International Journal of Mechatronics, Electrical and Computer Technology (IJMEC)
ISSN: 2305-0543 (Online), ISSN: 2411-6173 (Print)
Vol. 12 (46), Oct. 2022, pp. 5267-5273

Customer Segmentation Based on Mobile Banking User's Behavior

Zahra Mamashli *
Department of Management and Accounting
University of Shargh-e Golestan
Gonbad-e Kavus, Iran
zmamashli29@gmail.com

Sarfaraz Hashemkhani Zolfani
School of Engineering, Catholic University
of the North, Larrondo 1281
Coquimbo, Chile
sa.hashemkhani@gmail.com

***Abstract*— This study was conducted to integrate data mining and modeling of customer behavior in the RFMT model for working with mobile banking customers in private banks in Iran. The internet has overgrown and has become the need of the public in doing activities in various fields. One of them is the pecuniary segment or bank. Banks must provide customer satisfaction in delivering quality services. They expanded this segmentation model to know customer groups according to transaction record, regency, frequency, monetary, and time background. Mobile banking customers are classified into six clusters. This research showed that recognizing customers using behavioral scores facilitates the determination of marketing strategy.**

Keywords— Data mining, Mobile banking, RFMT, Customer behavior

I. INTRODUCTION

Today, online banking is becoming increasingly popular. The economic systems provide online services through various electronic channels, thus reducing the branch networks of banks[1]. Recent media development on online banking is rapidly increasing the mobile banking publishing approach that causes this research. Banking continues to be at the forefront of support services, with customers transferring face-to-face transactions to computer-mediated transactions. Including the expansion of e-commerce, comparable requirements have been introduced that many banking transactions currently done online over the Internet over a fixed-line are transferred to mobile devices. Like innovative technology, mobile banking is valuable to important financial institutions and can change people's lives [2].

For customers of all kinds, mobile banking enables financial transactions to be undertaken from any place, at any time [3]. To create and continue to compete with other competitors, banks must provide superior customer service to increase customer satisfaction. In these exceptional cases, customer relationship management (CRM) can help the bank accomplish this critical task. Customer relationship management (CRM) 's identity and significant relationship establish more profitable and long-term associations with customers [4] [5].

Data mining materials are essential, well-known tools for customer data analysis within the CRM framework. One of the most valuable data mining methods is classified, widely used in customer relationship management. Banks recognize customer behavior models applying clustering techniques to align their marketing strategies with customers' decisions and thus engage their customers. Market segmentation is one of the primary fields of awareness-based marketing. However, this challenge is in banks because databases are so many and multidimensional[6]. The advent of new computing technologies has significantly affected organizations' ability the store, collect and analyze giant data sets. Therefore, thousands of data can be stored concerning every customer, making the customer's purchase (or transaction) account possible. However, to identify and recognize valuable customers, they must be classified based on their behavior.

When it comes to customer-centric business intelligence, banks generally possess the conformity standard marketing and sales concerns:

- Who are the bank's worse and best valuable customers? What are their salient features?
- Who are the least and loyal customers, and how do they identify them?
- What are the patterns of customer business behavior? Which services do customers often buy together?
- What are the business patterns in terms of different views before-mentioned as service, regions, and time (weekly, monthly, quarterly, annual and seasonal), and so on [7]?
- What are the customer segments of different views?

Data mining has been widely validated to address these marketing concerns along with a set of well-known business metrics unto profitability and "customer" value, for example, the RFMT model and the lifetime customer value model. These standards, which are commonly applied in customer segmentation, are the RFMT model, which is composed of three behavioral variables: R (Recency), F (Frequency) and M (Monetary), T (time).

Research utilizing data mining materials in customer-centric business intelligence about a bank is presented in this study. This analysis was performed to assist the bank in better comprehend mobile banking customers and customer-oriented marketing behavior. As a result, the bank's customers are divided into influential groups based on a new segmentation model. Accordingly, it provided the bank on customer-centric marketing with a set of recommendations.

II. LITERATURE REVIEW

A. *Mobile Banking*

Financial institutions provide various services such as branch banking, mobile banking, internet banking, and automated teller machines (ATMs). However, with greater ubiquity and localization, mobile banking is the most promising and creative platform among all channels [8]. Mobile banking allows customers to carry out various banking operations using their mobile devices. Mobile banking is defined as banking activities that are performed using mobile internet technologies [9]. Mobile Banking is an innovative financial service provided via smartphone applications and software that allows interactive banking services in any location and interactive banking services [10]. Today, mobile banking assistance enables customers to, for example, request their account balances and recent account transactions, transfer funds between accounts, receive and sell orders to exchange stocks, and achieve account and price information [11].

