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Two-dimensional analysis of customer behavior in traditional and electronic banking

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ABSTRACT

The explosive growth of information technology has encouraged organizations to use new technologies in all areas. These changes are also visible in the banking industry. In this situation, customers have used both electronic and traditional services, and each has its own features. According to expectancy-value theory, customer value and expectations both affect customer buying behavior and should be considered by banking managers in designing their strategies. Better understanding of these features will help banks to provide customers with the services they need and, as a result, maintain them. Hence, using expectancy-value theory as a framework this study proposed a two-dimensional approach to examine the customers' behavior in both electronic and traditional banking in Iran. To this end, the data of one-year transactions of XYZ bank (one of the largest private banks of Iran) customers, consisting of one million records, was used and customers were clustered using the RFM model - recency, frequency, and monetary. The CRISP-DM methodology was used to extract knowledge from customer data and the K-Mean algorithm was used for clustering. Customer lifetime value was also calculated using Lawshe criteria. According to the results, customers who use both electronic and traditional bank services are more valuable. The two-dimensional approach proposed and provides a two-sided view of the customer, and thereby provides a more comprehensive knowledge and understanding of customer behavior, and contributes to the body of literature in this field. Using the proposed model, different banks can better classify their customers and can provide the right product / service to the right person.

1. Introduction

Information technology development has a significant impact on businesses (Barroso & Laborda, 2022; Hanafizadeh, Shafia, & Bohlin, 2021; Karimian, Sanayei, Hekmatpanah, & Faraghian, 2015; Karki & Porras, 2021; Tadayon, Ebrahimzade Dastgerdi, Gheitani, & Sadeghi, 2021). Along with the tremendous progress that has been made in this field, the destiny of societies, organizations and individuals is becoming more and more dependent on this technology. Banks are no exception and benefited from technological advances as institutions operating in various monetary and financial spheres (Singh & Tigga, 2012; Yousef, 2020). Data storage is centralized and seamlessly integrated into the database of various branches of banks. Moreover, the number of channels has multiplied to provide service and access to bank accounts. Technically, banking systems have become more powerful and more customer-centric, and they are competing with each other by providing services such as online trading, electronic money transfers and ATMs (Mohseni & Rabani, 2018; Moro, Cortez, & Rita, 2015).

Currently, the banking industry is divided into two sections, traditional banking and electronic banking (e-banking) (Rahi & Ghani, 2019). *E*-banking is a new form of information system in banking that has changed the way customers engage in various activities in cyberspace using the Internet and new Web-based techniques (Gebreslassie, 2017). Ease of use, easy access and speed in providing services are other benefits of e-banking, which lead customers to spend less time in banks (Mohseni & Rabani, 2018; Szopiński, 2016; Yousef, 2020). In this situation, customers have become both electronic and traditional, and each has specific behaviors. In order to retain customers, it is important to know each group (Oyewole, Abba, El-maude, & Arikpo, 2013). Customers have different needs, objectives and past experiences that influence their expectations (Pizam & Ellis, 1999). Based on expectancy-value theory, customers often judge a product, its benefits, and the possible consequences of using the product. People learn to do behaviors that they expect to lead to positive results. Their general attitude is a

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function of beliefs about the properties of an object and the power of those beliefs. The impact of feature importance on customer decision-making is driven by loyalty, customer care, and the mechanism by which the product provides the retention mechanism for customers (Warsame, 2017).

The success of banks depends on the performance that is determined by the level of customer satisfaction, it is therefore important for banks to manage good relationship with customers and meet the changing demands of customers to survive in a competitive environment (Mahdiraji, Kazimieras Zavadskas, Kazeminia, & Abbasi Kamardi, 2019; Osei, Ampomah, Kankam-Kwarteng, Bediako, & Mensah, 2021). In spite of this, many today's banks do not have the accurate recognition of customers and their habits, and matching services with the needs and demands of customers and efficient customer relationship management (CRM) are the major challenges for banks, especially when they have to convince customers with different needs to pursue their goals (Tadayon et al., 2021; Zouari & Abdelhedi, 2021). The main purpose of CRM is to attract and retain economically valuable customers, identify and discard the least valuable ones, which fully aligns CRM with modern customer-centric management theory through its ability to analyze and plan marketing strategies and Services that lead the company to achieve and maintain long-term partnerships (Guerola-Navarro, Oltra-Badenes, Gil-Gomez, & Gil-Gomez, 2021).

By using data mining, valuable customers can be identified and their future behaviors can be predicted (Alizadeh Zoeram & Karimi Mazidi, 2018; Chu & Palvia, 2017; Yadav, Desai, & Yadev, 2013). One of the most widely used methods of data mining, which also gives managers a very good view of customers, is the segmentation method (Bhambri, 2011). Customer segmentation is the process of dividing individuals into homogeneous subgroups based on their characteristics (Karki & Porras, 2021). Research shows that segmentation leads to greater consumer satisfaction because it offers a number of apparent benefits, including: better understanding of consumer demands and better budget allocation (Osei et al., 2021). Different algorithms and models can be used for customers' segmentation. RFM is the commonly used model for customer segmentation, which extracts customers' behavior patterns through the use of their recency (R), frequency (F) and monetary (M) values (Doğan, Ayçin, & Bulut, 2018; Peker, Kocyigit, & Eren, 2017).

