EMPIRICAL ARTICLE

A data mining approach for segmentation-based importance-performance analysis (SOM–BPNN–IPA): a new framework for developing customer retention strategies

Seyed Yaghoub Hosseini · Alireza Ziaei Bideh

Abstract Importance-performance analysis (IPA) is a simple but effective means of assisting practitioners in prioritizing service attributes when attempting to enhance service quality and customer satisfaction. The purpose of this study was to demonstrate how IPA can be used with market segmentation to develop customer retention strategies for different market segments. For this purpose, a new framework have been proposed that uses self-organizing maps for customers' segmentation and back-propagation neural network (BPNN) for implicity drive the importance of service attributes based on their effect on customers' loyalty in each segment. Then, individual IPA matrixes are developed for each market segment. Also, an example case is presented to demonstrate the implementation and application of the proposed framework. The results of the proposed framework compared with a conventional BPNN-IPA approach indicated that it can increase reliability and applicability of IPA results.

Keywords Importance-performance analysis (IPA) · Self-organizing maps (SOM) · Artificial neural networks · Customers segmentation · Customers loyalty

1 Introduction

Importance-performance analysis (IPA) was first introduced by Martilla and James (1977) as a means by which to measure customers' satisfaction with a product or service and also to develop strategies for maximizing their satisfaction. The IPA

S. Y. Hosseini · A. Ziaei Bideh (✉)
Department of Business Management, Persian Gulf University, Bushehr, Iran
e-mail: ess.ziaei@gmail.com

approach develop improvement strategies as the function of two components: the importance of a product or service attribute to customers and the performance of an organization in providing that attribute as perceived by customers (Martilla and James 1977). The IPA results help managers to identify improvement priorities, allocate and deploy scarce resources to where they are needed most and develop strategic plans to enhance relative competitiveness (Azzopardi et al. 2012).

IPA method has proven to be a broadly applicable tool which is relatively easy to administer and interpret resulting in extensive use among researchers and managers in various industries. But despite its wide diffusion, the original model has several potential drawbacks (Oh 2001). Previous researchers have suggested different revisions and used a variety of methods and approaches to increase the validity and applicability of IPA results (Arbore and Busacca 2011; Coghlan 2012; Deng and Pei 2009; Geng and Chu 2012). However, in most of the cases the revised versions also lack the accuracy required for effective decision-making support. One of the criticisms of original IPA model and also most of the revised versions is that they treat the study participants (the sample) as a homogeneous group regardless of potentially important distinctions between customer types. Several researchers argued that IPA will provide more insight if conducted separately for different market segments (Farnum and Hall 2007). They observed that customer groups with different activity type (Burns and Graefe 2003), motives, preferences, and expected benefits (Hendricks and Schneider 2004; Vaske and Kiriakos 2009) will place varying degrees of importance on service attributes and make different judgments regarding service encounters. Thus, conducting individual IPAs for distinct market segment will increase reliability and applicability of IPA results.

Another issue in IPA studies is that they are most focused on developing customer acquisition strategies and maximizing customers' satisfaction. While in most industries increasing customers loyalty become a strategic priority and also the relative costs of customer retention are substantially less than those of acquisition (Oliver 1999). Moreover, several authors argued that satisfaction does not necessarily lead to loyalty (Balakrishnan 2011; Kabiraj and Shanmugan 2010; Oliver 1999). It has been found that 60–80 % of the survey population said they were satisfied before defection to competitors (Balakrishnan 2011). Thus, using IPA for developing customer retention strategy is vital especially in mature markets.

With the purpose of acquit mentioned limitations this paper will propose a new framework for importance-performance analysis of service attributes base on customers segmentation, which not only provide individual IPAs for each customer segment, but also the importance of attributes will be calculated based on their effects on customers' loyalty for developing customer retention strategies.

The rest of the paper consists of following sections: The next section provide review of the relevant literature. Thereafter, proposed framework for IPA will be introduced. After that, the provided framework has been used for importance-performance analysis of service attributes in the mobile telecommunication industry to demonstrate its implementation and application. In the final section, we discuss conclusions and limitation of the study.

2 Literature review

2.1 Importance-performance analysis

Importance-performance analysis has been applied as an effective means of evaluating a firm's competitive position in the market, identifying improvement opportunities, and guiding strategic planning efforts (Arbore and Busacca 2011; Deng Kuo and Chen 2008). In IPA, service attributes are plotted in a two-dimensional matrix based on the importance (x-axis) and performance (y-axis) of each attribute. The mean or median of performance (satisfaction or service quality) and importance of all attributes divide the matrix into four quadrants. Priorities for improvement are then inferred based on the location of the points in the matrix (see Fig. 1).

Quadrant 1 (high importance and high performance): attributes falling within this quadrant are indicative of opportunities for achieving or maintaining competitive advantage. They represent major strengths that should be maintained or exploited. The management scheme for this quadrant is "keep up the good work".

Quadrant 2 (low importance and high performance): attributes located in this quadrant indicate that business resources committed to these attributes would be overkill and should be deployed elsewhere. These attributes are minor strengths. The management scheme for this quadrant is "possible overkill".

Quadrant 3 (low importance and low performance): attributes falling in this category are minor weaknesses and do not require additional effort. They are likely to attract low priority in the rationing of scare resource by decision-makers and are candidate for losing out completely on resource and effort. The management scheme for this quadrant is "low priority."