B. *Customer segmentation*

Market segmentation has shown to be one of the most influential theories in both marketing and preparation theories. Like any other service industry in the banking industry, Segmentation is considered a meaningful approach to operationalize the marketing theory and implement instruction concerning its marketing [12]. As a method, Segmentation is fundamental to marketing strategy because several customer groups

Article History:
Received Date: Apr. 18, 2022, Accepted Date: Jul. 11, 2022, Available Online: Oct. 01, 2022

implied the requirement for various marketing combine [13]. The method of this section is to divide the whole market into similar sections, select the target sections and create separate marketing programs to meet the needs and wants of these selected sections [12]. Benefit analysis allows a structured society or bank to concentrate its marketing effort on its stability and target profit segments in keeping with them. Various elements are appropriate for structured societies and banks with specific marketing strengths [14]. segmentation procedure and strategy's effectiveness depend on identifying noticeable, accessible, stable, considerable, and actionable [12]

C. RFMT Analysis

The Customer Relationship Management (CRM) system is one way to increase customer satisfaction with its services. A CRM method's main objective is to understand profitable customers' creation and continuity relations [15]. Thus, it is essential to segment customers based on their value and dedicates rank to them, and establish different associations with different customer segments and other levels. Customer segmentation is utilized in different backgrounds, such as applying customer segmentation to evaluate future customer value [16]. In database marketing, RFM analysis is a very popular client segmentation and identifiable technique [17]. Based on three factors, each customer under RFM is scored [18].

Moreover, R stands for the last purchase period until the present time, F for the transaction frequency in a specific period, and M for the nominal transaction value in a defined period [19],[18]. These descriptions are consistent and can vary from case to case. In recent years, several researchers have studied to expand the concept of RFM analysis. In many studies, days are used as the unit of the Recency period, but the range of more than 11 months can cause the number of days in the last transaction. Therefore, in this study, days were used as a unit of time. The fourth variable, transaction time (T), measures the average time interval between sequential transactions, in other words, the number of days since the first transaction. However, some studies examine the customer segments and RFM examination, centralizing banks over mobile banking platforms [20]. However, T has been introduced by Zhou et al.[21] into the extant RFM model for customer segmentation. Therefore, this study T into the RFM model creates a more extensive model, namely RFMT, for parsing customers' transaction mobile banking sequences over a long period. Furthermore, data mining methods' rapid growth facilitates extensive databases of customer data to exact information, supporting the marketing decision manner. While acquiring new customers and retaining being is crucial, mainly in the finance marketplace, the probability of customer segmentation via obtaining unknown hidden models possesses significant importance [22].

D. Data Mining

Data mining is the manner of discovering relationships, patterns, and trends as essential items with a substantial volume of information stored in the database with pattern recognition technology that can be investigated [23]. Data gathering, data cleaning, ETL, optimization and dimention reduction, model evaluation, pattern recognition, knowledge extraction are several phases of a data mining process [23],[24][26]. It is obvious that it is not mandatory to pass all phases and researchers design the phases according to the problem space. In addition, one of the important phases is providing a proper strategy for information and knowledge perception which is named data visualization [27], [28],[29] that is not in this research scope. In a highly competitive environment, banks must analyze customer preferences and characteristics and adjust their products and services accordingly to retain customers [30]. The banks can cut losses before it is too late by segmenting customers into non-benefit customers and profitable customers. These are incredibly desirable capacities where data mining could assist [31]. Data mining is the procedure of extracting hidden knowledge from large volumes of raw data. Therefore, the background must be new, transparent, related, and practical in the domain where this knowledge has been captured [31]. This research doesn't focus on data cleaning, ETL, optimization and data visualization phases. Therefore, there won't be any section related to this phases.

F. Cross-selling

Cross-selling is about trying to increase the number of products or services a customer uses in a company. It can only achieve proper cross-selling implementation if an information infrastructure allows managers to offer customers products and services that tap into their needs but have not yet been sold [32]. Cross-selling products and services current customers have a bottom associated cost than obtaining new customers because they already have some relationship. Growing product keeping guides to an enhanced number of relationship points with customers and developing the switching values they would face if they wanted to use their custom elsewhere. [32][33]. Improved commodity keeping provides a situation company, with more knowledge of purchasing habits, the business can better understand customers. By increasing the intensity of satisfactory customer interaction, the company acquires more information about the customer's wants and needs, increases customer loyalty, and eliminates the ability of competitors. Furthermore, enhanced commitment drives to rose profitability [32].

G. K-means

k-means is a conventional method for cluster analysis in data mining that is regularly employed to study. Levels of data clustering using the k-Means method can be determined by:

1. Specify the number of clusters k.;
2. Initialize k values as cluster centers (centroids) randomly;
3. Group every data in the nearest cluster. The proximity of two data is calculated using the Euclidean distance;
4. Recalculate each center by calculating the average of all center data with current cluster members;
5. Re-clustering each data (back to step 3) utilizing all new centroids when all centroids do not change anymore;
6. on condition that the orientation center has not changeable again. The clustering procedure is complete [34].