Previous studies used RFM to examine the behavior of customers in traditional and electronic channels separately (Aliyev, Ahmadov, Gadirli, Mammadova, & Alasgarov, 2020; Mozafari & Naeini, 2018; Nikumanesh & Albadvi, 2014; Khajvand, Zolfaghar, Ashoori, & Alizadeh, 2011); but, they have not compared the behavior of customers and their profitability in traditional and electronic channels in a two-dimensional mode. Since different customers in both traditional and electronic have different characteristics without the appropriate understanding of customers, banks are unable to identify valuable customers, predict their level of satisfaction with a new service, and gain competitive advantage and fit the marketing plan to the demands of customers. Therefore, the discovery of patterns in customer behavior in the use of banking services through both channels and the prediction of future customer behavior are of particular importance (Sharahi & Aligholi, 2015). Thus, these questions arise: What is the difference between the customers who use traditional and electronic channels? How have electronic channels affected the profitability of banking customers compared to traditional channels in Iran?

To answer these questions, the purpose of this study is to use expectancy-value theory and provide a two-dimensional approach of customers' behavior in both traditional and electronic channels using the RFM model in order to provide a better understanding of customer behavior in the banking sector of Iran. The banking sector in Iran shows various structural vulnerabilities that may affect the decision-making process on foreign loans and international portfolio investments (Birau, Spulbar, Yazdi, & ShahrAeini, 2021). The development of information technology (IT) has pushed Iranian banks toward electronic banking to provide services to customers at a more reasonable cost and in less time (Tadayon et al., 2021). The financial system in Iran is characterized by two main aspects. The first is that banks have a specific legal structure, and the second highlights the fact that non-bank financial institutions focus on trust (Nikumanesh & Albadvi, 2014), companies, foundations, and trust services. Iran is part of the global economy, and an efficient banking sector is a prerequisite for achieving sustainable development goals. Competitiveness in Iran's banking sector is affected by the unpredictability of the global economy (Birau et al., 2021).

Lack of using CRM techniques in public and private banks in Iran is one of the most important reasons for the failure of Iranian banks to retain their customers (Zaheri, Farughi, Soltanpanah, Alaniazar, & Naseri, 2012). Given the importance of implementing CRM in the banking industry, the need to create an appropriate mechanism for the success of CRM has been felt in the last decade in the Iranian banking system (Gu et al., 2021). Therefore, there is a need to study the behavior of customers in electronic and traditional banking and their value for banks through a two-dimensional approach. Using a two-dimensional approach provides a two-sided view of the customer, and thereby provides a more comprehensive knowledge and understanding of customer behavior, and contributes to the body of literature in this field. The proposed approach can provide a better knowledge about different customer segments, which can help banks to enhance CRM activities.

The study proceeded as follows: first the literature is reviewed, and then the research methodology is explained. The analysis and results are explained further. Finally, the conclusion including the Theoretical and Practical Implications and limitations and recommendations for the future research are discussed.

2. Literature review

Consumer satisfaction is one of the most important constructs and one of the main goals in marketing. Satisfaction is defined as the feeling of pleasure or frustration of a person that results from comparing the perceived performance (or outcome) of a product in relation to his or her expectations (Almsalam, 2014). Managing customer expectations is an important issue for customer satisfaction. Expectations act as the main determinants of evaluations and satisfaction with the quality of consumer services (Gures, Arslan, & Tun, 2014).

Expectancy-value theory holds that behavior is a function of the expectations that a person has and the value of the goal that he strives to achieve (Warsame, 2017). Customer value is the source of all values, including: competitive advantage, the basis of marketing activities, and predictors of customer behavior. Customer value is determined by customer perception, not by suppliers' assumptions or intentions (Potra, Pugna, Negrea, & Izvercian, 2018). Values act as a source of motivation for behavior and lead the person to choose between different goals and thus perform specific behaviors (Burcher, Serido, Danes, Rudi, & Shim, 2021). However, according to expectancy-value theory, although value motivates behavior, customer expectations are also effective in customers' decisions about the brand or type of product or service to be purchased (Almsalam, 2014; Burcher et al., 2021). Thus, organizations' success depends on effective customer behavior analysis (Mahdiraji et al., 2019) to meet customer needs and expectations, improve customer satisfaction and retention (Khajvand et al., 2011). In this regard, CRM has become a powerful strategy to increase companies' profitability (Zare & Emadi, 2020). The main goal of CRM is to attract and retain valuable customers (Guerola-Navarro et al., 2021; Zare & Emadi, 2020). The most important application of CRM in banking is customer analysis and clustering with the aim of identifying important customers and offering privilege to customers (Zaheri et al., 2012).

CRM in banking is considered as one of the marketing strategies that makes long-term relationships with their customers (Patil, 2020). CRM is different in banking because it deals with financial services that need more trust in interacting with people. Technically, banking systems have become more powerful and more customer-centric, and they are competing with each other by providing services such as online trading, electronic money transfers and ATMs (Mohseni & Rabani, 2018; Moro et al., 2015). Therefore, it is essential to serve customers at the right time when it comes to paying interest, issuing credit and debit ATM cards, and long-term deposits (Abu-Shanab & Anagreh, 2015).

