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Selecting Smart Strategies Based on Big Data Techniques and SPACE Matrix (FASE model)

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Abstract. One of the most important questions for managers of corporations is how they select a smart strategy for their corporations. To answer this question, Managers should consider some dimensions witch impact on the future of the corporation, and then they select a suitable strategy for their corporations. This paper presents a novel model (FASE model) for evaluating strategic position and choosing smart strategy based on Big Data techniques and SPACE matrix. In order to achieve the best position in the market, FASE model facilitates selecting the best strategy among: aggressive, conservative, defensive, and competitive strategies. FASE model consists of three main processes namely Fuzzy-Cmeans, Apriori association rule inducer, SPACE matrix. Fuzzy-Cmeans algorithm is used for clustering customers based on RFM values and behavioral scoring. The results of the clustering were then profiled on customers' attributes using Apriori association rule inducer. A SPACE matrix was used to evaluate the strategic position and to choose smart strategy. To get a better understanding of the FASE model, the banking case has been selected and FASE model is applied over that.

***Keywords*:** Big Data, smart strategy, Fuzzy-Cmeans, Apriori algorithm, SPACE matrix.

Big Data ve SPACE Matris Yöntemlerine Dayalı Akıllı Stratejiler Belirlenmesi (FASE Model)

Özet. Şirket yöneticileri için en önemli sorulardan biri, şirketleri için akıllı bir stratejiyi nasıl seçtikleridir. Bu soruyu cevaplamak için yöneticiler, kurumun geleceği üzerinde etkisi olan bazı boyutları göz önünde bulundurmalı ve ardından şirketleri için uygun bir strateji seçmelidir. Bu makale, stratejik pozisyonu değerlendirmek ve Büyük Veri teknikleri ve UZAY matrisini temel alan akıllı bir strateji seçmek için yeni bir model (FASE modeli) sunmaktadır. Piyasadaki en iyi pozisyonu elde etmek için FASE modeli, en iyi stratejiyi seçmeyi kolaylaştırır: saldırgan, muhafazakâr, savunmacı ve rekabetçi stratejiler. FASE modeli, Fuzzy-Cmeans, Apriori birlik kural uyarıcısı, UZAY matrisi olmak üzere üç ana işlemden oluşur. Fuzzy-Cmeans algoritması, müşterileri RFM değerlerine ve davranışsal puanlamaya dayalı olarak kümelemek için kullanılır. Kümelenmenin sonuçları daha sonra Apriori birlik kural uyarıcısı kullanılarak müşterilerin özelliklerine göre şekillendilir. Stratejik pozisyonu değerlendirmek ve akıllı bir strateji seçmek için UZAY matrisi kullanılır. FASE modelini daha iyi anlamak için, bir bankacılık vakası seçildi ve bunun üzerine FASE modeli uygulandı.

***Anahtar Kelimeler*:** Büyük veri, akıllı strateji, Fuzzy-Cmeans, Apriori algoritması, UZAY matrisi.

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1. INTRODUCTION

The concept of competition is vital and decisive for corporations that offer goods and services to customers in the oligopoly market. Any competitive corporation that has perfect connectivity with its market has to choose favorable competitive strategy to attain sustainable competitive position in the market. Competitive strategy can be understood as the collection of decisions and actions strategic managements undertake to lead corporations to gain a sustainable competitive advantage in a particular industry [1]. Many techniques and tools were developed for strategic management, e.g. Chen et al proposed analytical SWOT method that used strength, weakness, opportunity, and threats dimensions [2], Kangas et al. have used AHP technique to SWOT analysis [3], Paiva et al proposed a framework of manufacturing strategy process from a resource-based view [4], Yüksel and Dagdeviren utilized ANP to SWOT analysis to solve complex problems [5]. Aslan et al proposed SWOT can be applied to create TOWS (Threats-Opportunities-Weaknesses-Strengths) matrix in order to deploy strategies [6], A PEST analysis political, economic, social and technological dimensions [7], PESTLE model classifies issues as political, economic, social, Technological, legal and environmental [8], Zalengera et al implement PESTLE analysis for sustainable development of renewable energy [9]. All of the mentioned models should identify various dimensions that impact on strategic management. Due to the fact that identifying various dimensions that impact on corporation's strategy is so challenging, selecting favorable competitive strategy is very difficult for managers. As competitive conditions grow ever more turbulent, the importance of developing and using Big Data techniques appears to be increasing exponentially. The most important question for firm managers is that how they can make a connection between the Big Data technique and strategy. This paper presents a novel model for evaluating strategic position and choosing smart strategy (ESP&CSS) based on Big Data techniques and SPACE matrix. The proposed model has two main parts: Big Data techniques and SPACE matrix.

