town, consisting of 96 borrowers, including individuals and businesses. The target population represents a diverse range of economic activities typical of Hossana Town, with seven branches providing loan services.

3.4 Sample Size

This study focuses on loan users and managers from seven Commercial Bank of Ethiopia branches in Hossana town, Ethiopia. With 96 active users, the researcher plans to interview all loan users, 14 branch managers, and customer service managers for a comprehensive analysis.

3.5 Methods of Data Collection

The study used bank loan account statements, bank records, in-depth interviews with bank managers, transaction records, and credit scores to gather secondary data on loan users, analyze transaction metrics, and forecast customer lifetime value (CLV) in the banking industry, focusing on individual loan users.

3.6 Data Analysis

This study used quantitative and qualitative methods to analyze customer lifetime value (CLV) among loan users at the Commercial Bank of Ethiopia in Hossana town. It used multiple regression analysis and interview results to understand factors contributing to CLV.

3.7 Model Specification

The value of a dependent variable is defined as a linear combination of the independent variables plus an error term. In statistical modeling, a dummy variable is used to represent categorical data with two categories, typically coded as 0 and 1

Model Equation:

$Y = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \beta 6D6 + E$

$Y = \beta_0 + \beta_1 AG + \beta_2 GEN + \beta_3\ INC + \beta_4 OCC + \beta_5 CUT + \beta 6ITR + E$

- Y: Dependent variable, D: Dummy variable (0 or 1), β0: Intercept (mean of Y when D = 0), β1: Coefficient of the dummy variable (difference in means between D = 1 and D = 0), ϵ: Error term

Interpretation

- **β0**: The expected value of Y when D=0.
- **β1**: The change in the expected value of Y when D changes from 0 to 1.

4. Result and Discussion

4.1 Test of Regression Assumption

4.1.1 Normality Test

A normality test is a statistical method to determine if a dataset follows a normal distribution, often represented by a bell-shaped histogram, indicating well-distributed data points (Gravetter & Wallnau, 2017).

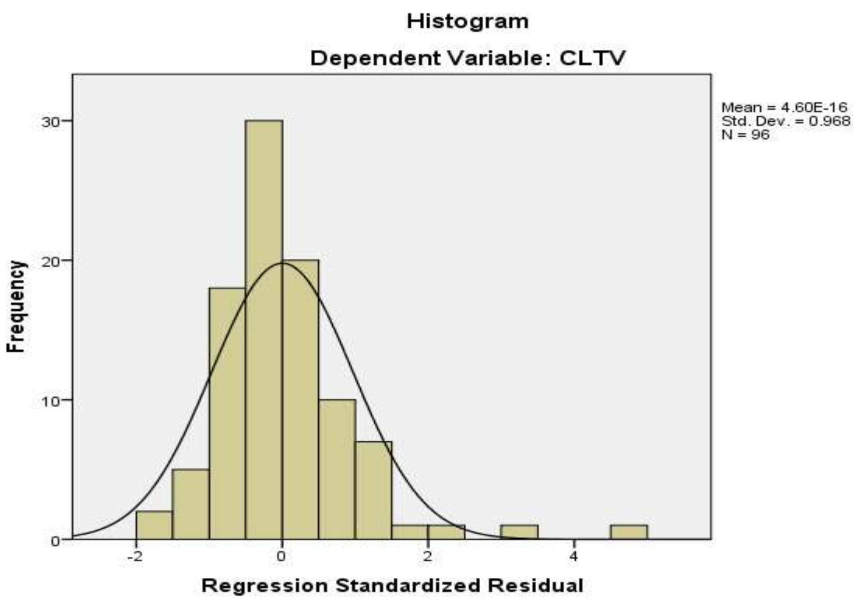

Fig 4.1 Normality test table
Source: Research Data (2024)

4.1.2 Linearity test

A linearity test is a statistical method used to verify the linearity of a regression model's relationship between independent and dependent variables, crucial for model validity.

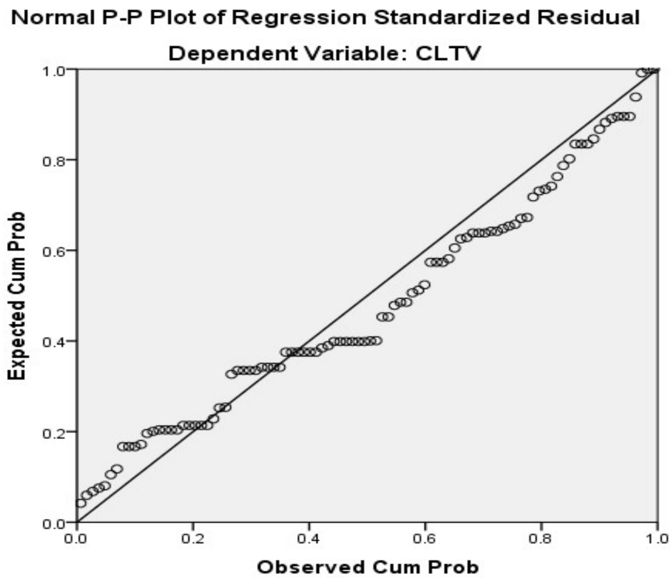

Fig 4.2 Linearity table
Source: Research Data (2024)