Target group marketing segmentation techniques are one of the techniques that help banks in meeting the needs of customers, and establishing and maintaining long-term relationships with customers (Karahan & Kuzu, 2014). Various techniques and models have been used to segment customers and analyze their behavior, the most common of which are data mining techniques including classification, clustering, and associative rule mining (Anitha & Patil, 2020; Gull & Pervaiz, 2018). Among different data mining techniques customer segmentation, which is used for more accurately identifying different customer groups (Tavakoli et al., 2018).

The best common method for customer segmentation is RFM (recency, frequency and monetary), which is used to predict customer behavior based on their purchasing behavior (Doğan et al., 2018; Peker et al., 2017). Using this model to segment the customer gives a picture of the past and shows how the customer has been. It also helps the organization to determine its next goal (Safari, Safari, & Montazer, 2016). Therefore, many studies have used this model to discover and analyze customer value based on their past transactions (Doğan et al., 2018). For example, Raja, Masthan, Balachandra Pattanaik, and Kumar (2020) used RFM model to predict customers' behavior at the Ethiopian Commercial Bank. They also used a logistic regression model for prediction of customers. Their results reinforced the belief that the use of information mining strategies could enhance CRM practices. In another study, Aliyev et al. (2020) used RFM model and unsupervised machine learning to calculate the customers' value and to segment the customers of the largest private banks of Azerbaijan. Taghavifard and Khajvand (2013) also used RFM model and clustered the bank customers and identified four clusters of customers. Patsiotis, Hughes, and Webber (2012) segmented customers into two groups of e-banking recipients and deniers. According to the customer perceptions of services, and variables of knowledge, interaction, human risk, and sensitivity, three segments were identified. Among demographic characteristics, only income was related to the membership of individuals in each segment. In another study, Bizhani and Tarokh (2010) proposed a RFM method in banking, and indicated that RFM-based segmentation would help the bank to gain a better understanding of customer groups.

Based on the studies, the main advantage of RFM is the use of lower criteria (three dimensions) to extract customer characteristics, so the complexity of the model is reduced (Cheng & Chen, 2009). However, despite the advantages of the RFM model in campaign management, it has limitations such as inaccuracy in calculating scores (Carrasco, Blasco, García-Madariaga, & Herrera Viedma, 2018). Therefore, researchers have tried to increase the accuracy of the model by adding new variables. For example, Horri, Moradi, and Nouri (2022) proposed a weighted-RFM model for customer segmentation and indicated the better performance of their proposed model in predicting customers' behavior than the initial RFM. Another study by Heldt, Silveira, and Luce (2021) proposed a RFM per product (RFM/P) model to estimate the overall value of customers through the products' value estimation. They demonstrated the better performance of their proposed model over RFM. In another study, Firdaus and Utama (2021) proposed a RFM + B model for customer segmentation and indicated that the proposed model can provide better segmentation of customers. Another study by Nekooei and Tarokh (2015) proposed a GLRFM model for banking customer segmentation based on four parameters of length, recency, frequency, and monetary. The results of this study indicated that their proposed approach allows an accurate and efficient cluster analysis. Noori (2015) added the customer deposit variable to the RFM model to classify mobile bank users, and proposed that customers identified through behavioral scoring facilitates the marketing strategy development and resource allocation. Alvandi, Fazli, and Abdoli (2012) proposed a LRFM model to calculate the customer lifetime value (CLV) in the banking sector. They indicated that their model was useful for calculating CLV and customer segmentation in the banking sector. The study by Khajvand et al. (2011) also proposed a weighted-RFM model to estimate customer future value in retail banking, and indicated the better performance of their proposed approach in customer segmentation. Table 1 indicates the previous research on RFM and its extension.

According to the studies conducted in this field, it is clear that researchers have examined the behavior of customers in traditional and electronic channels separately, and have not compared the behavior of customers in these channels two-dimensionally. Moreover, there is no study in this area in Iran, which is the objective of this study. Using a two-dimensional approach can provide a better insight into different customer segments and will help managers to better organize their strategies for maintaining valuable customers.

3. Methodology

This study aims to investigate the behavior of customers in electronic and traditional banking channels and analyze the impact of this behavior on banking. First, the CRISP-DM "*Cross Industry Process Model for Data Mining*" method, which is one of the most powerful analytical methods for conducting data mining projects, is used to extract knowledge from customer data. This methodology includes six phases of business understanding, data understanding and preparation, modeling, evaluating and deployment (Solano, Cuesta, Ibáñez, & Coronado-Hernández, 2022) (Fig. 1).

The data was from one-year transactions of 85,000 XYZ bank customers in both traditional and electronic channels, which was collected from the bank database. The XYZ bank is (of the largest private banks in Iran, which is considered as one of the banks providing new services in the country. With the aim of providing new banking services and earning profits for its depositors and shareholders, and relying on the country's interests, this organization tries to transform the country's banking system by providing the required new bank services.

The Davies-Bouldin criterion was used to determine the optimal number of clusters and the data were clustered using the K-Mean algorithm which is a common method for data clustering (Liu & Shih, 2005) using RapidMiner Studio software. The K-Means algorithm is based on partition clustering in which the number of clusters must be predetermined. Then, based on the number of primary clusters, data is placed in different clusters (Ghosh & Dubey, 2013).