The k-Means method frequently uses the Euclidean distance formula to specify data similarity in a cluster iteratively. In this study, the K-Means algorithm uses the Euclidean distance to divide customers for RFM values to group customers based on the amount generated by repeated trades and to divide customers based on the amount generated by recent trades. One of the prime difficulties concerning the k-Means method is determining the optimal number of k clusters. However, investigation via Subbalakshmi et al. [35] has determined that the precision of the k-Means method, if suitable, can be more significant in choosing the number of clusters and the first value. The resulting clusters are assessed utilizing a silhouette score index that examines how many clusters have been divided. The silhouette score index is in the range of [-1, +1]. If the value is close to +1, the targets (customers) are far enough away from the neighboring clusters. If it is -1, the targets (customers) may be set as an incorrect cluster, or the data preprocessing may not be correct [18].

The elbow method is known among the best methods. This square distance between the center of the cluster and the sample points of each cluster is supported. The sum of square errors (SSE) is the performance index determined for every value of K using the following equation (1) [36]:

$$SSE = \sum_{k=1}^{k} \sum_{x_i \in S_k} \|X_i - C_k\|_2^2 \qquad (1)$$

where x denotes the data available within every cluster and C_k is the kth cluster. The optimal k is obtained until the SSE value drops on the curve drastically, including forms a smaller angle; in this paper, the optimal number of k clusters utilizes the elbow index and silhouette index, determined six clusters.

H. Hierarchical clustering

The hierarchical clustering algorithm was utilized to perform the customer segmentation because it appeared not to need prime parameters and could benefit nonlinear or linear regression models to calculate the maximum hierarchical probability. Based on the bottom-up purpose, the aggregation clustering principal describes every data intent as its independent cluster, and then through merging two alike clusters, these clusters are greedily linked together [21]. Hong et al.[37] extended a hierarchical aggregation clustering algorithm to achieve customer segmentation in the mobile banking transaction dataset to determine relevant marketing strategies. In mutuality, dividing clustering is an up-bottom method into which all data points start in one cluster, and then every cluster is frequently divided in two clusters [38]. This research utilizes an agglomerative clustering algorithm proposed via Shihab et al. [39], who used the Ward method to measure similarities among data points. The number of purpose clusters is a critical parameter that must be set ere the hierarchical clustering algorithm can be implemented. An intuitive approach to determine the optimal number is to examine the clustering act via increasing the number of clusters from 1 into a larger integer.

To assess the clustering model, selected the silhouette coefficient index and Davies-Bouldin index. For our data set, the silhouette coefficient index -1 and +1 and the Davis-Boldin index were only between 0 and 1 (0 ="good" clusters and 1 ="bad" clusters). Therefore, we normalized the indicators on a scale of 0 and 1 for comparison. When the cluster number is 6, a relative silhouette coefficient (0.44) and a relatively low Davis-Boldin score (0.14) can be observed simultaneously. Therefore, number 6 was selected as the optimal number of clusters for this study.

I. Related work

As part of the data revolution, banking as a successor to information technology remains one of the fields used by data mining researchers. Constant advances in banking systems and rapid access to extensive banking data have made data mining necessary for the tasks required by the banking industry. The banking industry has used data mining techniques for various purposes, particularly mobile banking forecasting, segmentation of mobile banking customer identification, and analysis of mobile banking customer attitudes [40]. The main tasks of data mining are classification (or categorical prediction), clustering, regression (or numerical prediction) classification (or categorical prediction), irregularity detection, and association rule mining. Between these data mining duties, classification is repeatedly employed in the banking segment [41], followed through clustering. In every banking program, more than one data mining method has been used, in which pre-classification clustering has provided sufficient evidence of even popularity and application.

Anitha et al.[18] Case studies have been conducted to use business intelligence to identify potential customers by providing related and proper data to business entities in the retail industry. This research relies on the RFM (recent, frequency, and monetary) model and uses the K-Means algorithm to expand the segmentation of the set. Therefore, the results of sales transactions are compared with several parameters similar to sales frequency, sales duration, and sales volume.

Ernawati et al.[42] conducted a study with purposes to analyze data mining methods that assist with the RFM model and manufacture them to purpose a customer segmentation structure. The numerous widely utilized methods obtain clustering k means and visualization from seven data mining methods investigated. This study sponsors a new framework toward using data mining methods, including the RFM based segmentation into the Geographic Information Systems (GIS) conditions. This framework eases analysts' appropriate DM methods to reveal and comprehend customer features, as companies can originate the determined market and promote a marketing strategy to improve their competing advantage.