In this decade, Big Data technology has not only a great popularity in the research area but also in business world. This technology supports manager for A better understanding of business environment. Big Data technology can help corporations to demystify meaningful trends, patterns, relationships and correlations in their customers' behavior, products, services, and data. It also can support managers to evaluate strategic position and then selecting favorable competitive strategy. The Big Data techniques include classification, clustering, Sentiment analysis, association rules, Social network analysis, regression analysis, rule-based reasoning approach, genetic algorithms, decision trees, etc. The proposed model gets benefit from the advantages of Fuzzy-Cmeans algorithm and Association rules method.

There are many methods for developing organizational strategies that were formed based on the matrixes. For instant the strength, weakness, opportunity, and threats (SWOT) matrix or Boston Consulting Group (BCG) method that is a portfolio planning model, GE Matrix that is an extension of the BCG-matrix, or Growth-share matrix which involves portfolio decisions about priority and resources [10, 11, 12]. The Strategic Position & Action Evaluation (SPACE) matrix [13] is one of the most popular methods that can be considered as a supportive dimension in strategies development trend because of its speed in finding the competitive position of an corporation to determine what type of a strategy it should undertake. The proposed model uses Fuzzy-Cmeans algorithm, Association rules method, and SPACE matrix that is called FASE model.

To gain a better understanding of FASE model, this study is organized as follows. Section 2 explains the proposed novel model that is an integrated Big Data techniques and SPACE matrix. Section3 exhibits four processes of FASE model: first, explains how to make a preprocessing on data and after that how to extract RFM values and CBT value, Second, gives a thorough illustration of Fuzzy-Cmeans as a tool for clustering the customer using CBT value and RFM scoring variables, third, presents processes of creating cluster profiles using Apriori association rule inducer, fourth, explicates processes of evaluating strategic position and choosing smart strategy using SPASE matrix. Finally, conclusions are made in section 4.

2. RESEARCH MODEL

This research presents the FASE model for evaluating strategic position and choosing suitable strategy based on Big Data techniques and SPACE Matrix. As showed in Fig. 1; FASE model can be divided into five processes: (1) selecting the customer's dataset and data preprocessing (2) extracting RFM values as some of the input attributes for Big Data clustering algorithms (3) clustering customers based on c-means algorithm (4) Finding frequent patterns, associations, correlations, or causal structures from a cluster of customers using the Apriori algorithm. (5) Finally, determining what type of strategy a company should undertake using SPACE matrix method; Input of this process is the outcome of the analysis of strategic managers and Big Data mining methods. The details of the FASE model process are presented step by step as follows:

Process 1: selecting the customer's dataset and data preprocessing: At first, we select the customer's dataset and then preprocess the data to put it in a form that is most useful to the clustering algorithm. Thus, firstly we remove the attributes which include missing values or inaccurate values, eliminate the redundant attributes, normalize all numeric values in the dataset and transform the raw data into a format that will be more effectively processed for clustering customer.