Then, ANOVA was performed on the clusters to analyze the differentiation of the clusters. Shannon's Entropy, which is based on limit theorems of string matching (Feutrill & Roughan, 2021) was also used for valuation and determination of $R_TF_TM_T$ and $R_EF_EM_E$ weights. Finally the CLV of each cluster was calculated and customers were analyzed Two-Dimensionally.

4. Data analysis & results

4.1. Business understanding and data preparation

This study analyzes the value of XYZ Bank (one of the largest private banks in Iran) customers; so that the bank can provide appropriate services according to the value of each group in order to maintain and increase customer satisfaction and ultimately maximize its profits. The XYZ bank.

The data was collected from the XYZ bank database. Sample population used for this study is all individuals with current accounts in the bank under study. Features used to assess the value of bank customers and their segmentation, including recency, frequency and transaction value (monetary) of customers in both traditional and electronic channels were extracted from the raw data of one year period provided by the studied bank. The data of one-year transactions of 85,000 XYZ bank customers, consisting of one million records, including customer ID,

Table 1
RFM model and its extension.

Resource	Objective	Model	Added Variables	Results
Raja et al. (2020)	To predict customers' behavior at the Ethiopian Commercial Bank.			Their results reinforced the belief that the use of information mining strategies could enhance CRM practices.
Aliyev et al. (2020)	Bank customers segmentation	RFM		They indicated that RFM-based segmentation would help the bank to gain a better understanding of customer groups.
Taghavifard and Khajvand (2013)				They identified four clusters of customers, and indicated that RFM-based segmentation would help the bank to gain a better understanding of customer groups.
Patsiotis et al. (2012)				They segmented customers into two groups of e-banking recipients and deniers. According to the customer perceptions of services, and variables of knowledge, interaction, human risk, and sensitivity, three segments were identified. Among demographic characteristics, only income was related to the membership of individuals in each segment.
Bizhani and Tarokh (2010)				They indicated that RFM-based segmentation would help the bank to gain a better understanding of customer groups.
Heldt et al. (2021)	To estimate the overall value of customers through the products' value estimation.	RFM/P	RFM per product	They demonstrated the better performance of their proposed model over RFM.
Firdaus and Utama (2021)	To propose a RFM + B model for customer segmentation	RFM + B	Customer Balance	They indicated that the proposed model can provide better segmentation of customers.
Nekooei and Tarokh (2015)	Banking customer segmentation based on four parameters of length, recency, frequency, and monetary.	Group LRFM (GLRFM)	Customer Lifetime Value	Their results indicated that their proposed approach allows an accurate and efficient cluster analysis.
Noori (2015)	To add the customer deposit variable to the RFM model to classify mobile bank users	RFMD	Customer Despite	They proposed that customers identified through behavioral scoring facilitates the marketing strategy development and resource allocation
Alvandi et al. (2012)	To calculate the customer lifetime value (CLV) in the banking sector.	LRFM	Customer Lifetime Value	They indicated that their model was useful for calculating CLV and customer segmentation in the banking sector.
Horri et al. (2022)	To provide a conceptual framework to increase returns and reduce risk of bank through customer segmentation	weighted-RFM	–	They indicated the better performance of their proposed model in predicting customers' behavior than the initial RFM
Khajvand et al. (2011)	To estimate customer future value in retail banking			They and indicated the better performance of their proposed approach in customer segmentation

transaction number, deposit amount, withdrawal amount, transaction type, transaction code, and date of the last transaction was used (Table 2).

The Customer relationship data from the traditional channel was used to calculate the 'customer's R_T, F_T, M_T values and customer transaction data from the electronic channel was used to calculate the R_E, F_E, M_E values of the customers. Since the last customer transaction is considered by day, the last customer transaction date became the number of days that had elapsed since the period under review. Then the aggregation function was used to aggregate the data related to each customer and the data were prepared for modeling. Also, to obtain the monetary volume variable, the sum of two deposit and withdrawal amounts was calculated.

Data preparation involves the process of removing outliers and normalizing the data. RapidMiner Studio software was used to detect outliers and the Maximum function was used to count R_E and R_T of transactions in a way that one day after the last transaction date of the data set was considered as the snapshot date '2018–03–18' and the last transaction date of each customer was deducted from the this date. The date difference will give us how recent the last transaction was made. The lower amount is better (Gupta & Hill, 2014). The Sum function was also used to count the frequencies and monetary value of traditional and electronic transactions. Due to the existence of different intervals and different measures for each variable, normalization was required for all the features. In addition to duplicating variables, their skewness must also be eliminated. For this purpose, *Z*-SCORE and MIN-MAX methods were used; but, given the skewness of data the results were not good.