Abdulhafedh et al.[43] investigated the utilization of clustering algorithms into customer segmentation to define a marketing strategy of a credit card company. Customer segmentation divides customers into groups relying on standard features, which is helpful for banks, businesses, and companies to develop their products or service openings. The project applies two strategies for customer segmentation: first, recognizing all variables in the clustering algorithms utilizing the Hierarchical clustering and the K-means. Second, using the dimensionality compression through Principal Component Analysis (PCA) to the dataset, then recognizing the optimal number of clusters, and revolving the clustering analysis with the updated number of clusters. Outcomes determine that the PCA can efficiently be applied in the clustering manner as a check tool concerning the Hierarchical and K-means clustering.

Khalili et al.[44] The proposed combined method is to predict new entities in customer-centric companies. This research relies on techniques thus as clustering, rule decision tree method, extraction, and other methods. The author uses K-Means to predict future transactions based on historical customer behavior after multiple segmentation. The combined feature option is used for filtering and decision-making. The present study can also be applied in the telecommunications and insurance industry to forecast the transaction amount and plan the company's business profit. This process is highly efficient in predicting valuable customers and recognizing the behavior of the novel customer.

Zhou et al. [21] creating an RFMT model was developed to parse the online shopping sequence of customers over a long period to implement customer segmentation, a new dimension, the time between purchases (T) existing RFM model are investigated. Thus, the suggested RFMT model can follow customer behavior transaction mobile banking changes throughout their purchasing cycle. A web content retrieval method for fetching publicly available customer data on a retailer's website contains demographic information (age, location, gender, etc.) and product data (date, price, name, etc.) from every transaction was calculated in customer RFMT values of the retrieved data. Moreover then analyzed by hierarchical clustering to obtain seven homogeneous clusters with particular customer features.

Hu et al.[45] examined the features from customer data for online catering orders, and is presented an RFMT customer classification model that relies on customer behavior. The primary segment investigation method is utilized to determine the weight of every index, and the K-means++ clustering algorithm is used to categorize customers into five characters of customer sets: general, and low-quality, high-quality, stable, potential. The simulation outcomes show that the customer classification method relies on the developed RFM model to enable Internet catering merchants to aim customers with various targeted strategies.

In comparison to investigated papers literature, our study using data mining materials in customer-centric business intelligence for a bank. Data mining materials were applied in this study k-means algorithm and hierarchical clustering, and we assessed clusters with silhouette and elbow method. The main contributions of this study summarized as follows:

IEEE Office - SEET Complex, Federal University of Technology, Owerri, Nigeria, https://aeuso.org
EISSN: 2305-0543, PISSN: 2411-6173

1. An actual case study in bank used this study to identify mobile banking customers to determine the marketing strategy to reduce costs banks.
2. This study investigates with RFMT analysis customer segments focusing bank on the mobile banking system.
3. In this article, we have tried to understand the structures of bank behavior and examined their association with mobile banking customers.

III. Methodology

This research studied the numbers of mobile banking customers of a private bank in Iran. Table I shows the user demographics, and the data about private bank customers are reported in Table II. Table III shows that the four variables are on several units or unitless and have very various data ranges R-F-M, and transaction Time, respectively. These variables must be normalized or discretized at the same scale before clustering. If the amount of data skewness and kurtosis is about ± 2, the data utilized in this study can be normal.

The suggested methodology was applied to develop a new segmentation methodology, as shown in Fig. 1. In this study, it is the product of the average transaction amount or monetary (M), recency (R), Time(T) and customer frequency (F) ratings:

$$RFMT=R+F+M+T$$

Scoring is done in the range from 5 to 1. The top is assigned a rate of 5, and the others are assigned 4, 3, 2, and 1 The basis of the suggested procedure is that if customers have had similar purchasing behavior, they are likely to have identical RFMT values. The RFMT is divided into five groups according to the customer type table before using the K-means algorithm for clustering customer segments. RFMT values were used to collect customers into groups with identical RFMT values. The scaling of R–F–M-T attributes were showed in Table IV. Every customer is assigned four various scores for recency, frequency, and monetary, time variables shown in Table V.

In this study, the k-means clustering and hierarchical clustering are used to segment customers. Used the Elbow Method and Silhouette Index to determine K's optimal value and the best value K = 6 for the k-means clustering algorithm .To the data's similarity identify, each information is grouped in the nearest cluster, and the Euclidean distance is used to measure the distance between two data the result show in Table VI. The RFMT dispensation in the six clusters and Table VII. Shows the customer size and the average RFMT values of every cluster. This information is used to investigate the characteristics of clusters.

