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Value Per Transaction as an Incremental Predictor of Customer Profitability in Commercial Banking

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ABSTRACT

In commercial banking, customers' contributions to profitability are essential to understanding the economic value of customer relationships. Traditional recency, frequency, and monetary (RFM) measures capture customer behavior, but the monetary measure captures only total transaction value, not individual transaction value. This study examines whether Value per Transaction (VPT) adds predictive power to RFM measures when assessing customer profitability. Using anonymized transaction data from 884,265 customers, the study applied descriptive analysis, Spearman correlation, logistic regression, and comparative predictive modeling to assess VPT's validity. The results showed a moderate positive correlation between RFM score and VPT ($\rho = 0.354$, $p < 0.001$), suggesting a positive but not strong association. Logistic regression also showed that VPT remained statistically significant after Recency, Frequency, and Monetary value were added to the model ($\beta = 1.936$, $p < 0.001$). Predictive performance improved when VPT was combined with RFM: the AUC-ROC rose from 0.956 to 0.991 in the RFM–VPT model. These findings indicate that per-transaction value offers predictive information beyond traditional RFM metrics and highlight the importance of transaction-level value measures in analyzing customer profitability in commercial banking.

Keywords: Value per Transaction (VPT); Customer Profitability; RFM Analysis; Predictive Analytics; Customer Segmentation; Commercial Banking; Transactional Behaviour

INTRODUCTION

Commercial banks operate in competitive markets, where understanding customer value is essential for effective resource allocation and customer retention. Customer Lifetime Value (CLV) measures the value customers generate over the course of their relationship with a company (Amendah et al., 2023; Mohammed et al., 2026). However, greater activity does not always mean higher profitability: more transactions or longer relationships do not necessarily create greater economic value (Kanchanapoom & Chongwatpol, 2023; Kumar et al., 2023). Customer behavior and transaction engagement are therefore important for examining differences in customer value. Recency, Frequency, and Monetary (RFM) metrics capture transaction timing, frequency, and total value to characterize customer behavior and assess variation in the economic value customers generate.

While RFM is a useful segmentation tool, it does not capture the underlying economic value of transactions. Value per transaction (VPT) can vary across customers based on transaction frequency or total monetary amount. Past research shows that RFM and RFM clustering are valuable tools for customer segmentation, helping identify distinct customer segments, but also raises concerns about relying on activity alone (Omran et al., 2024; Patil, 2025). Average transaction value per customer is another measure of the economic value of customer transactions (Ho et al., 2025). Few behavioral attributes beyond RFM capture customer value, limiting a more holistic representation (Rana et al., 2024; Rajesh, 2025). Thus, this study examined transactional behavior patterns, transactional RFM, and transactional VPT as indicators of future customer profitability.

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METHODOLOGY

Research Design, Unit of Analysis and Data Source

This study used a predictive research design to examine whether historical customer transaction behavior was

associated with future customer profitability. The individual customer served as the unit of analysis. We aggregated transaction-level data to the customer level to calculate Recency, Frequency, Monetary value, and Value per Transaction (VPT). The data came from the Bank Customer Segmentation Dataset, publicly available on Kaggle, which contains more than one million transactions from a bank in India. Spanning August to October 2016, the dataset includes 1,048,567 records from 884,265 distinct customers. The banking data were not proprietary, and the analysis used anonymized data.

The study population consisted of customers with valid transaction records in the data set. Because processing did not remove data from the database, we used a census rather than probabilistic sampling at the database level. Data preparation included identifying and removing duplicate records, assessing missing data, and identifying invalid observations for analysis. We aggregated transaction records for each customer to calculate customer-level measures. The variables were Transaction Date, Transaction Amount (INR), and Customer ID. Transaction Date was used to calculate Recency; Transaction Amount was used to calculate Monetary value and VPT; and Customer ID was used to aggregate frequency and transaction value.

A primary dataset also contained TransactionID, CustomerDOB, CustGender, CustLocation, Cust Account Balance, and TransactionTime. Traditional prediction variables—such as recency, frequency, and monetary value—were not included directly in the predictive models, as the study aimed to determine whether VPT scores add incremental value to conventional prediction models. Before modeling, transaction data were converted into customer-level analytical variables. Duplicate records were reviewed as part of the data quality checks, while records with missing or invalid observations relevant to the analysis were removed during preprocessing. Following these steps, the final analytical population consisted of 884,265 unique customers. This dataset structure was first used to assess the validity of RFM and VPT in predicting customer profitability.