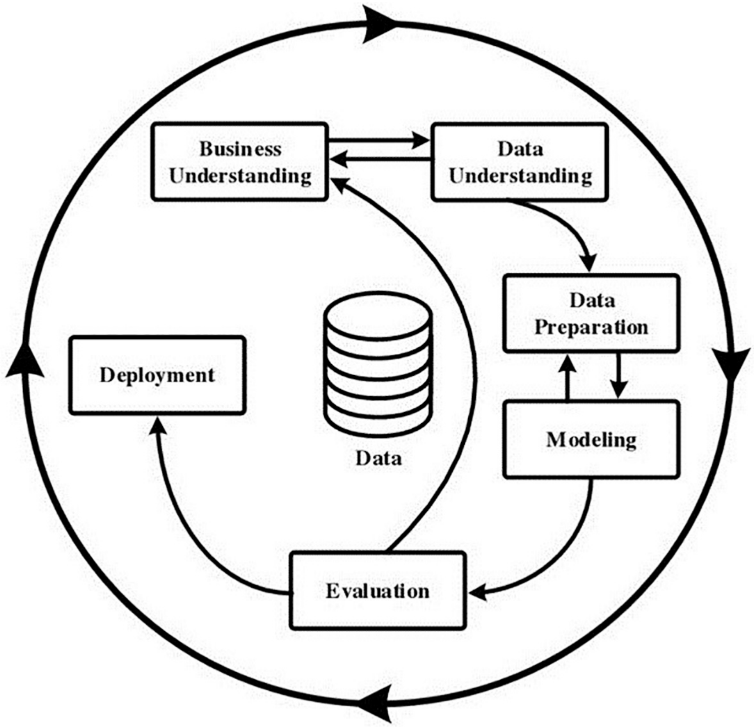

Fig. 1. CRISP-DM Methodology (Brandusoiu, 2020).

Table 2
The data descriptive.

Record	Data Type	The range of data values
Customer ID	Nominal	Not Important
Transaction Number	Numerical	0 to 586,156
Deposit Amount	Numerical	0 to 167,758,147,457
Withdrawal Amount	Numerical	0 to 5.207478791529
Transaction Type	Nominal	Not Important
Transaction Code	Nominal	Not Important
Date of the Last Transaction	History	1/10 to 12/29

Table 3
ANOVA test results.

Model	variable	SOS	df	Mean Square	F	Sig
	R_T	316,060.91	3	4.987	63,372.244	0.000
$R_TF_TM_T$	F_T	2,052,550,586	3	4.383	4835.263	0.000
	M_T	184,041.442	3	1.236	148,955.718	0.000
	R_E	299,831.667	3	5.727	52,357.543	0.000
$R_EF_EM_E$	F_E	234,759.755	3	5.588	42,014.436	0.000
	M_E	224,081.21	3	2.401	93,339.229	0.000

Therefore, the logarithmic statistical method was used to eliminate skew and to scale out the data. After completing these steps on the dataset, the number of customers in each $R_TF_TM_T$ (traditional channel) and $R_EF_EM_E$ (electronic channel) models reached 80,907.

4.2. Modeling and model evaluation

At this stage, the optimal number of clusters is determined using the Davis-Boldin criterion, which combines the two criteria of correlation and density (Davies & Bouldin, 1979). The lower values of the Davis-Boldin index indicate the best number of clusters (Khajvand et al., 2011). Based on the results, the best number of clusters for both traditional and electronic channels was four clusters (0.269 for each model). After determining the optimal number of clusters, the K-Mean algorithm was used to cluster customers of $R_TF_TM_T$ and $R_EF_EM_E$ models separately, and the data of each model was divided into four clusters.

In the next step, the ANOVA test was used to assess the Cluster differentiation (Table 3). According to the results, the significance level (Sig) of all variables in both traditional and electronic channels is less than 0.05 (Table 3). Therefore, the homogeneity of the mean of the clusters is rejected, which indicates that the clusters in both models are significantly different from each other and the clustering is done correctly.

- *Valuation and Determination of the weights of $R_TF_TM_T$ and $R_EF_EM_E$ Parameters through Shannon's Entropy:*

At this phase the weights of each parameter in both traditional and electronic channels is calculated separately using Shannon's entropy (Wang & Lee, 2009). To this end, first the indicators are normalized and a scalar matrix is created. Next, the entropy measurement of each indicator is calculated. Then, the divergences of indicators are defined and finally the normalized weights of indicators are obtained (Ranjbar Kermany & Alizadeh, 2012; Wang & Lee, 2009) (Table 4). According to the results, the frequency, recency and monetary of transactions are close to each other and the behavior of customers in traditional and electronic channels are the same.

At the next stage the CLV of customers is calculated using the formula 1:

Table 4
Shannon entropy weighting.

Criteria	Recency		Frequency		Monetary	
	$R_TF_TM_T$	$R_EF_EM_E$	$R_TF_TM_T$	$R_EF_EM_E$	$R_TF_TM_T$	$R_EF_EM_E$
Ej	0.9434	0.9437	0.9357	0.9332	0.7758	0.7828
Dj	0.0566	0.0563	0.0643	0.0668	0.2242	0.2173
Wj	0.1641	0.1654	0.862	0.1962	0.6497	0.6384

$$CLV_{cj} = NR_{ci} * WR_{ci} + NF_{ci} * WF_{ci} + NM_{ci} * WM_{ci} \quad (1)$$

In which, CLV_{cj} is the average CLV of the cluster ci (i: 0, 1, 2 …). WR_{ci}, WF_{ci}, and WM_{ci} are the weights of recency, frequency, and monetary clusters of ci, respectively, and NRci, NFci, and NMci are the normalized frequency, frequency, and polycluster of ci, respectively (Shih & Liu, 2008). The average CLV for each cluster is shown in Table 5.