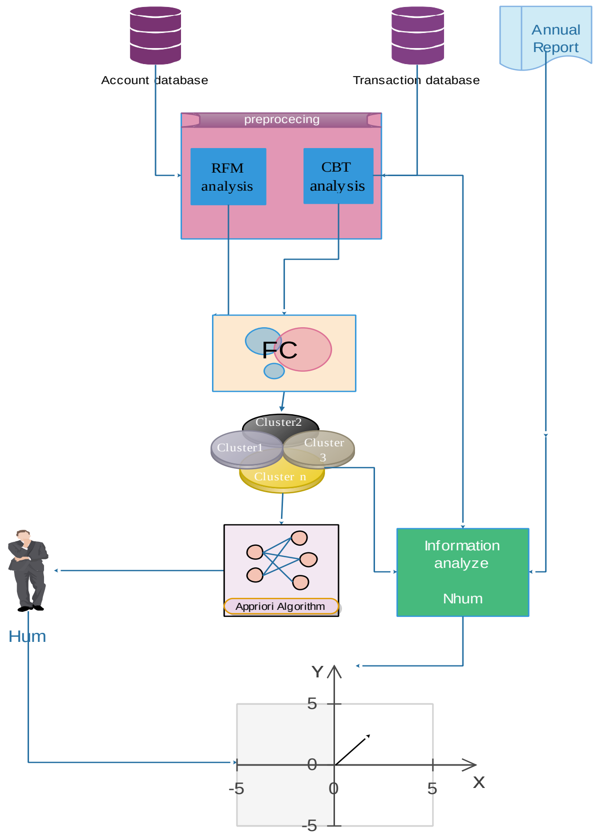

Figure 1. FASE model for evaluating a strategic position and selecting a smart strategy.

Process 2: extracting RFM values: RFM values are defined as follow: recency (R) of the last purchase, frequency (F) of the purchases over a specific time and Monetary (M) value of the purchases in a specific period time. RFM values are calculated for every customer as one of the behavioral scoring elements affecting customer segmentation.

Process 3: clustering customers. Customers are divided to clusters by Fuzzy-Cmeans method. Input of this method involves RFM values and some important attributes that impact on strategic decisions. Output of this process is membership values that indicate the degree to which every customers belong to each cluster.

Process 4: Finding association rules. FASE model finds association rules from clusters of customers by Apriori algorithm. This algorithm applies on each cluster and Inputs of this algorithm are RFM values and some important attribute values of each cluster. Also, the MinConf element and MinSup element determine the accuracy of the required rules. The extracted association rule is used to create profile of each cluster. These created profiles are used by strategic managers to realize their customer's behaviors.

Process 5: determining strategy: in final process, FASE model evaluates strategic position and chooses high performance strategy for a corporation based on SPACE matrix method. SPACE analysis matrix is a super technique for assessing the sense and wisdom in a particular strategic plan. The SPACE matrix contains the internal dimensions (Competitive Advantage (CA) and Financial Strengths (FS)) and external dimensions (Industry Strengths (IS) and Environmental Stability (ES)). In this process, internal dimensions and external dimensions are evaluated to find the strategic position of the corporation and then select smart strategy.

3. DETAILS OF THE RESEARCH MODEL

3.1. Data preprocessing

In this study we do not only describe the FASE model in detail but also, we apply our model on a banking dataset (Fig. 2). Banking datasets were provided by an Iranian debit card issuer. These datasets contain customers transaction dataset, customers profile dataset and financial annual reports data set. Customers profile dataset consists of effective debit card account information of 85,341 customers until November 2014. Customers transaction dataset consists of over than 64.32 million individual transaction records from September 2012 to November 2014. Obviously, all of data are not related to the chosen object, so extraction of knowledge from the banking datasets included the following three sub-processes. In the first sub-process, two datasets are integrated on a column to create a single dataset. Then the second sub-process was intended to extract only that data useful for the big data algorithms. Dataset contains unnecessary data fields and records which are removed. The next sub-process, the raw data, is transformed into a numeric format and then all of data in the dataset are normalized to a constant scale which will be more effectively processed.

Data preprocessing is a Big data technique that involves transforming raw data into an understandable format. This process prepared data to extract RFM values. RFM analysis [14] model is a marketing model that provides effective variables for customer segmentation. The model consists of three variables that are customer recent consumption, frequency and money amount. The definition of RFM analysis model is described as follows:

1) R represents recency of the last purchase that refers to the time interval between the last customer consumption and current.
2) F represents frequency of the purchases that refers to the number of transactions over a specific period of time.
3) M represents monetary value of the purchases that refers to the cumulative total of money spent for products by a particular customer in a specific period.

Recently, researches have proposed WRFM, RFMTC and LRFMC instead of RFM. WRFM model is a novel method that allocated weights to RFM variables using natural characteristics of an industry; Therefor disparate weights should be assigned to RFM variables. For instance, Stone [15] suggested that ordered weights should be assigned to RFM variables. he suggested highest weighting on the Frequency, followed by the Recency, with the lowest weighting on the Monetary variable. However Chuang et al. suggested that Recency had the least value and then Frequency higher value and Monetary had the most value [16]. Farajian suggested that Monetary and Frequency have more value than Recency [17]. In some researches, weights of RFM variables were ascertained by analytic hierarchy process (AHP) [18]. RFMTC model used to develop RFM model and added two parameters to these three parameters [19]. These parameters are “time since first purchase” and “churn probability” that are exploited using Bernoulli sequence in probability theory. LRFMC model expanded RFM model to two more parameters, length of customer relationship and cost of a customer [20]. Hu and Yeh proposed the RFM-pattern that can approximate the set of RFM-customer-patterns without customer identification information by a novel algorithm to ascertain complete set of RFM-patterns [21].

