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A New Approach to Customer Classification According to a Hybrid Non-linear Bayesian and Quantum Approach

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Abstract

The present study explains a customer classification model according to Bayesian-quantum approaches. This study is applied-exploratory research. This study investigated the information of 98,604 customers of one of Iran's banks. Four approaches were used including data mining, fuzzy, quantum, and nonlinear Bayesian averaging. In this study, information on 22 indicators related to customers was entered into nonlinear Bayesian models. According to the error rate, the BMA model had the highest accuracy. According to the results, four features including account balance, total deposit balance, total current facility balance, and volume of financial transactions were used as the primary features for customer classification. The results showed that the C-MEANS approach has higher accuracy than K-MEANS. Then, according to the C-MEANS approach, 16 clusters were identified and the characteristics of each 16 clusters were analyzed. Thus, the selected variables of the Bayesian averaging approach were used in estimating quantum models. According to the results, the harmonic oscillator approach had higher accuracy than the geometric Brownian motion and Heston approaches. The harmonic oscillator approach of the quantum model has high accuracy in all groups and has higher accuracy in the categories where customers are more loyal.

Keywords: Banking services, Customer relationship management, Fuzzy clustering and data mining, Quantum.

Introduction

The customer is the most important asset in the banking business. Banks worldwide are trying to make their businesses customer-centric (Kalaivani & Sumathi, 2019). Thus, customer orientation according to a deep understanding of customer needs with the help of customer behavior analysis, service customization, offering products to meet the needs of different customers, providing outstanding services, flexibility in customer orientation (KhatamiFirouzabadi et al., 2018), easy access and relationship orientation to retain customers (Aslam et al., 2022), preventing deviation from deeper penetration in the market, preventing asset value decline, and increasing profitability with existing customers is a vital issue (Safabakhsh, & Asayesh, 2023). Innovation in the banking industry has always been of special importance thanks to its dynamic nature (Kinge et al., 2022). The emergence of the Internet was vital in this regard (Vidal & Kristjanpoller, 2020). The importance of data and information increased with the advent of

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the Internet and artificial intelligence (Theodoridis & Tsadiras, 2022). The data and information quality plays a critical role in making sound decisions by managers (Zoynul Abedin et al., 2023). Thus, the process of converting data into information is crucial (Liu et al. 2022; Yuan et al., 2022; Aslam et al., 2022), Thus, data mining is a new science for data exploration (Kalaivani & Sumathi, 2019; De Caigny et al., 2020; Jain et al., 2021; Chen et al., 2021; Alam et al. 2021).

Data mining plays a vital role in banks' capability to meet customer needs as it reduces customer churn (Clerkin & Hanson, 2021; Berggrun et al., 2020; Liu et al., 2022). It is possible to extract the characteristics specific to each customer group from content-free data (Yuan et al., 2022; Aslam et al., 2022). Identifying these characteristics leads to better customer segmentation and better service provision (Long et al., 2019; Abedin et al., 2020; Zhang et al. 2021). Thus, the primary goal of this article is to classify bank customers according to the characteristics of each group and the importance of each of these characteristics in the profitability of the bank in each group (Keramati et al. 2016; Yuan et al., 2022).

Results of recent studies indicate that statistical physics and its complex systems, including quantum mechanics, are one of the most robust tools in behavioral analysis. The advantage of quantum models over traditional models is that they often describe the impact of different conditions on customer behavior better. This better description leads to much more accurate modeling. Thus, the primary issue of the present study is to identify the most important customer characteristics and the way they affect bank profitability (Ramezani et al., 2024). Accordingly, the present study is organized in this way. The second section presents the theoretical foundations and domestic and foreign literature review. The third section presents the research methodology, including the models and data used. The fourth section presents the empirical findings from the model estimation. The fifth section presents the conclusions and recommendations.

Theoretical Foundations and Research Background

Converting data into information and using it to gain profit from this information is the most crucial reason for banks' tendency toward innovation. The data mining approach is a new movement in this area (Noei et al., 2023). Data mining leads to greater adaptation of services to customer needs and identification of active and inactive customers (Wojnarski, 2002; Abbasimehr & Shabani, 2021). It also leads to extracting customer behavioral patterns (Baumann et al., 2007; Noshabadi et al. 2023). It improves customer communication (Ghabouli et al., 2023; Chen et al., 2021) and makes the identification of the indicators that cause customer churn possible (Keramati et al. 2016; Kalaivani & Sumathi, 2019). De Caigny et al., 2020 examined customer churn datasets using data mining techniques. It leads to customer retention (De Caigny et al., 2020) and increases customer trust in banks. It also improves data resolution and reduces the consequences of the curse of dimensionality (Kashani Kikoo et al., 2024).

Quantum Theory

As a theory of quantum theory, a quantum agent is like a particle that is under the influence of a quantum potential well. In quantum mechanics, the particle-in-a-box problem, also known as the "infinite potential well", describes the situation of a free particle trapped in a small and impenetrable space, moves in it, and is unable to escape. In classical physics and mechanics, a particle trapped in a large box can take any speed and, in the simplest state, only travels one path until its energy runs out. Quantum behaviors become more apparent as the dimensions of the box decrease to a few nanometers. In this case, the particle can only occupy some positive energy levels and move in those levels. Therefore, it can never have zero energy (there is no zero-energy level). In the quantum state, the probability of finding the particle depends on the distribution function, which depends on the energy levels. Moreover, the particle may never be found at certain points called spatial nodes. The particle in the box problem is one of the quantum mechanical problems that can be solved analytically without the need for complex mathematical relationships. This problem, which is according to the quantized (discrete) nature of energy levels, gives us a good understanding of dealing with more complex problems and describing atomic and molecular systems (Charte et al., 2021). (Figure 1) illustrates a typical example of quantum potential energy created by a quantum particle (such as an atom).