According to Table 5, in $R_TF_TM_T$ model the largest number of customers belong to cluster 1 with 35.31% of the members, and customers of this cluster have the highest recency, frequencies, and monetary. This cluster includes high-value customers. It seems that this cluster includes customers who select the bank's traditional services. The second cluster with 31.81% of customers has high frequency and monetary, but has low recency, in other words, customers of this group have been referred to the bank alternately and in a high monetary amount, but in a long time period; The account may belong to people who have very high earnings during certain seasons or times. The third cluster has the least number of customers (5.511% of customers). This cluster includes customers who have the least values for the three variables. It can be said that customers of this cluster use less traditional services. The fourth cluster of the traditional channel with 27.36% of the customers has high values for the two variables of recency and monetary but has a low value in the frequency. The customers of this cluster have come to the bank in shorter time periods, with high monetary, but with a low frequency. This cluster probably belongs to those who earn high income each month and earn their salaries in the final days of the month.

In the $R_EF_EM_E$ model, the first cluster with 28.63% of the customers has high monetary and recency, but it has a low frequency. In other words, customers have less electronic transactions, but with more money and in a long time. It seems that the customers of this cluster have become accustomed to using traditional services, but they have not had access to the branch and have used electronic services. The second cluster with 5.03% of customers has the lowest average of variables and the number of members who are likely to be those who are unwilling to use the technology. These customers may include Traditional traders and retirees, or have alternative banks to receive electronic services. The third cluster, with 34.38% of customers, has the largest number of customers. The customers of this cluster have the highest frequency and monetary, and their recency is moderate. According to the weight of the variables, this cluster also has the highest CLV. This cluster includes high-value customers. Customers of this cluster have used electronic channels for their financial transactions, which may reflect their confidence in the bank's electronic services but may also be served by other banks. The fourth cluster has the highest CLV. This cluster with 31.94% of customers has the highest recency and is modest in the other two components.

4.3. Two-dimensional clustering analysis

After analyzing and clustering the customers of each traditional and electronic channel, the customers of these channels were clustered two-dimensionally. In this approach, 16 new clusters were identified and the CLV value and percentage of members of each cluster was calculated (Table 6).

As Table 6 indicated, the highest CLV value belongs to the third electronic and the first traditional cluster with a value of 11.378, which is higher than the CLV value in the separate case (previous phase). In fact, these clusters are more valuable if they do transactions in both electronic and traditional channels. The frequency and monetary values of the third electronic cluster is high and is higher than the value of these variables in the first traditional cluster, but the traditional cluster has high recency and the recency of the electronic cluster is moderate. Besides, according to the results these customers use both traditional and electronic channels and are considered as loyal customers. These people have a high bank account turnover and their bank account is most likely related to their business. The highest percentage of members belongs to this cluster (third cluster in electronic channel and first cluster of traditional channel) with 18%.

In addition, the lowest amount of CLV belongs to the customers of the second cluster of electronic and third cluster of traditional channels. The CLV of these clusters are higher than the CLV of each distinct traditional and electronic cluster. These clusters have the lowest percentage of members, and the possibility of customer churn is high.

According to CLVs, customers can be classified into five levels of low-value, middle-value, high-value, and very high-value customers. The results are shown in Fig. 2.

As indicated in Fig. 1, the lowest CLV belongs to the customers of the second electronics cluster and the third traditional one, which is shown in red color. These two clusters also have the lowest amount of CLV among other distinct traditional and electronic clusters. It means that customers are leaving the bank. These customers may have an alternative bank that they are loyal to.

The orange groups have the lower CLV, high monetary and moderate frequency and recency. In this group, one of the two cluster dimensions has the lowest CLV. These customers use one of the traditional or electronic channels more. In cases where the use of traditional services is high and electronic services are not used at all, these traditional people can have a good financial position. In this group, traditional customers behave like traders.

In the middle-value group, which is marked with yellow, one of the two dimensions of the cluster is related to clusters in which one dimension has the highest CLV and the other dimension has the lowest CLV. The next group which is marked in blue has high CLV and has high values for features in both traditional and electronic channels. The last group, which is marked in green, is the most valuable cluster and includes the third electronic cluster and the first traditional cluster.

In fact, if customers perform both electronic and traditional transactions, they are more valuable. The frequency and monetary value in the third electronic cluster are higher than the same variables in the traditional first cluster. But the values of recency are high in the traditional cluster. This indicates that customers of this cluster use both the traditional channel and the electronic channel to a large extent, and are loyal customers. These people have a high cash flow and their accounts are likely to be related to their business. Based on to expectancy-value theory, although value motivates behavior, customer expectations customer expectations are also influential in customers' decisions about type of product or service to be purchased (Almsalam, 2014; Burcher et al., 2021). Thus, Service providers should identify and meet customer needs and expectations to increase their satisfaction throughout the service experience (Gures et al., 2014).

Table 5
Customers' average value.

Cluster	$R_TF_TM_T$						$R_EF_EM_E$					
	R_T	F_T	M_T	CLV	Members	Percentage	R_E	F_E	M_E	CLV	Members	Percentage
1	11.213	8.929	11.737	11.151	28,567	35.31	6.11	4.23	10.83	8.75	23,165	28.63
2	4.312	8.151	11.159	9.709	25,738	31.81	0.013	0.006	0.009	0.009	4072	5.03
3	0.032	0.025	0.172	0.121	4459	5.511	6.37	10.60	12.74	11.27	27,821	34.38
4	8.956	3.159	10.019	8.634	22,143	27.36	12.33	7.32	8.97	9.21	25,849	31.94
Weight	0.16	0.19	0.6497	–	80,907	100	0.17	0.20	0.64	–	80,907	100

Table 6
Two dimensional clustering.