This process tries to extract RFM values from banking dataset where R is a value measure that is reverse of the date of the time distance between the date of user's last transaction and the date of last transaction on the dataset[1]. For example, if the time distance related to the customer equals to 30, the value of the R equals to $\frac{1}{30}$. The value measure F is the average number of transactions per month. The value measure M is the average amount of financial transactions the user made per month.

Table 1. Score of Customer for evaluating of CBT factor.

Amount of Transaction During a Month (ATDM)	Score of Customer (SC)
0< ATDM <800	1
800<= ATDM <1800	2
1800<= ATDM <2900	3
2900<= ATDM	4

Another important variable, we need to cluster the Customer's Transactional Behavior (CBT). It is an implicit variable which cannot be retrieved directly from the data base. We needed to develop a method to extract the CBT. As shown in the following equation, this study employs CBT to extract customer's transactional behavior:

$$CBT = \frac{\sum_{i=1}^{j} w_i sc_i}{j} \quad \text{where} \quad w_i = \frac{2(j-i+1)}{j*(j+1)} \qquad (1)$$

The $\boldsymbol{w_i}$ indicates the degree of importance of SC; The recent SC is more important than other SCs. Where sc_i indicates the score of the customer during a month i, and the month j is the whole period of observation. Using table 1 values, Score of each customer during a month was calculated.

3.2. Clustering the Customers

Clustering is the process of grouping a set of various objects into groups of similar objects. A cluster is a collection of data objects that have high similarity in comparison to one another within the same cluster and are dissimilar to the objects in other clusters. There are a lot of algorithms for clustering the set of various objects, for instance neural network, Kmeans, Kmediod and so on. FASE model uses the customers' dataset to analyze the customer behaviors. Hence, we study algorithms that is used in this area. Many researches presented various methods for customers clustering such as Panel Data Clustering, support vector regression analysis, logistic regression analysis , linear discriminate analysis (LDA), multiple discriminate analysis (MDA), neural networks and so on [22, 25]. Baesens and et al. presented a purchase behavior modeling based on Bayesian neural networks [26]. Farajian utilized K-means to cluster the banking customer and predicted the customer behavior by Apriori algorithm [17]. Dasgupta et al. predicted market response using neural network models [27]. Davies examined how a variety of bank customer groups represent different expectations of the automatic teller machines service. Kim & Sohn managed customer loans using neural networks [28]. Nan-Chen [29] proposed an integrated model to manage existing credit card customers in a bank using self-organizing map(SOM). Chan used self-organizing map (SOM) and back propagation network (BPN) to perform data clustering, price prediction, and error prediction after information is crawled and stored into a dataset [30]. Yong used fuzzy clustering algorithm based on Axiomatic Fuzzy Set to cluster the customers [31]. Dibya mentioned FCM is suitable for overlapping clustering task while data belongs to more than one cluster [32]. The advantage of using fuzzy theory in customer clustering and CRM is that the business analyst can gain in-depth understanding into the data mining model [33]. Base on that FASE-model used the fuzzy C-mean algorithm to

[1] there is a constraint if this number is more than 300,R value equals with zero

clustering customers. This algorithm is described as follow:

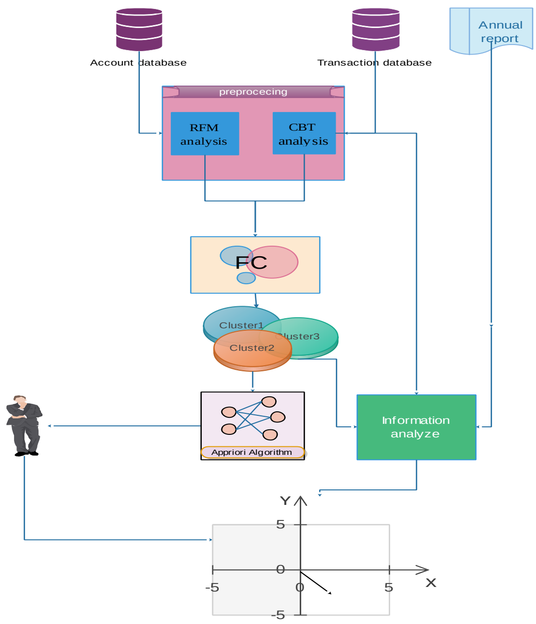

Figure 2. Result of FASE model on the national Iranian's debit card issuer.