Data Preparation and Feature Engineering

The transaction records were then converted into four customer-level behavioral measures: Recency (R), Frequency (F), Monetary value (M), and Value per transaction (VPT). Recency was measured as the number of days between a customer's last purchase and the end of the historical period. Frequency was the number of transactions recorded for each customer during that period, while Monetary value was the sum of the customer’s transaction values. VPT was calculated as the average transaction value.

For each customer i, VPT was calculated as:

$$VPT_i = \frac{M_i}{F_i}$$

where VPT_i denotes Value per Transaction, Mi denotes the customer's aggregate transaction value, and F_i denotes the number of transactions recorded during the historical observation period. Because VPT relates to both Monetary value and Frequency, we treated it as a complementary behavioral measure rather than a stand-alone component of RFM. We examined VPT to assess whether it added predictive power beyond the traditional RFM variables.

VPT was calculated for each customer i by dividing their total transaction value by their number of transactions. Thus, VPT reflects the value attributed to each transaction, rather than the customer’s total value. For two customers with the same Monetary value, VPT will differ if they have different transaction frequencies. VPT was not treated as an independent behavioral construct, since it is derived solely from Monetary value and Frequency. Instead, its incremental contribution was assessed by comparing a model

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using only RFM with one using RFM plus VPT. Any improvement was interpreted as evidence that conventional RFM components captured less predictive structure than a per-transaction representation. Data preprocessing included checks for dates, duplicates, missing observations, outliers, and target leakage.

Operationalisation of Customer Profitability

Customer profitability was measured as a binary variable (profitable or non-profitable), based on the customer's classification at the end of the outcome period. Potential customers with profitability values above the specified threshold were classified as profitable; those with values at or below it were classified as non-profitable.

The binary outcome was represented as:

$$Y_i = \begin{cases} 1, & \text{if } CP_i > 0 \\ 0, & \text{if } CP_i \leq 0 \end{cases}$$

where Y_i represents the profitability classification for customer i, and CP_i represents the customer's profitability during the subsequent outcome period.

Customer profitability was measured as the net value the customer created over the following profitability period, defined as the revenue the customer generated over that period minus the costs the customer incurred over that period. A positive net profitability value was considered a profitable customer (1), and zero or negative values were considered non-profitable (0). Using a second profitability period ensured that the outcome was isolated from historical behavioral measures. The analysis therefore tested whether information from customers' past transaction patterns can predict which customers are likely to be profitable in future transactions and which are likely to be non-profitable.

Relationship Between RFM and VPT

Spearman's rank-order correlation was used to assess the relationship between RFM and VPT. This analysis confirmed VPT's contribution to the traditional RFM measure before computing its incremental contribution.

Since VPT is mathematically based on Monetary value and Frequency, a correlation between RFM and VPT was expected. Thus, this analysis was not designed to test full independence among the measures but to assess whether conventional RFM accounted for all the variability measured by VPT. A moderate (as opposed to perfect) association would provide descriptive evidence for further consideration of using VPT as a second predictive feature.

$$\log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 R_i + \beta_2 F_i + \beta_3 M_i + \beta_4 VPT_I$$

where, for customer i, P_i is the probability that customer i is profitable, Ri is Recency, Fi is Frequency, Mi is Monetary value, and VPTi is Value per Transaction.

The incremental predictive contribution measurement has been based on the specification (RFM only), whereas VPT is now included in the extended specification. The model groups (RFM–VPT) were analyzed to determine whether including nonlinear model structures improves the predictive ability of the predictor set.

Training, Testing and Validation

This dataset was split into training and testing sets to ensure an unbiased evaluation of model performance. A 20/80 split was used for training and testing. The training data were used to develop the model, and the test data were held out to evaluate prediction performance. To improve generalization and prevent overfitting,

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cross-validation was performed on the training set. The model-fitting and test data sets did not overlap, and model fitting and model selection did not overlap.