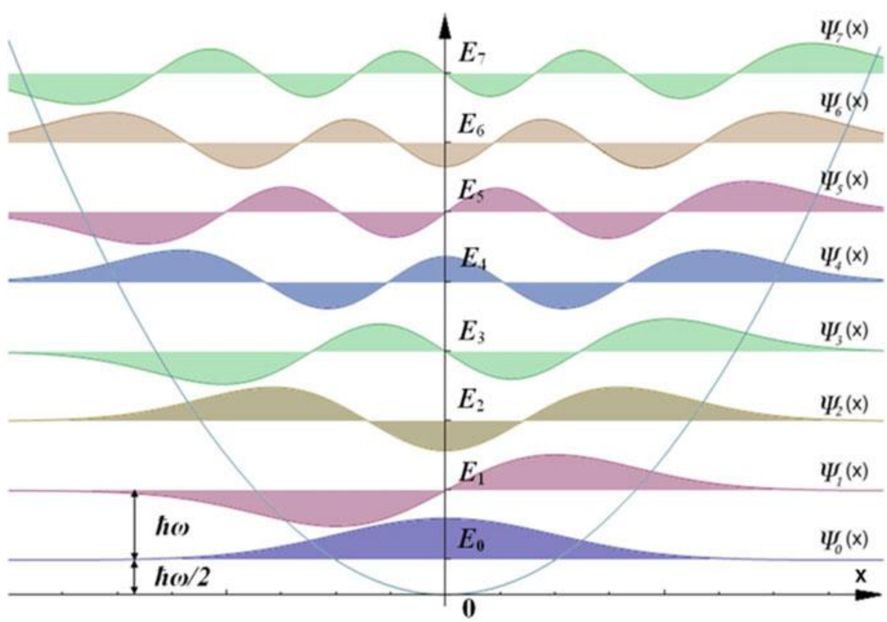

Figure 1. Quantum potential energy created by a quantum particle

Accordingly, the theory of quantum particles in quantum theory is well understood in the field of quantum theory and quantum particles.

Quantum Basic Components

Nowadays, various studies such as (Zadeh & Aliev, 2018) and (Lee, 2020) have indicated how quantum mechanics and quantum field theory can be used to model behaviors. Additionally, the study by (Lee, 2020) investigated how modern and advanced models such as artificial intelligence technologies such as artificial neural networks, fuzzy logic, genetic algorithms, chaos theory, and fractals can be integrated with the quantum model and implement intelligent systems in real-time. (Figure 2) illustrates the quantum concentric circles model. This model consists of the following layers (Lee, 2020):

Layer 1: This layer includes the energy field, the core, and the quantum field, which provide the quantum price field.

Layer 2: The chaotic neural network, which is used to generate financial quantum neural dynamics and support neural oscillators, and chaotic neural networks.

Layer 3: The financial technology artificial intelligence layer, which provides financial technology tools in the field of artificial intelligence. In other words, this layer supports fuzzy logic, genetic algorithms, chaos theory, fractal, and support vector machine models.

Layer 4: It is an applied layer supporting quantum price levels, short-term prediction, long-term trend prediction, and intelligent agent-based trading systems.

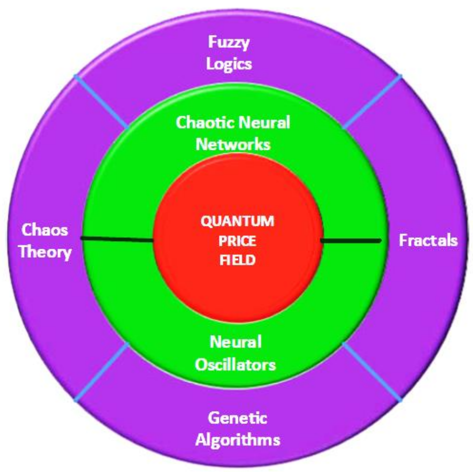

Figure 2. Concentric circles model for financial quantum
Source: (Lee, 2020)

Method and Material

This study was an applied and exploratory research. In this study, there were about 98,604 customers. The study models were estimated using Weka and MATLAB software. The following approaches were used in this study (Table 1).

Table 1. Applied models in the study

Row	Model	Definition	Application
Classification of customers	K-Means	K-means	It is an iterative algorithm that divides the unlabeled set into k different clusters such that each cluster belongs to only one group that has similar features.
Classification of customers	Means - C	C-means	In this approach, fuzzy properties are used to classify data.
Considering uncertainty in extracted information	Type-3 fuzzy	Type 3 Fuzzy	Considering the issue of uncertainty in the scoring of factors affecting customer differentiation by experts

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Identifying the best characteristics of bank customers	BMA, TVP-DMA, TVP-DMS	Nonlinear Bayesian Models	Selecting the most important characteristics of bank customers
(Modeling approaches)	PCA	Principal Component Analysis	Indexing customer characteristics
Component builder	Quantum	Quantum	Investigating the impact of the most important characteristics of bank customers on profitability

The research variables are presented below according to the extracted characteristics (Table 2).