Fuzzy clustering methods are based on fuzzy logic, while it permits an object to be assigned to different clusters. Fuzzy-CMeans (FCM) is a fuzzy clustering method which is based on K-means clustering concepts to partition collection of objects into clusters, i.e. FCM iteratively determines the cluster centers and updates the memberships of objects [34]. In the FCM clustering method, each object is belonged to clusters with a value of membership by membership function. Hence, every object may belong to several clusters with diverse membership values that are between 0 and 1. Moreover, there is a fuzzy rule that states the sum of the membership values of an object to all clusters must be 1. Let $O = (O_1, O_2, \dots, O_N)$ indicates an object with N attributes to be partitioned into a list of c cluster centers $C = (c_1, c_2, \dots, c_M)$ where O_i denotes value of attribute i belongs an object$O$. FCM attempts to determine the most characteristic point in each cluster then FCM computes the membership value for each object in the clusters to minimize the cost function defined as follows:

$$J = \sum_{x=1}^{N} \sum_{y=1}^{M} \varphi_{xy}^{\gamma} \left\| O_x - c_y \right\|^2 \qquad (2)$$

Table 2. Input variable for Apriori Algorithm.

Variable Name	Comments
Days–segments	Days segment of a month for each transaction 1, <11; 2, 11-20; 3, 21-30.
Month-segment	Month segment of a year for each transaction 1, <3;2,4-6;3,7-9;4,10-12.
Times-Segment	Times segmentation of a day for each transaction 1, <8; 2,8-16; 3, 16-24;
Education	2010, Elementary; 2020; middle school; 2030, high school; 2040Undergraduate; 2050, graduate; 2060, Postgraduate; 2070, Dr
Age-code	1, <20; 2, 20-40; 3, 40<.
Amount of transaction	Monthly amount of transaction 1, <200; 2,200-700; 3, 700-1200; 4,1200-2500;5,2500-4000; 6,4000<
Transaction type	for example: 1100,P-Payment;1110, Deposit; 1115, Transfer in; 1116,Transfer Out;….
Sex	0, men; 1, women.
Terminal type	Code of terminal type
Occupation	Encoded field
Block code	Card usage:1, limit;2, not limit

Where φ_{xy} $(0 \le \varphi_{xy} \le 1)$ indicates the value of membership O_x in the ith cluster, c_y is the yth cluster center, γ $(1 \le \gamma)$ ascertain the degree of cluster fuzziness. The membership value is computed by using membership function that is defined as follows:

$$\varphi_{xy} = \frac{1}{\sum_{k=1}^{M} \left(\frac{\|O_x - c_y\|}{\|O_x - c_k\|} \right)^{2/(\gamma-1)}} \qquad (3)$$

Every object O has a set of membership values that denoted degree of being in the yth cluster. The highest membership value is the most likely object belonging to that cluster. The cluster centers are updated by following function:

$$c_y = \frac{\sum_{x=1}^{N} \varphi_{xy}^{\gamma} O_x}{\sum_{x=1}^{N} \varphi_{xy}^{\gamma}} \qquad (4)$$

FCM method, at first step, starts with Chose M centers randomly, second step Computes a set of membership values, third step updates the clusters center, forth step Computes objective function J, fifth step Repeats steps second to forth until convergence $\|\varphi^{(k)} - \varphi^{(k-1)}\| \leq \varepsilon$ termination tolerance, ε.