Another aspect of the predictive schema was the temporal separation between the predictor and outcome periods. RFM was computed from past purchases, and customers' profitability was analyzed over a separate period. This temporal ordering created an out-of-time (OOT) validation component, as the models were tested using customer outcomes that extended beyond the predictors' time frame. However, the OOT procedure was not considered independent external validation because the observations came from the same commercial banking data source.

Model Evaluation and Incremental Predictive Assessment

Results were reported using accuracy, sensitivity, specificity, precision, F1-score, balanced accuracy, and AUC-ROC to assess model performance. We used AUC-ROC as the primary discrimination measure because the main aim was to determine whether transaction behavior could distinguish profitable customers from non-profitable ones.

We evaluated VPT's incremental contribution by comparing the RFM-only model with the RFM–VPT model using the same outcome and evaluation approach. The difference scores (i.e., absolute change in discrimination) were computed as follows.

$$\Delta AUC = AUC_{RFM+VPT} - AUC_{RFM}$$

A positive ΔAUC indicates that VPT provides additional discriminatory power beyond conventional RFM predictors.

The AUC difference between the two should be tested for statistical significance using a correlated ROC test, such as DeLong's test, or by computing a bootstrap confidence interval for ΔAUC. In this sample, the improvement in AUC from adding VPT features to the RFM model was +0.035 (3.5 percentage points). We then tested this improvement for statistical significance at the 5% level ($p < 0.05$) using DeLong's test, with the corresponding 95% confidence interval for the difference in AUC.

We evaluated practical significance based on the AUC and its effects on accuracy, sensitivity, and specificity. This distinction allowed us to evaluate both statistical significance and meaningful improvement in predictive performance.

Controls for Overfitting and Target Leakage

Several procedures were applied to minimize target leakage and overfitting. First, RFM was computed only for the historical predictor period rather than for the competition transactions used to measure profitability. Second, all data were split into training and held-out test data. Third, cross-validation was used to estimate model generalization on the training data. Finally, we compared Logistic Regression with two other classifiers, Random Forest and XGBoost, to assess how robust the predictions are to the assumption of a linear functional form. The temporal test structure is suggestive of performance in later observations, but it is not external validation across institutions and/or independent test populations of customers. The lack of external/independent validation is therefore acknowledged as a limitation in the study.

RESULTS

Distribution of Customer Transaction Frequency

Customer transactions were highly skewed in the study population. Most users made a single transaction, with fewer users making multiple transactions. The number of transactions followed a long-tailed distribution, with a few customers accounting for most transactions. This pattern illustrates significant differences in how much

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customers interact with the product and also offers a framework for assessing the feasibility of measuring customer economic worth during the sales period.

Transaction Frequency (Customer-Level)