Table 2. Characteristics of the extracted variables

Variable type	Variable	Description
Dependent variable	Customer profitability index	Revenues minus costs for each customer are used to calculate the customer profitability index (It should be noted that not all items presented in this index include all customers). Customer revenues Customer low-cost account balance (current in the short term) Revenue from obtaining facilities (interest paid to the bank) Revenue from providing general services to the customer Average of low-cost customer accounts (current in the short term) Revenues from obtaining facilities (interest paid to the bank) revenues from providing general services to the customer revenues from providing specialized banking services (fees) revenues from issuing guarantees and other obligations revenues from handling VIP customer affairs as a proxy revenues from customer affairs Customer expenses revenues received from the bank for long-term investment capital Commission discounts due to the being a VIP customer Expenses due to providing services to VIP customers such as customer club services, airport CIP Expenses for doubtful and non-current receivables Expenses due to failure to fulfill obligations on due date
Explanatory variable	Personal characteristics: Gender	If male, it is one, otherwise, it is zero.
	Personal characteristics: Age	Age ranges from 1 to 85 years
	Account Opening Date	Account opening day
	Account type	Qarz al-Hasan Savings Deposits (Number 0) Short-term Deposits (Number 1) Long-term Deposits (Number 2) Qarz al-Hasan Current Account (Number 3)
	Date of last customer visit	Date of last visit to Internet Banking or in-person visit to the branch
	Account status	Active number one Retard number zero

	Account usage period	Account active period
	Account points	The number of points awarded to the account based on the mean of the account from 1 to 10
	Account balance	Account balance at reporting in million Rials
	The period between the first and last customer visit	Length of using account
	Number of transactions during the period	Number of transfers or deposits to the account
	Checkbook status	There is a checkbook on the account: one, otherwise, zero
	Number of facilities	Number of short-term and long-term facilities
	Facility type	1-Qard-al-Hasan loan; 2. Marriage loan; 3. Housing loan; 4. Mudaraba loan; 5. Loan for the purchase of goods; 6. Loan for the purchase of raw materials; 7. Loan for the purchase of a car; 8. Pensioner loan; 9. Qard-al-Hasan loan for a child; 10. Home repair loan; 11. Self-employment loan; 12. Student loan
	Number of arrears	Number of periods in which the facility payment was not made on its due date
	Volume of financial transactions	Rial amount of transfer or deposit to the account
	Number of deposits	Number of accounts of a person
	Total balance of deposits	Mean deposit balance in the study period
	Number of current facilities	Number of active facilities that the person has in the study period
	Total balance of total current facilities	Current facility balance of the person
	Total arrears	Rial amount of facility installment payment that was not made on its due date
	Date of last claims	Last due date for three consecutive months

Results

Model Estimation

See the article by (Kashani Kikoo et al., 2024) (Table 3) to extract the desired features for customer classification according to the nonlinear Bayesian approach.

Table 3. The second stage of the sampling process and calculations assuming $\bar{K}$=5

Variable	The first sample includes 1,000 regressions.		The first sample includes 2,000 regressions.	
	Prior coefficient	Prior probability	Posterior coefficient	Posterior probability
Account Balance	0.496	0.530	0.151	0.677
Financial Transaction Volume	0.145	0.606	0.224	0.866
Total Deposit Balance	0.070	0.759	0.224	0.988
Total Current Facility Balance	0.225	0.226	0.052	0.571

Source: Researcher's calculations

According to the nonlinear Bayesian approach, the variables of account balance; total deposit balance; total balance of current facilities; and volume of financial transactions were determined as the most important characteristics of customers for their classification.

Determining the Optimal Cluster

After determining the influential indicators of customer clustering, it was necessary to determine the number of clusters. (Table 4) presents the optimal number of clusters, the average silhouette coefficient using two algorithms, K-Means, and fuzzy C-Means.

Table 4. Mean silhouette coefficient using K-Means and fuzzy C-Means algorithms

Log number	k-means	fuzzy C- Means
2 clusters	0.8703	0.8723
3 clusters	0.7745	0.7935
4 clusters	0.7355	0.7482
5 clusters	0.7106	0.7003
6 clusters	0.6909	0.6839
7 clusters	0.6705	0.6394
8 clusters	0.5995	0.6183
9 clusters	0.6342	0.5934
10 clusters	0.6982	0.5582
11 clusters	0.7150	0.5255
12 clusters	0.7835	0.5184
13 clusters	0.8245	0.7394
14 clusters	0.7222	0.7573
15 clusters	0.6932	0.8284
16 clusters	0.6533	0.9203
17 clusters	0.6286	0.9043
18 clusters	0.6074	0.8432
19 clusters	0.5873	0.7447
20 clusters	0.5534	0.6462

Source: Researcher's calculations

According to the results, 13 clusters in the K-Means state and 16 clusters in the Fuzzy Means-C state were selected as the optimal clusters. (Table 5) presents the error rate of each of the above approaches.

Table 5. Comparison of the accuracy of the K-Means and Fuzzy Means-C models

Log number	k-means	means - c fuzzy
RMSE	0.1384	0.0936

Source: Researcher's calculations

According to the model error results, the accuracy of the Fuzzy Means-C model is higher than the accuracy of the K-Means model (Figure 3) and (Figure 4).