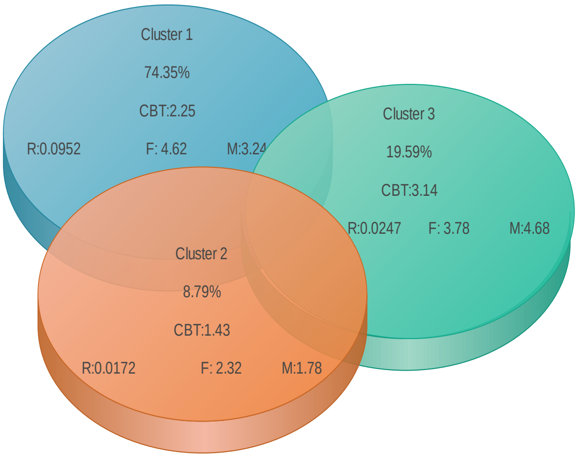

Figure 3. Statistical summarized data of clusters after customer 's clustering.

FASE model uses Fuzzy-CMeans method to cluster the bank dataset after integrating information in a single dataset. The attributes are used for clustering contains RFM values and CBT value as predicated variables to classify each customer into several homogenous clusters. In this experimental dataset, FASE model supposes N=4 and M=3 for Fuzzy-CMeans method. Result of Fuzzy-CMeans method executed on all existing customer's data arranges three profitable groups of customers. As showed in Fig. 3, the number of customers, ratio of number of customers relative to the overall customers, average RFM and to the overall customers was 74.35% and the number of customers is 63,452. The next clusters include 7504 and 16726 customers in order. The next major step is to choose the target cluster of customers, so FASE model selects clusters which have ratio of number of customers relative to the overall customers greater than 15%. All customers who belong to selected clusters become candidates for conducting suitable strategies for a bank.

3.2. Creating cluster Profiles by Association rule mining

Once the customers' clusters are created, FASE model tries to understand practical patterns in bank customers' clusters so that it could better figure out behaviors of various customers. The association rule inducer is a rule-based machine learning method to generate the customers' profiles that contain practical patterns and important information. The bank dataset after Data preprocessing contained 27 attributes. Some of these attributes are un-important or irrelevant which must be ignored for the purpose of more accuracy customer profiles. Association rule mining is a method for discovering relationships between a set of items that occur frequently together in a dataset [35, 37]. In the following we describe the concept of association rules mining: Let I = {i1, i2, . . ., im} be a set of items in which each item denotes a particular literal. Let BD= {t1, t2, . . ., tn} be a big dataset of transactions, where each transaction T is a non-empty subset of items that $T \subseteq I$. Suppose W is an item set $W \subseteq I$, a transaction T contains W only and only if $W \subseteq T$. Support (W, BD) indicate the present of iteration W in BD. The association rule is a denotation of the form W⇒Z (s%, c%), where $W \subseteq I$, $Z \subseteq I$ and $W \cap Z = \varnothing$. The support of rule W⇒Z is percent of transactions contain both W and Z in BD (i.e. Support(WUZ,BD)=s%), The confidence of rule W⇒Z is percent of a transaction in DB which contains W.

Table 3. Result of executing Apriori Algorithm on Cluster-1.

Rule ID	Association rules	Support	Confidence
1.	Transaction type =1100← Days–segments=1&sex=0& Times-Segment=3	6.1%	84%
2.	Terminal type =3020← Days–segments=1&sex=1& Times-Segment=3	16.2%	86%
3.	Transaction type =1100← Days–segments=2&sex=1	26.2%	94%
4.	Transaction type =1100← Month-segment=2& sex=0	17.6%	93%
5.	Transaction type =1100← Month-segment=2& sex=0& Days–segments=2	10.4%	82%
6.	Terminal type =3010← Days–segments=1&sex=1& Transaction type=1117	12.3%	85%
7.	Terminal type =3020← Days–segments=1&sex=1& Transaction type=1100	9.8%	84%
8.	Terminal type =3020← Times-Segment=2&sex=1& Transaction type=1110	6.3%	87%
9.	Terminal type =3020← Days–segments=1&sex=1& Transaction type=1110	11.8%	84%
10.	Terminal type =3020← Days –segments=1&sex=1& Transaction type=1120	21.4%	91%
11.	Terminal type =3030← Days–segments=1&sex=1& Transaction type=1120& Times-Segment=2	12.6%	87%
12.	Terminal type =3030← Days –segments=1&sex=1& Transaction type=1120& Times-Segment=3	14.0%	93%
13.	Terminal type =3040← Days –segments=1&sex=0& Transaction type=1115	11.6%	83%
14.	Terminal type =3010← Days –segments=1&sex=0& Transaction type=1116	15.1%	85%
15.	Terminal type =3010← Days –segments=1&sex=1& Transaction type=1116	7.3%	87%
16.	Terminal type =3020← Age-Segments=2&sex=1& Times-Segment=2	10.7%	83%
17.	Terminal type =3020← Age-Segments=2&sex=1& Times-Segment=3	15.8%	87%
18.	Terminal type =3030← Age-Segments=2&sex=0&Transaction type=1121& Marital Status=1	7.3%	83%