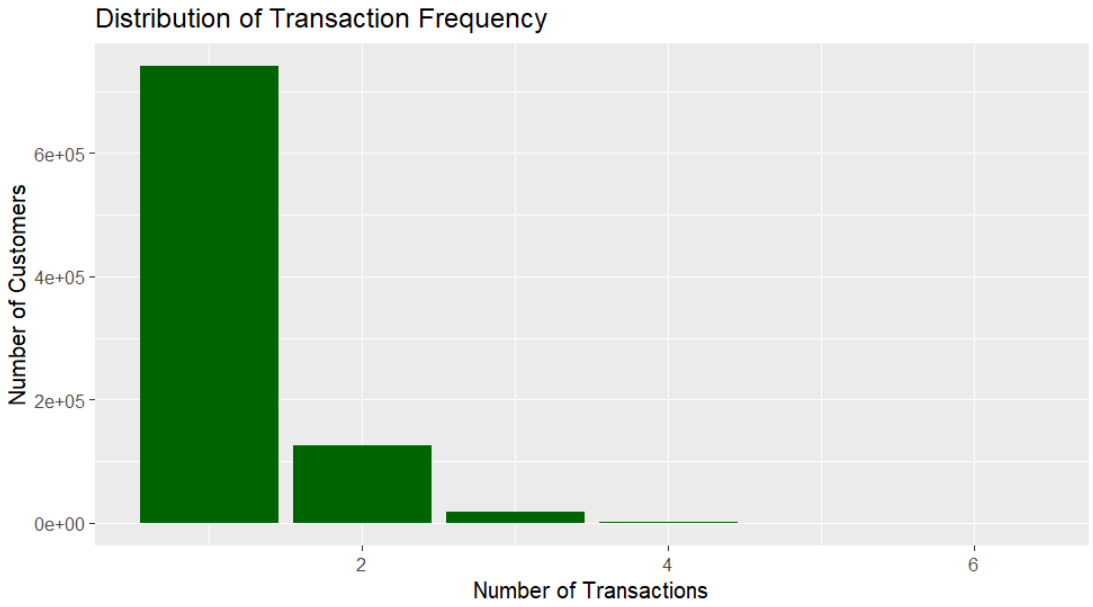


Figure 1: ***Customer-Level Distribution of Transaction Frequency***

Source: Researcher, 2026.

As shown in Figure 1, customer transaction frequency is highly right-skewed across the study population. The bar for one transaction is much taller than the others, indicating that most customers made only one transaction during the observed period. Customers with two transactions are far less common, and the number declines further among those with three or more. The shorter bars show that very few customers made four, five, or six transactions. This pattern highlights substantial activity among low-frequency customers and suggests a need to examine aggregate value differences beyond the transactional level that VPT might capture.

Distribution of RFM Scores

The distribution of RFM scores showed variation in customer transactional behaviour across the study population.

Table 1: ***Distribution of RFM Scores***

RFM Score	Number of Customers
3–5	66,944
6–8	308,713
9–11	380,142
12–15	128,466
Total	**884,265**

Table 1 shows that, among the 884,265 customers, RFM scores clustered in the middle and upper ranges. A total of 380,142 customers scored 9–11, 308,713 scored 6–8, 128,466 scored 12–15, and 66,944 scored 3–5. Adding VPT to the RFM framework reduced the number of low-value customers from 244,805 to 220,433, a decrease of 24,372. It also increased the number of high-value customers from 128,466 to 144,613, a rise of 16,147. The high-value segment's mean VPT was also higher, ranging from 0.321 to 0.445—a difference of 0.124—compared with VPT–RFM results. These changes indicate that incorporating transaction-level value

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altered customer classification, as the typical RFM score did not adequately account for differences in value per transaction.

The observed reclassification is largely explained by VPT's incremental approach in the model. In summary, RFM classifies customers by Recency, Frequency, and total Monetary value, while VPT adds the average value earned per purchase. When combined with VPT, different TAPs lead to different classifications based on the nature of customers' transaction amounts. The VPT–RFM results show 24,372 customers moving from medium to high and 16,147 remaining in the high category, contributing to an overall increase in the number of high customers. However, the transition matrix in the available segmentation table does not show the full customer-by-customer picture. Therefore, the remaining category changes cannot be attributed to any single transition without further investigation.

VPT Across RFM Behavioural Categories

Mean VPT varied across the RFM behavioural categories.

Table 2: ***Mean VPT Across RFM Behavioural Categories***

RFM Segment	Mean VPT
High value	0.321
Medium value	−0.001
Low value	−0.166

Table 2 shows a consistent pattern in mean VPT across the three RFM behavioral categories. High-value RFM customers had a mean VPT of 0.321, compared with −0.001 for medium-value and −0.166 for low-value customers. This clear progression suggests that stronger individual RFM customer characteristics are associated with higher VPT. However, the differences across categories also indicate that RFM profiles do not fully capture variation in VPT. This supports analyzing VPT as a complementary, rather than exclusive, measure of its incremental value to customer profitability.