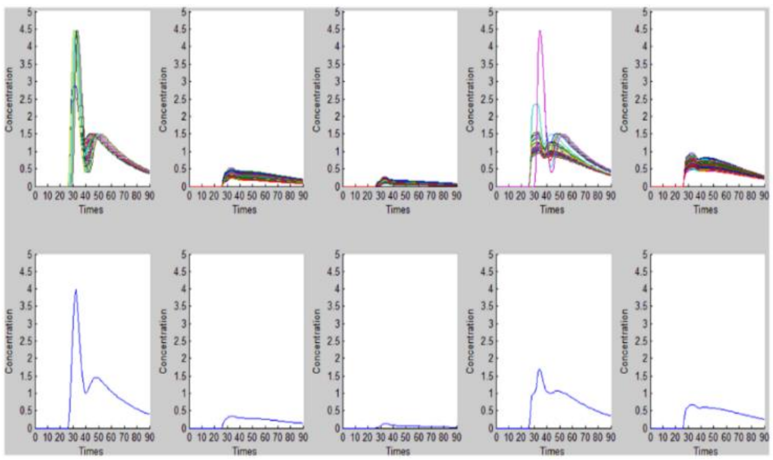

Figure 3. Fuzzy Means-C results in different clusters
Source: researcher calculations

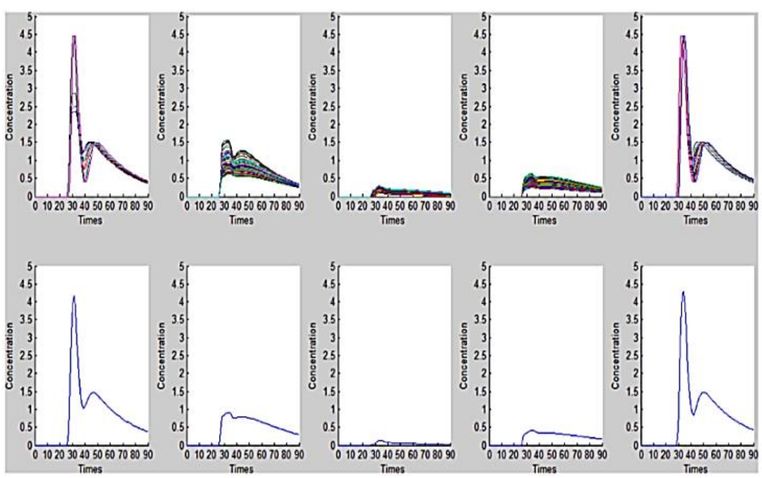

Figure 4. K-Means results in different clusters
Source: Researcher's calculations

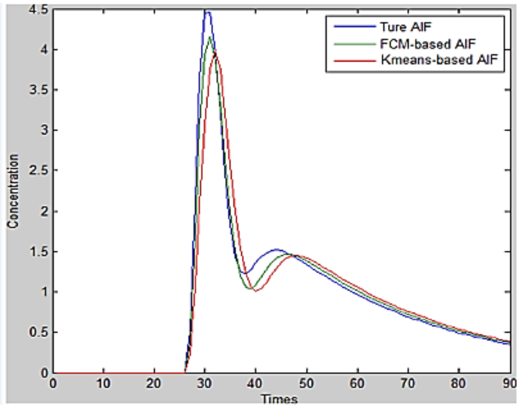

Figure 5. Comparison of results of K-Means and Fuzzy C-Means models
Source: Researcher's calculations

According to (Figure 5), the fuzzy Means-C model has a higher capability to cluster data according to real data. Using the Means-C approach, customers are divided into 16 categories according to the 4 extracted dimensions. (Table 6) shows the categories extracted from this stage. (Table 6) presents the mean features.

Table 6. Mean values of the 4 indicators for each group and type of customer groups

Scenario	Approach			
1	L lower than mean	R lower than mean	F lower than mean	M lower than mean
2	L lower than mean	R lower than mean	F lower than mean	M higher than mean
3	L lower than mean	R lower than mean	F higher than mean	M lower than mean
4	L lower than mean	R lower than mean	F higher than mean	M lower than mean
5	L lower than mean	R lower than mean	F lower than mean	M lower than mean
6	L lower than mean	R lower than mean	F higher than mean	M higher than mean
7	L lower than mean	R higher than mean	F lower than mean	M higher than mean
8	L lower than mean	R lower than mean	F lower than mean	M higher than mean
9	L lower than mean	R higher than mean	F higher than mean	M lower than mean
10	L lower than mean	R higher than mean	F higher than mean	M lower than mean
11	L lower than mean	R higher than mean	F lower than mean	M lower than mean
12	L lower than mean	R higher than mean	F higher than mean	M higher than mean
13	L lower than mean	R lower than mean	F higher than mean	M higher than mean
14	L lower than mean	R higher than mean	F lower than mean	M higher than mean
15	L lower than mean	R higher than mean	F higher than mean	M lower than mean
16	L lower than mean	R higher than mean	F higher than mean	M higher than mean

Source: Researcher's calculations

Note: Green: indicates loyal customers; Orange: indicates relatively loyal customers; Yellow: indicates non-loyal customers; Red: indicates unrealistic customers

Estimating customer recognition models according to quantum models

Before estimating the model, it is necessary to identify the type of quantum that matches the research data. There are three primary types of quantum approaches. (Table 7) presents the accuracy of these three approaches.