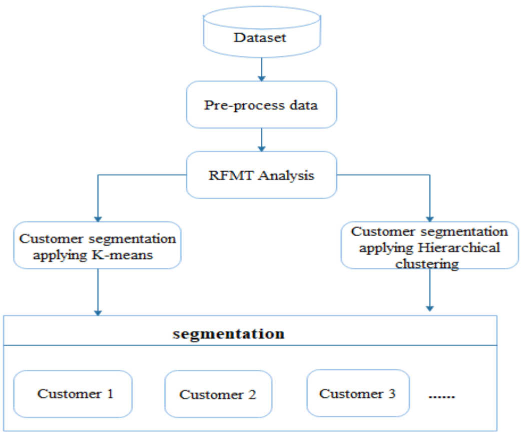

Fig.1. Research methodology using RFMT variable, K-means and hierarchical Clustering

TABLE I. DEMOGRAPHICS OF MOBILE BANKING

Education	Per cen t	Occupation	Perce nt	Gender	Per cent	Age	Perce nt
Graduate	0.39	management	0.22	Male	0.62	young	0.29
Advanced/ Professional	0.42	student	0.4	Female	0.38	middle	0.60
Undergrad	0.19	Self-employed	0.20			old	0.090
		unemployed	0.2				
		admin	0.14				
		Blue-collar	0.3				
		technician	0.18				
		service	0.12				
		entrepreneur	0.2				

TABLE II. COSTUMER TABLE

Field name	Data type	Description	Value set
id	text	customer id cod	-
acc-no	text	customer account number	-
birth-date	text	below 30;30-40;40-60;60 and above	{y, m, o}
gender	text	gender	{f, m}
marital-status	text	married, single, divorced	{m, s, d}
occupation	text	management, self-employed, unemployed, admin, blue-collar, technician, entrepreneur, housemaid	-
education	text	graduate, advanced/professional, undergrad,	-
balance	number	account status	-
amount	number	-	-
transaction-date	date-time	-	-

TABLE III .SUMMARY OF THE RFMT DATASET INCLUDING 50,265 PURCHASES FROM 4397 CUSTOMERS.

Variable	Minimum	Median	Maximum	Std. Deviation	Skewness Statistic	Skewness Std. Error	Kurtosis Statistic	Kurtosis Std. Error
R	0.4	13.5	134	2.2296	.955	.063	-.030	۰,۱۲۵
F	3	3	59	11.515	.027	.063	1.184	۰,۱۲۵
M	3.59	85	1521.38	8.522	.009	.063	1.186	۰,۱۲۵
T	0	295	182.96	102	-.036	.063	-1.241	۰,۱۲۵

TABLE IV. THE SCALING OF RFMT ATTRIBUTES

Field Name	Description	Value set
ID	-	-
recency	Below 8;9-16;17-24;25-31;32 and above (day)	{5,4,3,2,1}
Transeaction Frequency	Below 6;7-12;13-18;19-24;25 and above (in a fiscal years)	{1,2,3,4,5}
Transeaction amount Average	NT$ 120 below; 121-2,399; 2,400-14,380; 14,381-36799; 36800 and above	{1,2,3,4,5}
Transeaction time	Below 2 month,3-4 month, 5-6 month,7-9 month, and 10 months above	{1,2,3,4,5}

TABLE V. RFM T VALUES FOR EACH CUSTOMER

ID	Acc-No	Recency	Transeaction Frequency	Transeaction amount avrege	Time (month)	R	F	M	T
0017755	0027880	11	21	54700	10	1	4	5	4
0017552	0027982	18	7	1200	6	2	5	2	3
0017808	0028201	32	15	120	3	3	3	1	2

TABLE VI. CUSTOMER CLUSTERING OF SIX BASED ON RFMT PARAMETERS K

Cluster	C1	C2	C3	C4	C5	C6
R	132.25	145.25	249.54	384.27	452.15	521.32
F	3.56	4.85	5.25	2.65	4.95	3.61
M	95.02	225.25	326.36	395.25	268.02	326.45
T	6.25	0.26	3.47	1.25	3.26	2.47
Number of members	1250	984	510	430	375	1223

TABLE VII. AVERAGES OF THE SIX CLUSTERS RFMT PARAMETERS

Cluster	C1	C2	C3	C4	C5	C6
R	48.54	46.25	15.39	22.95	36.15	18.61
F	3.02	4.26	2.63	465	3.95	5.69
M	85.02	125.25	256.36	295.25	195.02	362.45
T	0.40	8.5	1.75	6.25	0.26	3.47
Number of members	1129	966	469	451	286	1079

Illustrated RFMT ranking was in Table VIII. according to RFMT would be between 1 and 20, which could determine the current customer value. It is calculated for every collected customer data (Table IX). After RFMT computation should estimate the potential value of the customer based on future opportunities. The potential value of customers is the main factor concerning customer segmentation.

TABLE VIII. SUGGESTED RFMT TABLE FOR SEGMENT EACH CLUSTER

Customer Segment	**RFMT**	**Cluster**
Potential value	18-20	Cluster 1
Extremely important	15-17	Cluster 6
Moderate loyalty	11-14	Cluster 2
Middle value	7-10	Cluster 3
High value	4-6	Cluster 4
Low value	1-3	Cluster 5

TABLE IX. SEGMENTATION RESULTS

ID	RFMT	Customer type of cluster	Customer segment	Marketing strategy
0017755	17	Cluster 6	Extremely important	Relationship management
0017552	11	Cluster 2	Moderate loyalty	reward
0017808	6	Cluster 4	High value	Growing

IV. CONCLUSION

Mobile phone handsets, which were originally applied just particularly toward voice calls, are presently frequently employed to transfer data and take up financial transactions. In current years, mobile banking makes the most important strategic change in retail banking. Customers today need more personalized products and services to access such services at any time and any place [46].