4.1.3 Multicollinearity Test

The almost perfect relationship between two variables is known as collinearity. Regression models are called multicollinear when they contain numerous variables that strongly correlate with the independent variable, the dependent variable, and each other (Young, 2017).
Field (2005) suggests a multi-collinearity issue exists if tolerance figures are below 0.10 or VIF statistics are 10.0 or higher. However, the model's tolerance for each independent variable is greater than 0.10 and VIF is less than the limited value (10), indicating no multicollinearity issue.
Table 4.1 Multicollinearity test

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	Age	.335	2.987
	Gender	.254	3.933
	Income	.206	4.856
	Occupation	.502	1.992
	Interest rate	.309	3.235
	Customer tenure	.504	1.984

a. Dependent Variable: CLTV
Source: Research Data (2024)

4.1.5 Model Summary

Based on the provided model summary table, below R-value or multiple correlation coefficient, The dependent variable and the independent variables (age, gender, occupation, customer tenure, and interest rate) have a significant positive association (R-value = 0.830).

Table 4.2 Model summary table

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.525[a]	.276	.227	872899.95591
a. Predictors: (Constant), Customer tenure, OCC, Gender, Age, interest rate, Income				
b. Dependent Variable: CLTV				

Source: Research Data (2024)

4.1.6 ANOVA

The value of Significance (Sig.) is 0.000, indicating a lower degree of significance than the standard 0.05. This indicates that there is a statistically significant relationship between the independent variables and the dependent variable overall and that the regression model as a whole is statistically significant.

Table 4.3 ANOVA table

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25832814552425.930	6	4305469092070.988	5.651	.000[b]
	Residual	67813935638938.914	89	761954333021.786		
	Total	93646750191364.840	95			
a. Dependent Variable: CLTV						
b. Predictors: (Constant), Customer tenure, OCC, Gender, Age, interest rate, Income						

Source: Research Data (2024)

4.2 Regression Analysis Results

Table 4.4 Regression table

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	886496.640	176389.626		5.026	.000
	Age	1136172.968	309032.871	.573	3.677	.000
	Gender	289170.242	377862.235	.137	.765	.446
	Income	1079202.761	399749.980	.537	2.700	.008
	Occupation	386080.133	251943.659	.195	1.532	.012
	interest rate	726945.003	323954.388	.364	2.244	.027
	Customer tenure	531336.032	264179.806	.256	2.011	.047
a. Dependent Variable: CLTV						

Source: Research Data (2024)

The coefficient in the above table indicates that older customers have a customer lifetime value that is higher by 886,496.64 birr compared to younger customers, with this difference being statistically significant ($p < 0.05$). This strong effect underlines age as a significant predictor of CLTV. A similar study by Homburg & Giering, (2001) found that age significantly affects customer behavior and CLV. Older customers tend to have higher CLV due to their longer relationship duration with banks and greater product usage over time. Kumar, V., & Rajan (2012) found that younger customers tend to have lower initial CLV but higher potential for growth as they age and increase their financial activities. Cohen, J., & Eimermann (2016) The empirical analysis revealed that age is a crucial determinant of CLV, with older customers exhibiting more loyalty and higher transaction values, leading to increased CLV. Nguyen, B., & Simkin (2017) This research highlighted that age-related preferences significantly influence customer engagement and CLV. Older customers preferred traditional banking methods, while younger customers were more inclined towards digital banking, affecting their respective CLVs. Lemon, K. N., & Verhoef (2013) the study explored how age influences the customer journey and experience, impacting CLV. It found that older customers often have more complex financial needs, which can lead to higher CLV when effectively managed by banks.