Table 7. Prediction performance criteria in different quantum approaches

Model		Description	MAFE	MSFE
Deep Neural Network	LSTM	Long short-term memory neural network	0.0013	0.0101
	RNN	Recurrent Neural Network	0.0017	0.0205
	CNN	Convolutional Neural Networks	0.0019	0.0273
Traditional Approaches	OLS	Ordinary Least Squares	0.0762	0.0341
	GLS	Generalized Least Squares	0.0573	0.0246
	NLS	Nonlinear Least Squares	0.0426	0.0217
Quantum Physics	GBM	Geometric Brownian Motion	0.0010	0.0114
	Heston	Heston	0.0012	0.0062
	QHO	Quantum Harmonic Oscillator	0.0009	0.0049

According to the results, the quantum harmonic oscillator approach has higher accuracy than other approaches. Thus, customer behavior simulation was performed using this approach. (Figure 6) illustrates the movement of customer behavior simulation. According to the results, the accuracy of the model moved toward one (vertical axis) with the increase in the improvement of customer behavior simulation according to customer characteristics.

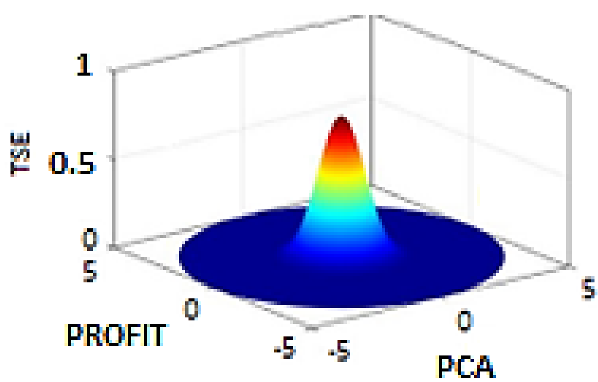

Figure 6. Behavioral match maximization process in the quantum model

(Table 8) presents the simulation of the quantum model results in different classes.

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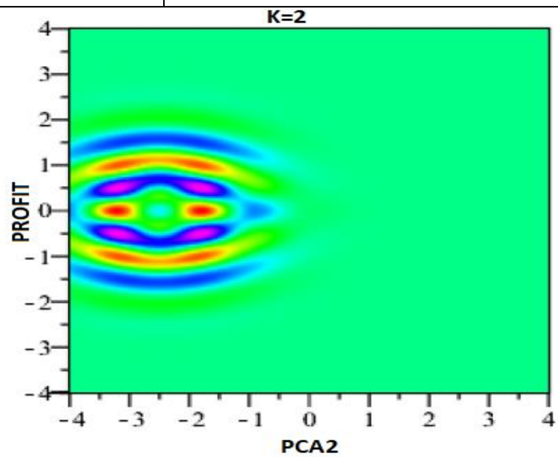
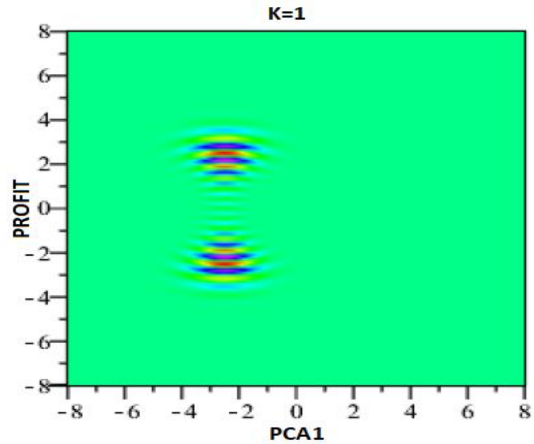
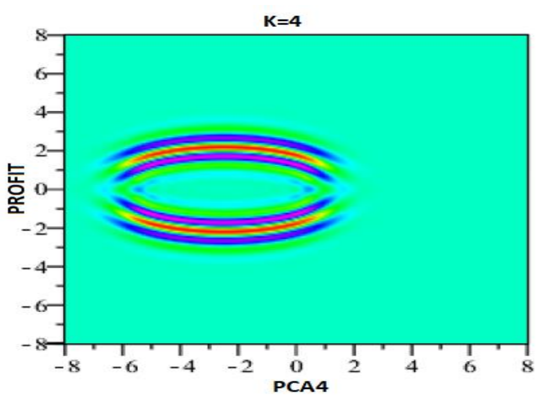
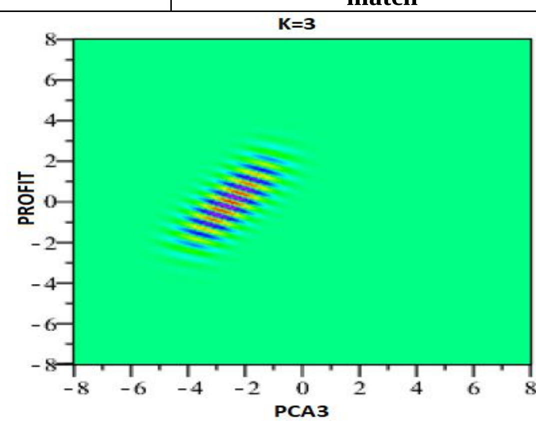
Table 8. Results of different groups

Second group		**First group**	
Impact size	**variable**	**Impact size**	**variable**
-0.369	**Account balance**	**-0.376**	**Account balance**
-0.307	Total deposit balance	0.1887	Total deposit balance
0.362	Total current facility balance	-0.1285	Total current facility balance
0.196	Financial transaction volume	-0.1775	Financial transaction volume
0.8361	**Level of simulated behavior match**	**0.8284**	**Level of simulated behavior match**
			
Fourth group		**Third group**	
Impact size	**variable**	**Impact size**	variable
-0.392	**Account balance**	**-0.311**	Account balance
0-0954	Total deposit balance	0.048	Total deposit balance
0.087	Total current facility balance	0.129	Total current facility balance
0.224	Financial transaction volume	0.166	Financial transaction volume
0.8251	**Level of simulated behavior match**	**0.8396**	**Level of simulated behavior match**
			