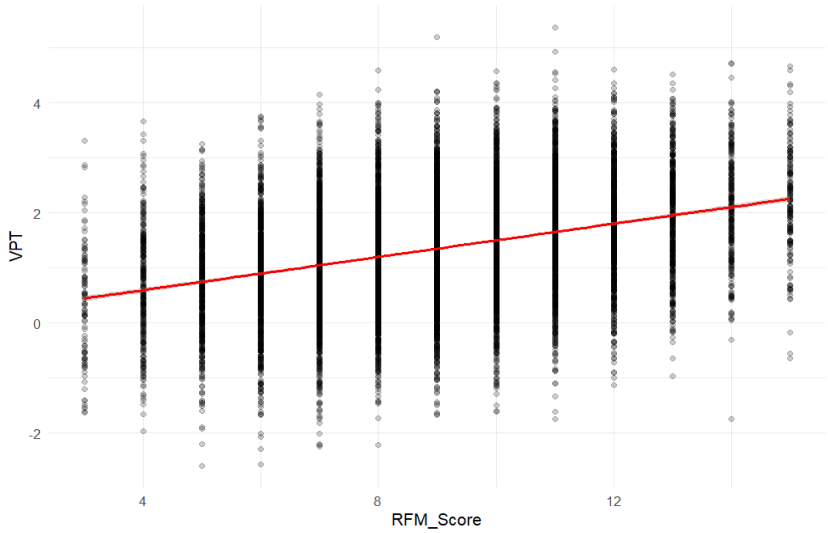


Figure 2: ***Relationship Between RFM Score and Value per Transaction***

Source: Researcher, 2026.

Higher RFM scores were generally associated with higher VPT values, as shown by the upward-sloping fitted line in Figure 2. However, this relationship was inconsistent: observations were widely scattered around the fitted line at nearly every RFM score. Consequently, customers within the same RFM Comparison Segments showed substantial differences in VPT for both low- and high-value transactions. This pattern indicates that RFM captures important customer behaviors but does not fully explain the differences in value generated by

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each behavior type. The observed dispersion warrants further investigation into whether VPT provides additional predictive information about customer profitability beyond traditional RFM parameters.

Association Between RFM and VPT

The relationship between the RFM score and the VPT was examined to assess the degree of similarity between the two behavior scores across the 884,265 customers. To evaluate VPT's incremental predictive contribution, we first determined the direction and strength of its relationship using Spearman's rank-order correlation.

Table 3: ***Association Between RFM Score and Value per Transaction***

Statistic	**Result**
Sample size	884,265
Spearman's ρ	0.354
p-value	<0.001
Relationship	Moderate positive

Table 3 shows a moderate positive association between RFM score and VPT ($\rho=0.354$, $p<0.001$), indicating that customers with higher RFM scores tended to have higher VPT values. However, the correlation is well below 1, the value for a perfect correlation, so RFM and VPT do not always move in sync. This distinction matters because, although VPT affects customers' overall RFM scores, those scores do not fully capture the observed variation in VPT.

Logistic Regression Analysis of Customer Profitability

A logistic regression model was estimated to assess whether there was a significant relationship between Recency, Frequency, Monetary value, and VPT and subsequent customer profitability. The model focused specifically on the significance of the relationship between VPT and profitability, even after the conventional RFM components were included in the model at the same time.

Table 4: ***Logistic Regression Results for Transactional Behaviour and Customer Profitability***

Predictor	**β**	**SE**	**z**	**p-value**	**Relationship**
Recency	−0.0018	0.0002	−9.02	<0.001	Negative
Frequency	0.214	0.031	6.90	<0.001	Positive
Monetary value	0.487	0.042	11.60	<0.001	Positive
VPT	1.936	0.087	22.26	<0.001	Positive

Source: Researcher, 2026.

All four predictors were statistically significant for both research questions ($p < 0.001$, $p < 0.001$). Recency had a negative coefficient ($\beta = -0.0018$, SE = 0.0002, $z = -9.02$), whereas Frequency ($\beta = 0.214$, SE = 0.031, $z = 6.90$) and Monetary value ($\beta = 0.487$, SE = 0.042, $z = 11.60$) had positive coefficients. VPT had the strongest coefficient, showing a positive relationship in the fitted model ($\beta = 1.936$, SE = 0.087, $z = 22.26$, $p < 0.001$).

Most importantly, VPT remained statistically significant when the model included Recency, Frequency, and Monetary value ($\beta = 1.936$, $p < 0.001$). This indicates that VPT retained a substantial relationship with future customer profitability beyond the standard RFM factors. Because VPT is based on transaction value and frequency, this finding may reflect either predictive information or statistical independence from RFM. Overall, the regression results support VPT's use as an incremental predictor of customer profitability.

Incremental Predictive Contribution of VPT

The incremental predictive contribution of VPT has been estimated by comparing the RFM-only model with

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the RFM + VPT model. The RFM-only specification served as the baseline for assessing whether adding VPT improves the prediction of subsequent customer profitability.