		Electronic					
		cluster 1	cluster 2	cluster 3	cluster 4		CLV Traditional
Traditional	cluster 1	9.916	5.451	11.378	10.147	CLV	11.151527
		5.174	0.398	18.099	11.638	Percentage	
	cluster 2	8.933	4.271	10.787	9.420	CLV	9.7097383
		6.647	0.756	13.989	10.419	Percentage	
	cluster 3	4.046	2.238	5.339	4.459	CLV	0.1217719
		3.549	0.064	0.147	1.751	Percentage	
	cluster 4	8.584	4.088	9.893	8.969	CLV	8.6341522
		13.262	3.814	2.152	8.140	Percentage	
CLV Electronic		8.753508	0.009073	11.27083	9.206106		

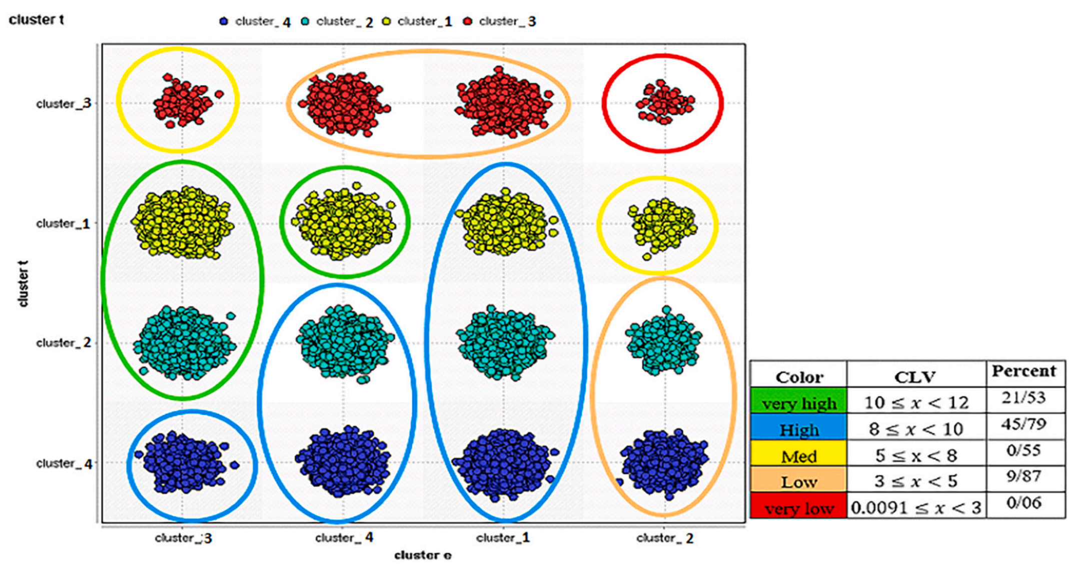

Fig. 2. Two-dimensional clustering.

5. Discussion & conclusion

Banks as one of the financial institutions that are in direct relationship with people require a deeper understanding of customers as the most important asset of their organization to increase their share in the competitive market and optimize the use of banking resources in providing services tailored to the needs of customers. With the introduction of electronic channels, this need has been increased, as various factors affect the use of these new banking channels. In this situation, customers have used both electronic and traditional services, and each has its own features. According to expectancy-value theory, customer value and expectations both affect customer buying behavior and should be considered by banking managers in designing their strategies. Better understanding of these features will help banks to provide customers with the services they need and, as a result, maintain them. Hence, this study for the first time used expectancy-value theory and proposed a two-dimensional approach to examine the behavior of customers in both electronic and traditional banking channels. To this end, customer buying behaviors were systematically analyzed based on their transaction data from both channels using RFM and K-Means clustering algorithms. Then customers were classified into four groups based on their buying behavior. Customer lifetime value was also calculated using Lawshe criteria, and then customers were classified and analyzed two-dimensionally. Using the proposed approach, 16 clusters were identified in which the cluster with the highest CLV in both traditional and electronic channels was identified as the highest and most valuable cluster.

According to the results, customers who use both electronic and traditional bank services are more valuable and should be targeted for banking purposes and strategies should be developed to maintain them. The results indicated that integrating traditional and electronic channels provides a deeper understanding of customer behaviors, which can be misdirected by considering only one dimension. However, according to expectancy-value theory, customers often judge a product, its benefits, and the possible consequences of using the product (Warsame, 2017), and customer value and expectations both affect customer buying behavior (Almsalam, 2014; Burcher et al., 2021) that should be considered by banking managers in designing their strategies.

5.1. Theoretical and practical implications

This study seems to be one of the pioneering researches for applying EVT and presenting a two-dimensional approach to study customer behavior in electronic and traditional banking and contributes to the body of literature on customer segmentation and valuation and advances the theoretical development and knowledge in understanding the customers' behaviors in both electronic and traditional banking and their value for banks through a two-dimensional approach.