Iranian banks now face extreme contests in and outside Iran. Therefore, it has applied those banks to be rather focused on their customers. The main focus of this research was customer segmentation. Banks that have a marketing strategy want to know what their customers want. However, they must be capable of identifying the requirements concerning every recognized customer segment efficiently. Here, research indicates that the customers' Segmentation is necessary for banks to identify each segment's behavior and provide specific marketing processes that best suit these behaviors. This study's results provide an applied manner to Iranian banks to determine mobile banking customers' right segments [12].

Besides, one concerning these necessary effects toward a bank industry's success is to monitor theirs customers' behavior. The bank wants to identify its customers' behavior while obtaining attractive ones into benefit from more transactions, resulting in most benefits and assets. Therefore, the RFMT analysis remains a procedure for getting customers' behavior and is a reason for CRM and marketing.

Furthermore, this research showed a structure segmentation through using it to one of Iran's private banks' customers. Moreover, that research showed a manufactured sample of segmentation in the banking division. Each aimed model developed a present understanding of mobile banking customers. From a functional view, the study's insights can support mobile banking supervisors manage mobile users' behavior. Also, this research showed the division of the framework through utilizing it in one of the customers of private banks in Iran. This model has built a current perception of mobile banking customers. Functionally, the understanding of this study can help mobile banking managers to manage the behavior of mobile users.

REFERENCES

[1] C. ChauShen, "Perceived risk, usage frequency of mobile banking services," *Manag. Serv. Qual. An Int. J.*, vol. 23, no. 5, pp. 410–436, Jan. 2013, doi: 10.1108/MSQ-10-2012-0137.

[2] R. Malaquias and Y. Hwang, "An empirical study on trust in mobile banking: A developing country perspective," *Comput. Human Behav.*, vol. 54, pp. 453–461, Jan. 2016, doi: 10.1016/j.chb.2015.08.039.

[3] T. Zhou, "Understanding users' initial trust in mobile banking: An elaboration likelihood perspective," *Comput. Human Behav.*, vol. 28, no. 4, pp. 1518–1525, 2012, doi: https://doi.org/10.1016/j.chb.2012.03.021.

[4] M. Farooqi and N. Iqbal, "Effectiveness of Data mining in Banking Industry: An empirical study," *Int. J. Adv. Comput. Res.*, vol. 8, pp. 827–830, May 2017.

[5] P. Sharma and P. Sangle, "The importance of value and context for mobile CRM services in banking," *Bus. Process Manag. Journal, Vol. 19 Iss 6, pp.864 - 891*, vol. 19, pp. 864–891, Nov. 2013, doi: 10.1108/BPMJ-06-2012-0067.

[6] D. Zakrzewska and J. Murlewski, *Clustering algorithms for bank customer segmentation*, vol. 2005. 2005.

[7] D. Chen, S. L. Sain, and K. Guo, "Data mining for the online retail industry: A case study of RFM model-based customer segmentation using data mining," *J. Database Mark. Cust. Strateg. Manag.*, vol. 19, pp. 197–208, 2012.

[8] A. Shankar, C. Jebarajakirthy, and M. Ashaduzzaman, "How do electronic word of mouth practices contribute to mobile banking adoption?," *J. Retail. Consum. Serv.*, vol. 52, p. 101920, 2020, doi: https://doi.org/10.1016/j.jretconser.2019.101920.

[9] A. Y.-L. Chong, "Predicting m-commerce adoption determinants: A neural network approach," *Expert Syst. Appl.*, vol. 40, no. 2, pp. 523–530, 2013, doi: https://doi.org/10.1016/j.eswa.2012.07.068.

[10] S. K. Sharma, "Integrating cognitive antecedents into TAM to explain mobile banking behavioral intention: A SEM-neural network modeling," *Inf. Syst. Front.*, vol. 21, no. 4, pp. 815–827, 2019, doi: 10.1007/s10796-017-9775-x.

IEEE Office - SEET Complex, Federal University of Technology, Owerri, Nigeria, https://aeuso.org
EISSN: 2305-0543, PISSN: 2411-6173

[11] T. Laukkanen, "Internet vs mobile banking: Comparing customer value perceptions," *Bus. Process Manag. J.*, vol. 13, pp. 788–797, Nov. 2007, doi: 10.1108/14637150710834550.