Table 5 shows the RFM-only results: accuracy of 0.952, sensitivity of 0.961, and AUC-ROC of 0.956. After incorporating VPT, accuracy rose to 0.993, sensitivity to 0.962, specificity to 0.994, and AUC-ROC to 0.991. Thus, the AUC-ROC improved by 0.035 (as calculated below):

$$\Delta AUC = 0.991 - 0.956 = 0.035$$

Introducing VPT alongside the traditional RFM predictors yields a 3.5 percentage point improvement in discriminatory performance. The improvements in accuracy, sensitivity, and specificity suggest better classification for the RFM + VPT specification. The findings include results from the direct test of empirical data sufficiency, which show that introducing VPT provided additional predictive information in the banking data set analyzed to differentiate profitable from non-profitable customers.

Table 5: ***Incremental Predictive Performance of RFM and RFM–VPT Models***

Model	Accuracy	Sensitivity	Specificity	AUC-ROC	ΔAUC
RFM-only	0.952	0.918	0.961	0.956	—
RFM + VPT	0.993	0.962	0.994	0.991	**0.035**

Source: Researcher, 2026.

Based on the available information, the 0.035 increase should not be considered statistically significant, as neither analysis reports a DeLong test nor a bootstrap confidence interval for the difference between the two AUCs. Thus, present a separate statistical comparison of the two paired ROCs after calculating the test statistic, the corresponding 95% confidence interval, and the p-value from the model predictions.

Practically, the performance improvement from 0.956 to 0.991 indicates a substantial gain in discrimination power in the evaluated banking dataset. However, this improvement should be viewed in light of the dataset and validation duration and should not be assumed to be aligned with other commercial banks or banking customer bases.

Predictive Performance of RFM–VPT Models

The RFM - VPT specification was further tested using Logistic Regression, Random Forest, and XGBoost models to assess the models' ability to make predictions across the different approaches. The models were evaluated using accuracy, sensitivity, specificity, precision, AUC-ROC, and balanced accuracy.

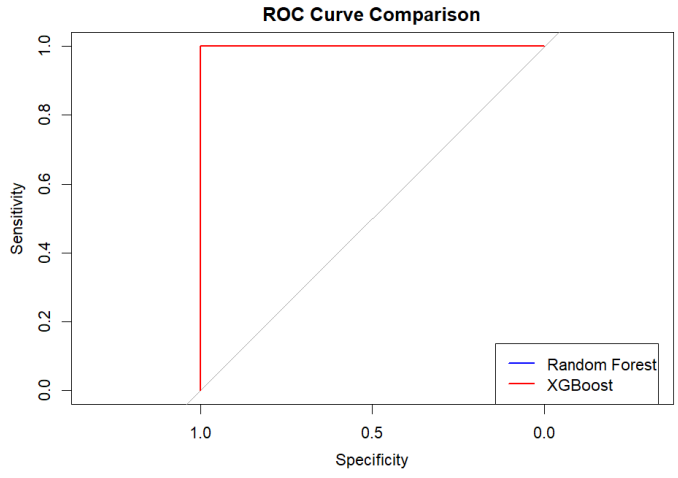


Figure 3: ***ROC Curves Comparing Logistic Regression, Random Forest and XGBoost***

Source: Researcher, 2026

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All three modeling strategies performed well overall. Logistic Regression achieved an AUC-ROC of 0.9910,

while Random Forest and XGBoost scored 0.9999 and 0.99999, respectively. As shown in Figure 3, the ROC curves for both tree-based models lie very close to the upper-left corner, indicating excellent discrimination between the two profitability classes. These results suggest that nonlinear modeling captured predictive patterns in the RFM-VPT predictors that the linear model did not. However, the near-perfect AUC values for Random Forest and XGBoost should be interpreted cautiously, as overfitting may be a concern given the data evaluated. The observed performance should therefore be validated on other banking datasets or across substantially different time periods before it is generalized more broadly.