The coefficient in the table indicates that males have a higher customer lifetime value (CLTV) than females by an amount of 289,170.242 birr. However, since the significance value is greater than 0.05, this suggests that there is no statistically significant difference in CLTV between males and females. Different studies like Homburg, C., & Giering (2001) This research highlighted that male and female customers have different banking needs and preferences, which affect their CLV. Male customers were found to be more likely to engage in higher-risk financial products, while female customers preferred more conservative options, impacting their overall lifetime value. Nguyen, B., & Simkin (2017)This study explored how gender influences customer engagement strategies, revealing that banks that tailor their services to address gender-specific preferences can enhance CLV. Female customers often respond better to personalized communication and services, leading to increased lifetime value. Friedman, M., & Rosenman (2016) This research found that gender differences in financial decision-making styles impact customer loyalty and CLV. Female customers were more likely to seek advice and build long-term relationships, contributing to higher CLV over time.

For customers with higher income, CLTV increases by approximately 1,079,203, and this effect is statistically significant at ($p < 0.05$). Higher-income is associated with higher CLTV. This finding is also supported by Venkatesan, R., & Kumar (2004) The study developed a model showing that customers with higher income levels exhibit greater loyalty and retention, leading to increased CLV. It emphasized the importance of focusing marketing efforts on these high-value segments. Nguyen, B., & Simkin (2017) this study highlighted that income disparities create a divide in customer engagement levels, with higher-income customers often receiving more personalized service, thus increasing their CLV. The research suggested that banks should adjust their strategies to cater to different income segments effectively. Bharadwaj, P. R., & Awasthi (2016) The literature review indicated that income level significantly influences CLV, noting that banks should focus on understanding the financial behaviors of different income groups to optimize their marketing strategies and improve customer retention.

A coefficient suggests that occupations with business can lead to an increase in CLTV by about 386,080 birr than non-business occupations. The difference in CLTV is significant at ($p < 0.05$), suggesting that occupation influences customer value. Similarly study by Kumar, V., & Rajan (2012) this study found that customers' occupations significantly impact their financial behaviors and preferences Nguyen, B., & Simkin (2017) the research indicated that customers' occupations influence their financial literacy and product usage. Higher CLV was observed among customers in professional occupations who are more likely to invest in multiple financial products. Cohen, J., & Eimermann (2016) the research found that customers in high-income occupations tend to have a higher CLV due to their ability to maintain larger account balances and their likelihood of utilizing premium banking services. Verhoef, P. C., & Lemon, (2013) this study indicated that occupation affects customer loyalty and retention, which are critical components of CLV. Customers in stable and prestigious occupations are more likely to remain loyal to their banks, thus enhancing their lifetime value.

The coefficient in the table indicates that higher interest rates are associated with an increase in CLTV of approximately 726,945 birrs, and this difference is statistically significant ($p < 0.05$). Thus, an increase in the interest rate correlates with a rise in CLTV. Similar findings by Gonzalez, A., & Garcia (2015) this study examined how interest rates affect customer behavior in banking. It found that competitive interest rates significantly influence customer acquisition and retention, leading to higher CLV as customers are more likely to stay with banks offering favorable rates. Kumar, V., & Rajan (2012) the research indicated that customer responsiveness to interest rates plays a crucial role in determining CLV. Customers who benefit from lower interest rates on loans and higher rates on deposits tend to exhibit higher loyalty and engagement, positively impacting their lifetime value Homburg, C., & Giering (2001) this study found that interest rate changes can significantly affect customer retention and product usage. Customers are more likely to increase their banking activities when interest rates are favorable, leading to increased CLV. Cohen, J., & Eimermann (2016) this study found a direct correlation between interest rates offered by banks and customer lifetime value. Customers who receive better interest rates on savings and loans are more likely to utilize additional banking services, thereby increasing their overall CLV.

Longer customer tenure correlates with an increase in CLTV of about 531,336 birr. The difference is statistically significant ($p < 0.05$). indicating that retaining customers over time enhances their lifetime value. These findings are supported by Cohen, J & Eimermann (2016) this research found that longer customer tenure is associated with higher CLV due to increased trust and satisfaction. Customers who have been with a bank for a longer time are more likely to recommend the bank to others, further enhancing its customer base. Kumar, V., & Rajan (2012) this study established that longer customer tenure is positively correlated with higher CLV. Customers who stay with a bank for an extended period tend to engage in more transactions and utilize a wider range of services, resulting in increased lifetime value. Homburg, C., & Giering (2001) the research indicated that customer tenure significantly influences loyalty and satisfaction, which in turn enhances CLV. Longer-tenured customers are more likely to trust their banks and engage in repeat business, leading to higher overall value. Verhoef, P. C., & Lemon, (2013) this study found that customer tenure is a critical factor influencing CLV, as longer relationships with customers lead to deeper engagement and higher product usage. The research emphasized the need for banks to focus on retention strategies to maximize CLV. Nguyen, B., & Simkin (2017) The study tinted that customer tenure affects the likelihood of cross-selling and upselling, which are crucial for increasing CLV. Customers with longer tenure are more receptive to additional products and services offered by their banks.