The two-dimensional approach proposed in this study is easy to use and provides a two-sided view of the customer. This approach is significantly different from other research in this field and the innovation of this study is that it provides a more comprehensive knowledge and understanding of customer behavior. Using a two-dimensional approach can provide a better knowledge about different customer segments, which can help banks to enhance CRM activities. This study provides bank managers with useful information about customer behavior in both traditional and electronic channels. Using the proposed model, different banks can better classify their customers and provide a better understanding of the behavior of each group of customers, provide the services they need and thus retain customers. Besides, banks can use this framework to create transparent strategies to provide the right product/service to the right person. It can also assist decision-makers in planning better strategies and customer retention policies leading to cost reduction and revenue growth.

The results of the study can also be used to grant facilities, in such a way that the group value rating of each customer requesting the facility should be preferred as one of the input factors for measuring the customer's credit for granting the facility.

Today, there is a huge amount of information about customer transactions, including customer details, frequency of transactions, type and volume of transactions in the database of banks, and it is clear to marketers of these large enterprises that they can use this data in all aspects of customer relationship management.

Analyzing customer behavior in different industries such as banking, which are faced with a large number of customers with different natures and behaviors, is one of the goals of marketers and managers in the banking industry. In these industries, using the customer segmentation approach as one of the data mining techniques to divide heterogeneous customers into homogeneous groups with similar transactional behaviors, help to better understand customer behavior and communicate effectively with each segment of customers, which in turn will be useful in attracting and retaining customers, attracting new customers and ultimately the survival of these organizations.

Customer perceptions can vary depending on the situation, the customer mentality, the complexity of the structure, or the changes that take place over time (Potra et al., 2018). Therefore, “customer voice” should be considered in the design process, and after providing services, service providers should monitor the extent to which customer expectations are met. In banking also understanding the needs and expectations of customers and then developing high quality services that meet them will bring a competitive advantage over its competitors.

Bank managers must not only improve the quality of service and customer satisfaction, but also understand the value of the customer in their activities. Ignoring customer value may reduce customer satisfaction. By identifying different groups of customers, banks can design various services and products for customers of different groups, especially “valuable and loyal” customers. They can also explain the maintenance plans of “golden customers” who provide the bulk of the bank's resources.

In addition, customer satisfaction is an important prelude to customer loyalty. Bank managers who seek to ensure customer loyalty, first of all, must maintain the quality of service at a high level and provide customer satisfaction. So they may maintain customer loyalty. If customers become loyal to the bank, they may use the services of the same bank and establish a positive verbal communication by saying positive things about the bank.

In addition, the issue of value segmentation is important for a bank to coordinate and synchronize products and services with market trends, as well as to set goals such as profitability. If the bank is aware of its investment potential and capabilities, it will be more careful and knowledgeable in its strategic investments, and this will definitely help improve the bank's ROI (return on investment).

Considering the high economic and industrial potential of Iran, this country can save billions of Rials with the attention to the infrastructure of e-commerce and e-banking by reducing the cost and time of customer services. Developing appropriate communication infrastructures can be effective in e-baking usage. It should be noted that instead of paying high costs to attract new customers, the business should attempt to identify and maintain valuable and loyal customers. According to Perwangsa (2016) cultural issues are very important in developing a long-term relationship with customers in banks.

Bank management must understand that the image of banks is based on the unique customer experience to provide an acute environment for loyalty. And the customer experience, in turn, drives both his/her positive and negative advice. So a bank literally lives or dies based on how it treats its customers.

Management in the bank must understand that excellent customer service is not only about meeting customer needs, but also meeting their expectations. In highly competitive markets such as banking, failure to provide high quality services can lead to damage to reputation and business loss. Therefore, the need for stability and quality of banking services is felt.

The cost and time of customers will be reduced with the use of e-banking and the possibility of customer participation in banking operations will increase. Moreover, the services offered in electronic banking are very diverse compared with traditional banking. Therefore, bank managers should inform and introduce new services offered or being launched to take advantage of the capacities and capabilities of the electronic banking system.

5.2. Limitations and future research directions

Given that the policies and strategies of each bank are different in the provision of traditional and electronic services, the results of this study should be accompanied by considerations for banks and other financial institutions. Considering the enormous investment of the country's banking system, conducting similar investigations in other banks will bring about the alignment of approaches, programs, and policies to increase customer satisfaction. Therefore, it is suggested that this two-dimensional approach be examined in other branches of the bank and in other cities, and the results be compared with each other.

Considering the novelty of the two-dimensional approach in clustering, further research is needed in this area. Given that this research was conducted using the RFM method and did not use the demographic information of customers, it is recommended that the demographic information of bank customers and their lifestyle be used in future research. Also, customer surveys and scores provided to the performance of the bank should be collected and be used as an evaluation index in combination with other characteristics in order to evaluate the performance of different branches of the bank. Moreover, the use of other variables, such as Variety of products and services, can be the subject of future research. Additionally, variables such as geographical region and culture are effective on people's decision to adopt new technologies. Therefore, studying the impact of these factors on the use of banking electronic channels can lead to better results.

In addition, it is suggested that future studies develop the proposed model and predict how customers will receive services in the future. Besides, future studies are recommended to use other clustering methods to evaluate customer behavior in different channels.

The proposed approach of this study can be employed and adjusted in other industries. Therefore, it is suggested that future research expand the scope of the study to other industries and compare the results. Besides it is recommended that.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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