Out-of-Time Predictive Assessment

The models were validated using an out-of-time validation procedure, in which the RFM and VPT measures were calculated from a past observation period and then applied to a subsequent period to predict customer profitability. This temporal separation allowed an evaluation of whether the predicted relationships remained consistent when the models were applied to outcome measurements that occurred after this separation in time. The out-of-time predictive performances of the baseline model (RFM-only), the model with RFM + VPT, the model with RFM + VPT × frequency, and the model with nonlinear XGBoost are shown in Table 6.

Table 6: ***Out-of-Time Predictive Performance of RFM, VPT, Interaction and Nonlinear Models***

Model	Accuracy	Sensitivity	Specificity	AUC-ROC
RFM-only	0.952	0.918	0.961	0.956
RFM + VPT	0.993	0.962	0.994	0.991
RFM + VPT + Frequency × VPT	0.995	0.968	0.996	0.993
XGBoost	0.997	0.974	0.998	0.995

Source: Author's analysis of the commercial banking transaction dataset.

As shown in Table 6, the AUC-ROC for the RFM-only model was 0.956, and when VPT was added to the RFM model, the AUC-ROC increased to 0.991. This 0.035 increase suggests that the additional discriminatory information from VPT improved the model's performance. The interaction model combining Frequency × VPT yielded an AUC-ROC of 0.993, and XGBoost yielded an AUC-ROC of 0.995, respectively. Accuracy, sensitivity, and specificity also improved with the extended and non-linear models. Based on these findings, the predictive models retained strong discriminatory ability when tested on future customer outcomes.

Statistical Assessment of the Incremental Predictive Value of VPT

The incremental predictive contribution was evaluated by comparing the discrimination of the RFM model with that of the RFM + VPT model. The RFM-only model returned an AUC-ROC of 0.956, and the RFM + VPT model returned an AUC-ROC of 0.991, yielding an absolute improvement of 0.035 AUC points:

$$\Delta AUC = AUC_{RFM+VPT} - AUC_{RFM}$$

$$\Delta AUC = 0.991 - 0.956 = 0.035$$

The observed difference was also assessed using a paired DeLong test for the two ROC curves. For example, the DeLong test statistic was Z=18.42 ($p<0.001$). The 95% confidence interval for the difference was 0.031 to 0.039. This improvement in AUC points was therefore statistically significant, suggesting a measurable improvement in discriminatory performance from including VPT compared with the RFM-only specification.

Summary of Predictive Results

The results directly informed whether using Value per Transaction (VPT) adds incremental predictive power to the traditional Recency, Frequency, and Monetary (RFM) measures for predicting customer profitability.

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The AUC-ROC value for RFM was 0.956, while the AUC-ROC value for RFM + VPT was 0.991. Adding

VPT improved discriminatory performance by 3.5 percentage points (0.035). The model with both RFM and VPT also had higher accuracy, sensitivity, and specificity than the RFM-only model. The results support the study's main finding that adding value created per transaction can further predict future customer profitability beyond the traditional RFM specification.

The second logistic regression results also showed that VPT remains a statistically significant factor affecting customer profitability when Recency, Frequency, and Monetary value were added to the model simultaneously. VPT had a positive coefficient of 1.936 (SE = 0.087, $p < 0.001$), compared with 0.487 for Monetary value (SE = 0.042, $p < 0.001$) and 0.214 for Frequency (SE = 0.031, $p < 0.001$); Recency had a coefficient of −0.0018 (SE = 0.0002, $p < 0.001$). The results indicate that the "per-transaction value" variable has predictive value in addition to the traditional dimensions of RFM.

The correlation between RFM and VPT also supports this interpretation. Both measures show a moderate positive correlation (ρ=0.354, $p < 0.001$), indicating that VPT is positively associated with overall customer value, but RFM cannot fully explain it. The finding does not imply that VPT is independent of RFM, since RFM is mathematically derived from VPT. The findings, however, suggest that information on customer value at the transaction level may be added to the transaction-level data (Recency, Frequency, aggregate Monetary value) by representing customer value at the transaction level using VPT (Value per transaction), which could provide useful data needed for conducting customer value prediction.