Sixth group		**Fifth group**	
Impact size	**variable**	**Impact size**	variable
0.385	**Account balance**	**-0.245**	Account balance
0.245	Total deposit balance	-0.179	Total deposit balance
-0.140	Total current facility balance	0.138	Total current facility balance
0.341	Financial transaction volume	0.164	Financial transaction volume

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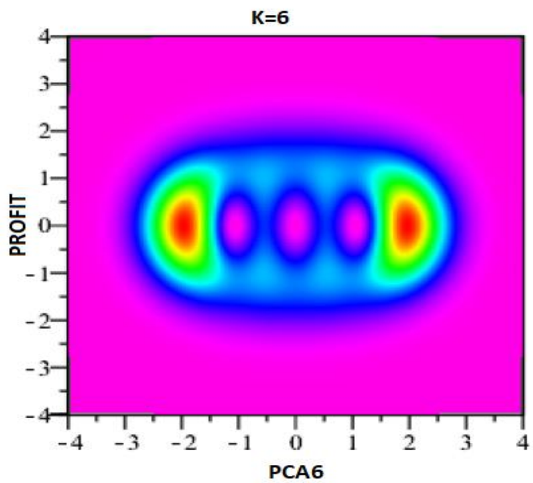
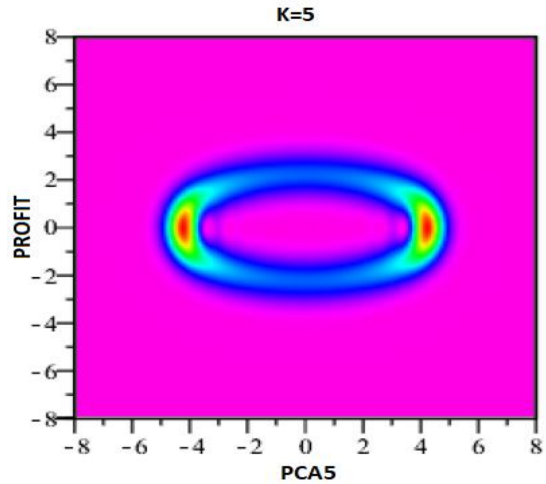
<tr><td colspan="2">
</td><td colspan="2">
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<tr><td>Impact size</td><td>variable</td><td>Impact size</td><td>variable</td></tr>
<tr><td>0.102</td><td>Account balance</td><td>0.225</td><td>Account balance</td></tr>
<tr><td>0.394</td><td>Total deposit balance</td><td>0.306</td><td>Total deposit balance</td></tr>
<tr><td>0.368</td><td>Total current facility balance</td><td>0.241</td><td>Total current facility balance</td></tr>
<tr><td>0.355</td><td>Financial transaction volume</td><td>-0.113</td><td>Financial transaction volume</td></tr>
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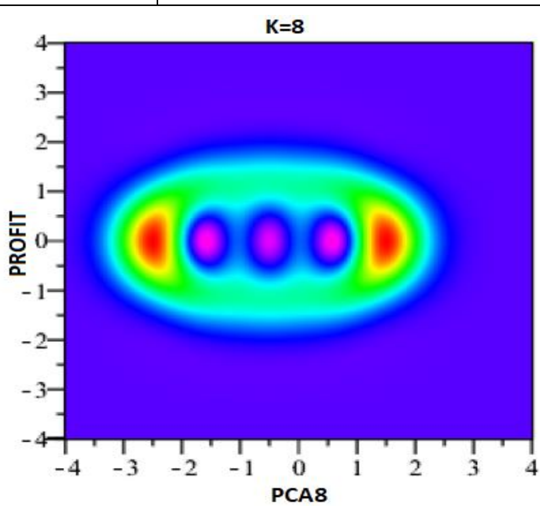
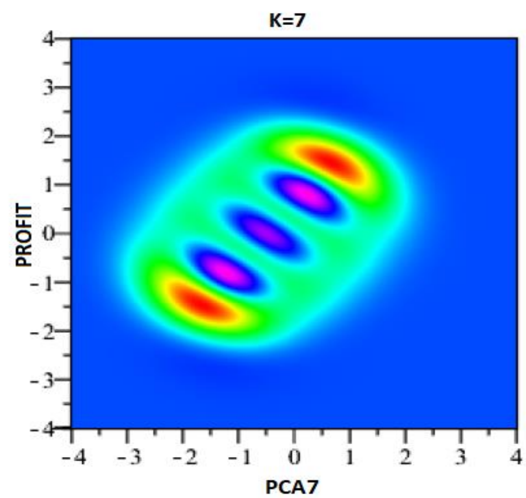
<tr><td colspan="2">
</td><td colspan="2">
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<tr><td>Impact size</td><td>variable</td><td>Impact size</td><td>variable</td></tr>
<tr><td>0.101</td><td>Account balance</td><td>0.141</td><td>Account balance</td></tr>
<tr><td>0.174</td><td>Total deposit balance</td><td>0.405</td><td>Total deposit balance</td></tr>
<tr><td>0.459</td><td>Total current facility balance</td><td>0.265</td><td>Total current facility balance</td></tr>
<tr><td>0.282</td><td>Financial transaction volume</td><td>0.199</td><td>Financial transaction volume</td></tr>
<tr><td>0.906</td><td>Level of simulated behavior match</td><td>0.890</td><td>Level of simulated behavior match</td></tr>
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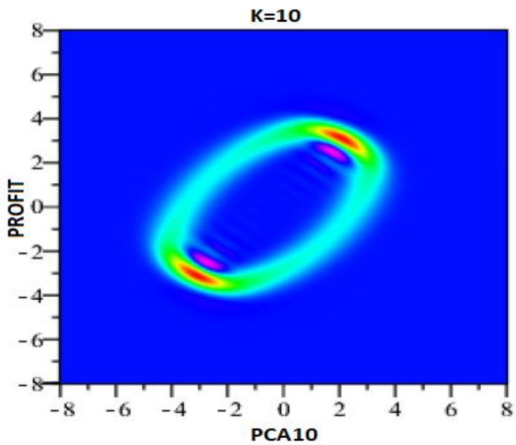
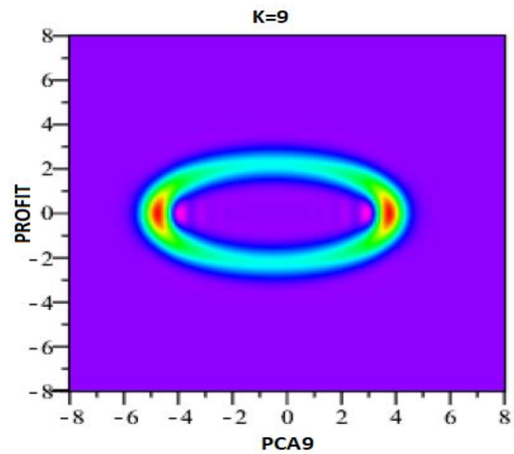
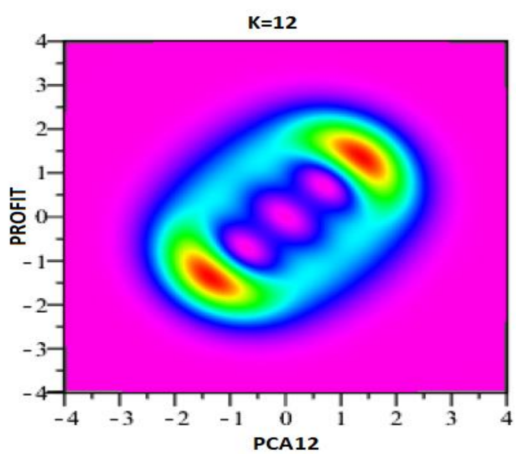
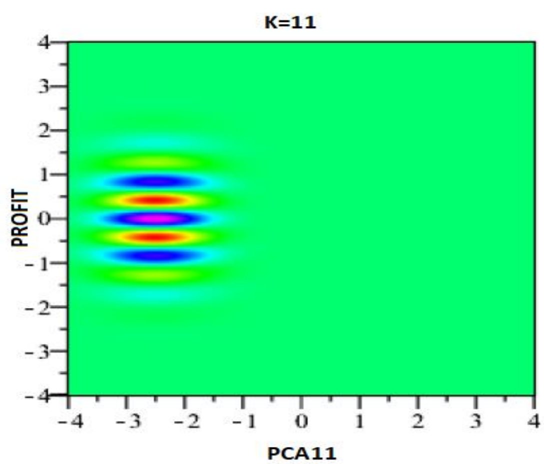