[12] T. Edris, "Services considered important to business customers and determinants of bank selection in Kuwait: a segmentation analysis," *Int. J. Bank Mark.*, vol. 15(4), 126, 1997.

[13] P. Doyle, "Managing the marketing mix. In Baker, M. (Ed.), The Marketing Book, The Marketing Book, Heinemann, London, Ch. 12," 1987.

[14] M. Safari, M. Tive, A. Babania, and M. Hesan, "Analyzing the Applications of Customer Lifetime Value (CLV) based on Benefit Segmentation for the Banking Sector," *Procedia - Soc. Behav. Sci.*, vol. 109, Jan. 2014, doi: 10.1016/j.sbspro.2013.12.511.

[15] A. F. Handoko and A. Wibowo, "Three-Layer Data Clustering Model for Multi-View Customer Segmentation using K-Means," *Int. J. Recent Technol. Eng.*, vol. 8, no. 6, pp. 1840–1846, 2020, doi: 10.35940/ijrte.f7962.038620.

[16] M. Khajvand and M. J. Tarokh, "Analyzing Customer Segmentation Based on Customer Value Components (Case Study: A Private Bank) (Technical note)," *Adv. Ind. Eng.*, vol. 45, no. Special Issue, pp. 79–93, 2011, [Online]. Available: https://jieng.ut.ac.ir/article_23328.html.

[17] A. J. Christy, A. Umamakeswari, L. Priyatharsini, and A. Neyaa, "RFM ranking – An effective approach to customer segmentation," *J. King Saud Univ. - Comput. Inf. Sci.*, 2018, doi: https://doi.org/10.1016/j.jksuci.2018.09.004.

[18] P. Anitha and M. M. Patil, "RFM model for customer purchase behavior using K-Means algorithm," *J. King Saud Univ. - Comput. Inf. Sci.*, 2019, doi: https://doi.org/10.1016/j.jksuci.2019.12.011.

[19] A. Ansari and S. Ghalamkari, "Segmenting online customers based on their lifetime value and RFM model by data mining techniques," *Int. J. Inf. Sci. Manag.*, vol. 0, 69-82., no. SPL.ISSUE1, pp. 69–82, 2014, [Online]. Available: https://ijism.ricest.ac.ir/index.php/ijism/article/view/349.

[20] B. Wang, Y. Miao, H. Zhao, J. Jin, and Y. Chen, "A biclustering-based method for market segmentation using customer pain points," *Eng. Appl. Artif. Intell.*, vol. 47, Jun. 2015, doi: 10.1016/j.engappai.2015.06.005.

[21] J. Zhou, J. Wei, and B. Xu, "Customer segmentation by web content mining," *J. Retail. Consum. Serv.*, vol. 61, p. 102588, 2021, doi: https://doi.org/10.1016/j.jretconser.2021.102588.

[22] E. Ngai and D. Chau, "Application of data mining techniques in customer relationship management: A literature review and classification," *Expert Syst. Appl.*, vol. 36, pp. 2592–2602, Mar. 2009, doi: 10.1016/j.eswa.2008.02.021.

[23] M. Kantardzic, "Data Mining: Concepts, Models, Methods, and Algorithms, 3rd Edition," *Data Min. Concepts, Model. methods, algorithms.*, 2003.

[24] S. Q. Salih *et al.*, "River suspended sediment load prediction based on river discharge information: application of newly developed data mining models," *Hydrol. Sci. J.*, vol. 65, no. 4, pp. 624–637, 2020, doi: 10.1080/02626667.2019.1703186.

[25] N. F. Zainol, "Factors Influencing Mobile Banking Adoption," vol. 9, no. 1, pp. 1–18, 2011.

[26] J. Han, M. Kamber, and J. Pei, "Data Mining: Concepts and Techniques," *Data Min. Concepts Tech.*, 2012, doi: 10.1016/C2009-0-61819-5.

[27] R. H. Koochaksaraei, I. R. Meneghini, V. N. Coelho, and F. G. Guimarães, "A new visualization method in many-objective optimization with chord diagram and angular mapping," *Knowledge-Based Syst.*, vol. 138, pp. 134–154, 2017, doi: https://doi.org/10.1016/j.knosys.2017.09.035.

[28] I. R. Meneghini, R. H. Koochaksaraei, F. G. Guimarães, and A. Gaspar-Cunha, "Information to the Eye of the Beholder: Data Visualization for Many-Objective Optimization," *2018 IEEE Congr. Evol. Comput. CEC 2018 - Proc.*, 2018, doi: 10.1109/CEC.2018.8477889.

[29] R. H. Koochaksaraei, R. Enayatifar, and F. G. Guimarães, "A new visualization tool in many-objective optimization problems," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 9648, pp. 213–224, 2016, doi: 10.1007/978-3-319-32034-2_18.

[30] V. Bhambri, "Application of data mining in banking sector.," *J. Comput. Sci. Technol*, vol. 2, no. 199–201, 2011.