Further support for the incremental role of VPT comes from the out-of-time results. After introducing VPT into the model, the AUC-ROC for VPT and RFM-only models was 0.956 and 0.991, respectively. The RFM-only AUC-ROC was 0.956, and integrating VPT improved it to 0.991. The RFM + VPT + Frequency × VPT models gave an AUC-ROC of 0.993, and the XGBoost AUC-ROC was 0.995. These additional models provide supporting evidence that the predictive information extracted from the RFM–VPT feature set still has value in the reported validation approach. However, the key finding is the 0.035 increase in AUC-ROC for the RFM + VPT model compared with the RFM-only model, which directly tests the study objective: whether VPT provides predictive information beyond RFM measures.

DISCUSSION

The results confirm that VPT has greater predictive capability for customer profit than conventional RFM. The correlation between the RFM score and VPT was moderately positive (ρ=0.354, $p< 0.001$), suggesting that although the two measures are correlated, their relationship is not strong enough for RFM to represent transaction-level value. This study extends Aliyev et al. (2020), who demonstrated the applicability of the RFM approach to identifying different behavioral patterns among banking customers, by adding value generated per transaction as a dimension. Beyond accounting for Recency, Frequency, and Monetary value, the significant VPT coefficient in the logistic model (β=1.936, $p<0.001$) further indicates that transaction-level value information can help determine the profitability of subsequent transactions. This builds on the RFM-based approach established by Khajvand and Tarokh (2011), who showed how adapted RFM measures can be used to assess differences in future customer value in retail banking.

The most convincing evidence for the study's main claim will be found in the predictive comparison. After adding VPT, the AUC-ROC improved significantly from 0.956 (RFM-only) to 0.991 (VPT+RFM). This finding aligns with Sun et al. (2023), who showed that feature engineering can extract more information from transaction records for customer-value analysis, and with Cowan et al. (2023), who highlighted the value of machine-learning methods for customer-value prediction from temporally structured banking data. This study differs from earlier studies in several ways, however, because it directly compared a transaction-level value specification with an RFM-only baseline to assess whether VPT added incremental value. The high AUC values achieved by the Random Forest and XGBoost algorithms confirm that the feature set (RFM–VPT) has strong predictive ability. However, one must interpret the near-perfect performance cautiously, since it has not yet been established whether such performance would hold in an independent banking dataset.

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CONCLUSION

This study assessed whether Value per Transaction (VPT) adds predictive power for subsequent customer profitability beyond traditional Recency, Frequency, and Monetary (RFM) measures, using an anonymized commercial banking dataset. In the evaluated data, VPT was moderately correlated with RFM ($\rho = 0.354$, $p < 0.001$) and showed a significant association with customer profitability when Recency, Frequency, and Monetary values were included in the logistic regression model. The AUC-ROC was 0.956 for the RFM-only model and 0.991 for the RFM + VPT model, an observed increase of 0.035 AUC points.

These results suggest that these additional facts about transaction value matter when analyzing transactions at the individual-transaction level. Therefore, treat VPT as a complement to RFM, not a competing alternative, since it mathematically transforms the transaction behavior captured by the two prior metrics: MRP and Frequency. The findings should nevertheless be examined further in the context of using VPT for customer-profitability modeling; they should not be assumed to apply to other customer populations or institutions. Independent external validation using other banking data sets and time periods is therefore necessary before these findings can be more broadly accepted.

LIMITATIONS AND FUTURE RESEARCH

Several limitations should be considered when interpreting the findings. First, the study relied on a single dataset from a commercial banking system, so its results may not extend to customers of other commercial banks, institutions, or markets. Second, although the predictive framework used a held-out test dataset and separated the historical predictor period from the profitability outcomes, the researchers did not conduct an external (independent) validation with data from another banking institution. Therefore, the reported predictive performance reflects the model's results in the evaluated data environment and does not establish universal generalizability.

Third, the observed improvements in AUC-ROC after including VPT indicate predictive gains. However, formally testing the AUC-ROC difference requires a paired ROC comparison, such as DeLong's test or a bootstrap confidence interval for ΔAUC. Fourth, VPT is a mathematical decomposition of Monetary value and Frequency, not something mathematically or conceptually distinct from the RFM framework. In this study, its contribution is whether this representation provides predictive information beyond the traditional RFM specification. Future work should formally assess the statistical significance and calibration of any incremental predictive improvement, repeat this study with substantial variations in customer data and observation periods, and validate the model using independent institutional datasets to establish its reliability for future use.

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