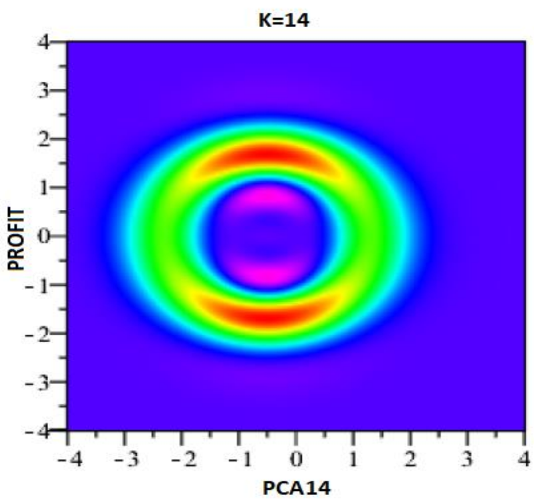


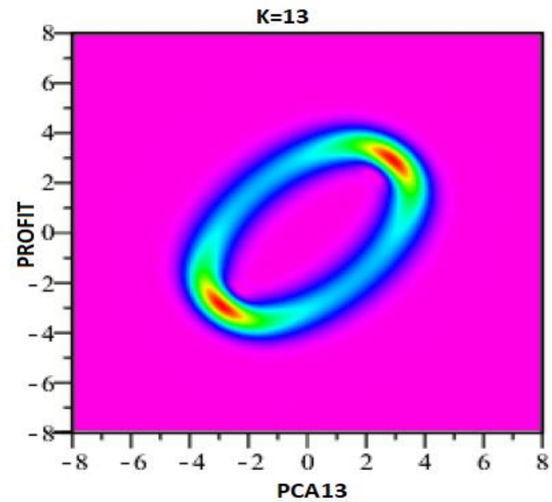
Twelfth group		Eleventh group	
Impact size	**variable**	**Impact size**	**variable**
0.609	**Account balance**	**-0.259**	**Account balance**
0.575	Total deposit balance	-0446	Total deposit balance
0.695	Total current facility balance	0.247	Total current facility balance
0.554	Financial transaction volume	0.705	Financial transaction volume
0.948	**Level of simulated behavior match**	**0.816**	**Level of simulated behavior match**