Apriori algorithm is one of most successful algorithms was proposed for mining association rules in a transaction dataset by Agrawal and et al [38, 39]. This algorithm contains two essential steps which are 1) Support Satisfaction 2) confidence satisfaction. The first step is detecting all the association rules whose support is greater than a minimum support (MinSup); and the second step evaluates association rules to have confidence greater than minimum confidence (MinConf). In this process for explanation, we chose only cluster-1 for mining association rules. Table 2 lists the input variable for creating cluster profiles by Apriori algorithm. Criterions were set up to recognize association rules that had at least 80% confidence and 6% support. Table 3 shows the profile of cluster-1 in the form of association rules, where each rule represents customers' behavior in different conditions that strongly associated with the customers. These rules can be guidelines for managers to learn more about their corporation's customer behavior to make more accuracy decisions about strategy of corporation.

3.4. SPACE Matrix

SPACE matrix [13] includes four-quadrant which indicates aggressive, conservative, defensive or competitive strategies. The SPACE matrix analysis functions upon two internal and two external strategic dimensions in order to determine the organization's strategic posture in the market environment. This matrix has been improved during years by some researchers for instance Tuncay and Jelena [10, 40]. The axes of the SPACE Matrix represent horizontal and vertical dimensions of a firm. The horizontal dimension shows financial strength (FS) and competitive advantage (CA). The vertical dimension shows environmental stability (ES) and industry strength (IS). These dimensions are the most important determinants of an overall strategic position of corporation in the market environment. Each of dimensions in the SPACE matrix has its own specific measures that is shown Table 5. The following are a few technical assumptions of SPCSE matrix:

- The domain for CA and IS values in the SPACE matrix are plotted on the X axis.
  CA values can range from -1and -5
  IS values can range from +1and +5
- The domain for the FS and ES values of the SPACE matrix are plotted on the Y axis.
  ES values can take -1 to -5

FS values can take +1 to +5

The SPACE matrix is erected by a point contain X and Y. X is calculated by average score of environmental stability and financial strength dimensions. Y is calculated by the average score of industry strength and competitive advantage dimension.

Table 4. Formulas and expected min and max scale for factors.

Factors	Formula	Min	Max	score
Return on investment	(gain from investment – cost of investment) / cost of investment	**1.25**	**2.35**	**3.61**
Leverage (debt to equity ratio)	total liabilities / total shareholders' equity	**1.35**	**2.20**	**3.78**
Liquidity ratio	LR = liquid assets / short-term liabilities	**1.5**	**2.9**	**2.62**
Capital required versus capital available	capital available/ Capital required	**0.9**	**1.9**	**3.24**
The bank's revenue	revenue in the current year/ revenue in the last year	**1.0**	**1.3**	**2.93**
Customer loyalty	Loyal customer /total customers	**0.12**	**0.19**	**2.12**
Data processing services in the bank	Total tools use for analyzing bank data / Total Standard tools used for analyzing bank data	**0.2**	**0.5**	**3.72**
Market share	(Bank's Revenue in Specific Time) / (Relevant Market's Total Revenue in Specific)	**0.10**	**0.23**	**2.52**
The bank has a large customer base	Total customer of the bank / Total customer of banking in Iran	**0.08**	**0.18**	**2.86**

FASE model evaluating factors can be methodologically grouped into two group: Nhum factor and Hum factor. Nhum computes score of factors related to each dimension by analyze the banking dataset, dataset of financial annual reports and result of clustering customers. Hum calculates the scores of factors by managers of bank.

Table 5. Score of important factors for evaluating strategic dimensions.