4.3 Discussion for Interview Questions

Managers discussed their understanding of customer lifetime value (CLV) in banking, a tool used to evaluate long-term profitability. CLV considers customer expenses and money received. Some managers believe CLV aids in resource allocation, while others suggest optimizing profitability by customizing marketing, sales, and service initiatives. Some also suggest dividing customers into profitable groups. Banks use Customer Loyalty (CLV) to target low-CLV customers with affordable offers and high-CLV customers with personalized services. This approach emphasizes customer loyalty, long-term profitability, and enduring connections, ensuring consistent expansion and maintaining a competitive advantage.

The majority of respondents believe that their bank's main strategies to increase customer lifetime value (CLV) are investing in first-rate customer service, offering incentives like rewards on credit card purchases, special discounts, and exclusive services, which encourages customer retention.

Two managers announced offering financial advisors to customers for personalized investment and wealth management advice, aiming to strengthen customer bonds and increase customer satisfaction, loyalty, and CLV through new features and services.

Banks implement strategies to increase customer lifetime value (CLV) by rewarding long-term customers with incentives, identifying opportunities for marketing add-ons, providing excellent customer service, gathering customer feedback, and building relationships. They also customize products and services based on financial behavior and preferences, fostering loyalty and satisfaction, and ensuring customer satisfaction.

Bank managers recommend tailoring communications and offers to customers' tastes and habits, establishing incentive programs like lower fees or exclusive services, and providing exceptional support by anticipating customer needs and addressing issues before they worsen, often with committed account managers.

Customer satisfaction is a key factor in determining customer lifetime value (CLV) strategies. It is evaluated using various metrics, such as customer recommendation likelihood and service efficacy. Two respondents recommend implementing feedback mechanisms for platforms and customer interactions to improve loyalty programs and customer retention.

Banks can proactively address at-risk customers by understanding customer satisfaction levels, enabling proactive interaction, resolving issues, and prioritizing investment in customer care and digital platforms. Banks face challenges in predicting customer lifetime value due to various factors. The quality of data is a significant obstacle, as it often lacks accuracy. External variables like market, economic, and regulatory changes also impact consumer behavior and values. Economic downturns, new rules, and competitor actions can change consumer preferences and loyalty, making it difficult for banks to accurately predict customer lifetime value.

5. Conclusion and Recommendations

5.1 Conclusion

Accurately forecasting CLV has become vital for financial institutions to maximize resource allocation and improve customer loyalty due to growing competition and changing consumer behavior.

The study's analysis identifies the key variables affecting customer lifetime value in the banking industry. Banks must comprehend these factors for efficient customer relationship management since the regression results show that factors including age, income, occupation, interest rates, and customer duration have a major impact on CLTV.

Major findings show that higher CLTV positively correlates with older customers, higher income levels, and involved occupations. Although gender seems to affect CLTV, the difference was not statistically significant, indicating that banks would need to put less emphasis on gender-based segmentation. Since longer ties result in more loyalty and value, the significance of customer longevity is also emphasized.

Furthermore, the qualitative information obtained from bank management offers an understanding of viewpoints on methods to improve CLTV. These include proactive engagement efforts that address specific customers' requirements, loyalty programs, and individualized customer service.

A thorough strategy that incorporates both quantitative and qualitative data is required to address the issues that banks have in precisely forecasting CLV, such as data quality and outside market impacts. Banks can optimize their marketing strategy and resource allocation to maximize customer value by utilizing sophisticated analytical approaches and comprehending customer behavior.

5.2 Recommendations

Develop focused marketing techniques that cater to different customer segments based on their financial and demographic characteristics. To increase consumer involvement, create initiatives like financial education seminars and individualized financial advising services. These efforts will contribute to developing more solid customer relationships and trust.

Design and implement loyalty programs that reward long-term customers with incentives such as reduced fees, higher interest rates on deposits, and exclusive access to financial products. This will encourage retention and enhance CLTV.

Create reliable feedback mechanisms to continuously collect consumer understandings. By using this input to inform product development and service improvements, offers may be made to better meet the requirements and expectations of customers.

Strengthen CRM strategies to cultivate enduring connections with customers. This entails teaching employees how to provide exceptional customer service and using CRM technologies to monitor customer interactions and feedback efficiently.

Familiarize marketing strategies according to thorough consumer segmentation. Banks should identify high-value customer segments, such as high-income individuals and long-tenured customers, and create tailored marketing campaigns to meet their unique requirements and preferences.

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