[31] S. Pulakkazhy and S. Balan, "Data mining in banking and its applications- A review," *J. Comput. Sci.*, vol. 9, pp. 1252–1259, Oct. 2013, doi: 10.3844/jcssp.2013.1252.1259.

[32] W. A. Kamakura, M. Wedel, F. de Rosa, and J. A. Mazzon, "Cross-selling through database marketing: a mixed data factor analyzer for data augmentation and prediction," *Int. J. Res. Mark.*, vol. 20, no. 1, pp. 45–65, 2003, doi: https://doi.org/10.1016/S0167-8116(02)00121-0.

[33] B. Noori, "An Analysis of Mobile Banking User Behavior Using Customer Segmentation," *Int. J. Glob. Bus.*, vol. 8, no. December, pp. 55–64, 2015.

[34] R. Gustriansyah, N. Suhandi, and F. Antony, "Clustering optimization in RFM analysis Based on k-Means," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 18, p. 470, Apr. 2020, doi: 10.11591/ijeecs.v18.i1.pp470-477.

[35] C. Subbalakshmi, G. R. Krishna, S. K. M. Rao, and P. V. Rao, "A Method to Find Optimum Number of Clusters Based on Fuzzy Silhouette on Dynamic Data Set," *Procedia Comput. Sci.*, vol. 46, pp. 346–353, 2015, doi: https://doi.org/10.1016/j.procs.2015.02.030.

[36] D. Marutho, S. Hendra Handaka, E. Wijaya, and Muljono, "The Determination of Cluster Number at k-Mean Using Elbow Method and Purity Evaluation on Headline News," *Proc. - 2018 Int. Semin. Appl. Technol. Inf. Commun. Creat. Technol. Hum. Life, iSemantic 2018*, pp. 533–538, 2018, doi: 10.1109/ISEMANTIC.2018.8549751.

[37] P. D. Hung, N. T. T. Lien, and N. D. Ngoc, "Customer Segmentation Using Hierarchical Agglomerative Clustering," in *Proceedings of the 2019 2nd International Conference on Information Science and Systems*, 2019, pp. 33–37, doi: 10.1145/3322645.3322677.

[38] A. Sharma, Y. López, and T. Tsunoda, "Divisive hierarchical maximum likelihood clustering," *BMC Bioinformatics*, vol. 18, no. 16, p. 546, 2017, doi: 10.1186/s12859-017-1965-5.

[39] S. H. Shihab, S. Afroge, and S. Z. Mishu, "RFM Based Market

Segmentation Approach Using Advanced K-means and Agglomerative Clustering: A Comparative Study," in *2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, 2019, pp. 1–4, doi: 10.1109/ECACE.2019.8679376.

[40] D. Birant, "Data Mining in Banking Sector Using Weighted Decision Jungle Method," 2021.

[41] H. Karjaluoto, R. Glavee-Geo, D. Ramdhony, A. A. Shaikh, and A. Hurpaul, "Consumption values and mobile banking services: understanding the urban–rural dichotomy in a developing economy," *Int. J. Bank Mark.*, vol. 39, no. 2, pp. 272–293, Jan. 2021, doi: 10.1108/IJBM-03-2020-0129.

[42] E. Ernawati, S. S. K. Baharin, and F. Kasmin, "A review of data mining methods in RFM-based customer segmentation," *J. Phys. Conf. Ser.*, vol. 1869, no. 1, p. 12085, 2021, doi: 10.1088/1742-6596/1869/1/012085.

[43] A. Abdulhafedh, "Incorporating K-means, Hierarchical Clustering and PCA in Customer Segmentation," *J. City Dev.*, vol. 3, no. 1, pp. 12–30, 2021.

[44] K. Khalili-Damghani, F. Abdi, and S. Abolmakarem, "Hybrid soft computing approach based on clustering, rule mining, and decision tree analysis for customer segmentation problem: Real case of customer-centric industries," *Appl. Soft Comput.*, vol. 73, pp. 816–828, 2018, doi: https://doi.org/10.1016/j.asoc.2018.09.001.

[45] X. Hu, Z. Shi, Y. Yang, and L. Chen, "Classification Method of Internet Catering Customer Based on Improved RFM Model and Cluster Analysis," in *2020 IEEE 5th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA)*, 2020, pp. 28–31, doi: 10.1109/ICCCBDA49378.2020.9095607.

[46] A. W. Siyal, D. Donghong, W. A. Umrani, S. Siyal, and S. Bhand, "Predicting Mobile Banking Acceptance and Loyalty in Chinese Bank Customers," *SAGE Open*, vol. 9, no. 2, 2019, doi: 10.1177/2158244019844084.

IEEE Office - SEET Complex, Federal University of Technology, Owerri, Nigeria, https://aeuso.org
EISSN: 2305-0543, PISSN: 2411-6173