Factors	Score of factor	Nhum/ Hum
Factors Determining Environmental Stability-		
1.Technological changes of banking	4	Hum
2. Less-developed countries have rate of inflation	5	Hum
3.Demand variability (much to little)	3	Hum
4.Barriers to entry into market	1	Hum
5.Competitive pressure/rivalry	2	Hum
6.Price range of competing service	2	Hum
Impact of International Economic Sanctions	5	Hum
Average	-3.14	
Competitive Advantage-		
1. Market share	2.52	Nhum
2. Services quality	5	Hum
3. Data processing services in the bank	3.72	Nhum
4.bank service replacement cycle	4	Hum
5.Customer loyalty	2.12	Nhum
6.Competition's capacity utilization	3	Hum
7.Technological know-how	2	Hum
8. The bank has a large customer base.	2.86	Nhum
9. Speed of new service introductions	1	Hum
Average	-2.91	
Industry Attractiveness+		
1. Growth potential	5	Hum
2. Profit potential	5	Hum
3. Financial stability	4	Hum
4.Technological know-how	3	Hum
5.Resource utilization	3	Hum
6.Capital intensity	4	Hum
7.Ease of entry into the market	3	Hum
8.Productivity; capacity utilization	2	Hum
Average	3.62	
Financial Strength+		
1. Return on investment	3.61	Nhum
2. Leverage (debt to equity ratio)	3.78	Nhum
3. Liquidity	2.62	Nhum
4. Capital required versus capital available	3.24	Nhum
5. Cash flow	4	Hum
6. Ease of exit from market	1	Hum
7. Risk involved in the business	3	Hum
8. Inventory turnover	4	Hum
9. The bank's revenue	2.93	Nhum
Average	2.81	

After evaluating the company across four dimensions, SPACE matrix can recommend four different strategies: aggressive strategy, conservative strategy, competitive strategy, or defensive strategy.

Nhum utilizes table 4 to estimate some factors of each dimension[41, 43]. FASE model determine amount of each Nhum factor utilize the precise formula and then result of each factor compares with the expected value (min and max values) of each factor in the corporation's strategy. Score of each factor is calculated by normalizing the score between 1 and 5. For instance, the scale of Liquidity ratio calculated by above formula equals 2.42 and the score for this factor 2.62. After calculating all factors of each dimension, then Find the average scores for FS, CA, IS and ES and then Plot the average score for each dimension on the appropriate axis in the SPACE Matrix. The Result of directional vector in the banking case equals [0.71, -0.33].

[3.62, -2.91], [2.81, -3.14] = [0.71, -0.33]

Calculations are summarized in the Fig. 4.

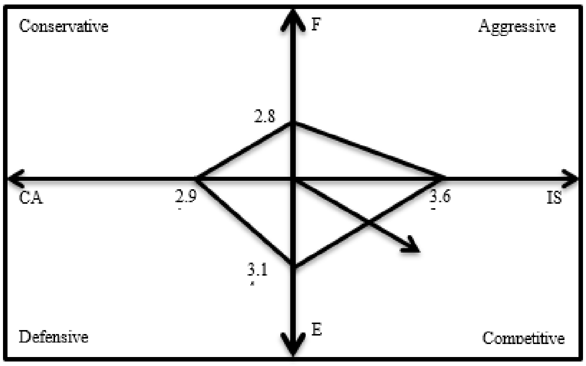

Figure 4. Result of performing SPACE Matrix the national Iranian's debit card issuer.

According to Fig. 4 showed the strategic position of the bank is competitive. Therefore, the bank can follow a competitive strategy which is characteristic of an attractive industry in a relatively unstable environment. SPACE analysis recommends that bank in such position take the following actions: 1. Obtain financial resources to increase customers thrust. 2.cooperate with a special bank that is looking for opportunities to expand. 3. Reduce its variable and fixed costs to improve or extend the service line. 4. invest in differentiation competitive advantages.

4. CONCLUSION

The Strategic management science propose for managers to find the proper orientation in order to lead their corporations. Since market environments change constantly and corporations face the new situations, knowing the strategic position of corporations can be a good solution to overcome these changes. We have presented FASE model to be a semi-automatic selecting smart strategy for all corporations. FASE model consist of Fuzzy-Cmeans clustering algorithm, Apriori rule inducer, and SPACE matrix for evaluating strategic position and selecting smart strategy. Using Big Data mining is one of the novelties of FASE model; Therefore, managers have comprehensive analysis of factors that relate to dimensions of the strategic. At end of this research, the FASE model applied over the Iran bank institute. The results reveal that the strategic position of the bank is competitive position and the bank can follow a competitive strategy.

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