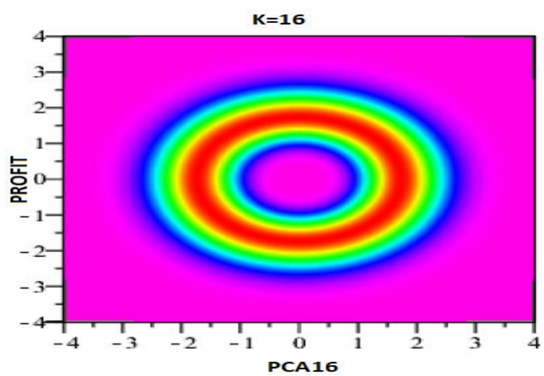


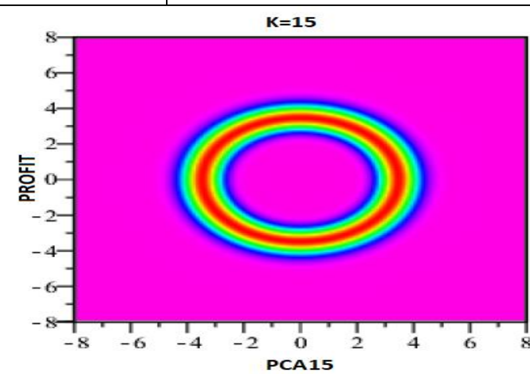
Fourteenth group		Thirteenth group	
Superior model: Ant Colony		**Superior model: Harmony Search**	
Impact size	**variable**	**Impact size**	**variable**
0.909	Account balance	0.466	Account balance
0.813	Total deposit balance	0.683	Total deposit balance
0.722	Total current facility balance	0.619	Total current facility balance
0.589	Financial transaction volume	0.590	Financial transaction volume
0.984	**Level of simulated behavior match**	**0.959**	**Level of simulated behavior match**





Fifteenth group		**Fifteenth group**	
Impact size	**variable**	**Impact size**	variable
0.927	Account balance	0.824	Account balance
0.842	Total deposit balance	0.725	Total deposit balance
0.935	Total current facility balance	0.611	Total current facility balance
0.616	Financial transaction volume	0.582	Financial transaction volume
0.966	**Level of simulated behavior match**	**0.973**	**Level of simulated behavior match**





According to the matching results, the quantum approach has high accuracy in all groups and has higher accuracy in the categories where customers are more loyal. More concentrated circles indicate the higher desirability of identifying the behaviors affecting each category.

Discussion and Conclusion

In this study, the BMA model had the highest accuracy according to the error rate. After estimating the model, four primary variables were identified. According to the results, the variables of account balance, total deposit balance, total balance of current facilities, and volume of financial transactions were identified and defined as non-fragile variables.

Then, the results revealed that 16 clusters were identified in the C-MEANS approach, and the characteristics of each 16 clusters were analyzed. Finally, the impact of each variable in each cluster was examined according to the three quantum models. According to the matching results, the quantum harmonic oscillator approach has high accuracy in all groups and has higher accuracy in the categories where customers are more loyal. According to the results, the following recommendations can be presented:

1- Since several variables affect customer clustering and their importance in each cluster can be different, in the designed recommender system for each cluster, the influential and non-fragile variables should be identified and recommendations should be provided depending on the non-fragile variables of each indicator.

2- Since the probability of occurrence of each variable changes over time in Bayesian models, the weight of each factor in each cluster will be variable. It is necessary to review the dynamic enough in the designed recommender system to allow for customer change in clusters.

3- Since there are different approaches to clustering customer variables and each of the approaches provides a different number of optimal clusters, using dynamic averaging models of customer clusters can help the bank avoid being misled in providing recommendations to different clusters.

4- Since the intensity of impact and significance is different in different clusters, policy recommendations should be provided in each cluster based on the level of impact and significance of the relevant indicator.

5- Due to the higher accuracy of type 3 fuzzy models in the present study and according to Gaussian and triangular data distributions, it is necessary to provide recommendations based on the level of risk-taking of customers from appropriate distributions that can cover and identify types of risk from customers.

6- Due to the dependence of each cluster on the account balance variable and the positive impact of this variable on improving the position of each cluster in bank income generation, the recommendation system considers recommendations such as the use of facilities with flexible repayments and dependent on the amount of long-term account balance.

7-Given the results of the quantum approach, it was concluded that this model has a high capability to simulate the behavior of bank customers. Thus, the use of quantum-based approaches is more accurate than traditional approaches. Accordingly, it is recommended that quantum-based approaches be used instead of traditional approaches to simulate customer behavior in banks.

8- It is recommended to identify and segment customers according to their level of participation and loyalty and implement different strategies and actions for each segment to optimally utilize resources and gain more value from customers. If banks seek to optimally utilize their resources and gain more value from customers, they should adopt the customer segmentation strategy according to their relationship models and provide personalized services to customers. All branches should invest in the customer participation value to gain direct customer participation (customer lifetime value). However, they should be cautious about customers with market pricing relationship models. However, branches that seek to gain customer knowledge value should invest more in customers with collective and non-social relational models. Branches with a higher interest in gaining customer influence value should seek customers with an equal matching relational model.

9- Using modern communication technologies to gain more value from customers: Since advanced communication technologies create an appropriate infrastructure for transferring experiences and facilitating customer participation, it is recommended that banks employ all modern communication channels such as telephone banking, mobile banking, social networks, etc. so customers can easily participate in the value creation process for the company using these technologies in the form of sharing their experiences with others, conducting word-of-mouth advertising, and providing ideas and feedback.

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