Quadrant 4 (high importance and low performance): this quadrant is the most critical categorization because it indicated that the firm fails to satisfy customers perceived level of performance in areas they judge as salient. Attributes falling

Fig. 1 IPA Matrix
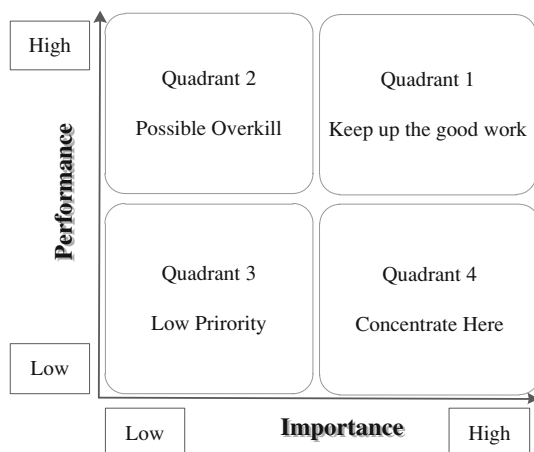
within this quadrant require immediate attention for improvement and are major weaknesses. The management scheme for this quadrant is ''concentrate here.''

Although IPA is an extremely valuable method and widely used by both practitioners and academic researchers, some limitations and deficiencies of original IPA model lead several researchers to provide and use modified or extended models (Bacon 2003). For example there are many researches that used Kano's model to distinguish between different quality attribute types in IPA (Arbore and Busacca 2011; Deng et al. 2008a, b; Matzler and Bailom 2004; Pezeshki and Mousavi 2009). Kano's model divides product or service quality attributes into three distinct categories (must-be, one-dimensional, and attractive), each of which influences customer satisfaction differently (Kano and Seraki 1984). Mikulic and Prebezac (2008) offer a modified IPA to measure the range of an attribute's impact on overall customer satisfaction, as well as highlight the asymmetrical impact that a particular attribute may have on satisfaction (Mikulic and Prebezac 2008). The asymmetrical impact refers to the extent to which an attribute has a satisfaction-generating potential compared with its dissatisfaction-generating potential. After that, some researchers used this modified version of IPA to determine various attributes' range of impact on, and asymmetrical contribution to, customers' satisfaction (Back 2012; Coghlan 2012). More recently, Mikulic and Prebezac (2012) provide another modified version of IPA that uses a multidimensional operationalization of attribute-importance, and that considers competitive performance levels (Mikulic and Prebezac 2012). There are more other researches that used different method such as fuzzy set theory (Deng 2008a, b; Deng and Pei 2009) and DEMATEL technique (Geng and Chu 2012; Ho and Feng 2012; Hu and Lee 2009) to increase reliability and applicability of IPA results.

2.2 Measuring importance of attributes

The different methods that researchers used for estimating importance of attributes in IPA can be classified in two categories: customers' self-stated importance, and statistically inferred importance (implicit) (Pezeshki et al. 2009). Oh (2001) suggests that asking respondents to rate the importance of attributes one by one overinflates importance ratings, thereby confusing absolute and relative importance, and reducing the predictive ability of the model (Oh 2001). To overcome this problem, practitioners of IPA frequently use statistically inferred importance (implicit) ratings. Methods such as multiple regression analysis, structural equation modeling (SEM) or partial correlation are normally used for statistically inferred importance ratings. These statistical methods assume that (1) data are relatively normal, (2) the relationships between independent and dependent variables are linear, and (3) multicollinearity between independent variables is relatively low (Deng and Chen 2008). However, in customer satisfaction research, such assumptions are almost always violated (Garver 2002). Garver (2002) indicated that artificial neural networks (ANN) can be employed to overcome the mentioned constraints of conventional statistic methods. Recently, several researchers suggested ANN for measuring importance of attributes in IPA (Deng et al. 2008a, b; Deng and Pei 2009; Geng and Chu 2012; Hu et al. 2009).

In this study, a back-propagation neural network (BPNN) will be adopted for estimating the importance of service attributes based on their effect on customers' loyalty. Thus, the new framework that will be proposed for IPA helps managers to develop customers' retention strategies.

2.3 IPA and market segmentation

IPA studies typically treat the sample as a homogenous group. However, the accuracy of results may diminish when users differ in their importance ratings of attributes (Hendricks et al. 2004). Vaske et al. (1996) argued that when different market segments are combined, the ensuing IPA generates misleading results (Vaske and Beaman 1996). Also, Matzler and Fuller (Füller and Matzler 2008) concluded that the satisfaction drivers according to the three-factor theory of customer satisfaction strongly differ between lifestyle market segments (Füller and Matzler 2008).

In spite of many revised and modified framework offered for IPA, surprisingly, the studies that addressed the issue of heterogeneity sample are very rare. For example, (Hendricks et al. 2004) extended IPA by first segmented visitors based on their expected benefits and then estimate importance and performance of attributes in each segment separately. Their research findings show differences among groups for importance attributes, but few differences in the performance ratings of attributes (Hendricks et al. 2004). Farnum and Hall (2007) did a loyalty-based market segmentation and then provide individual IPA for each market segment, but their empirical study results revealed highly similar patterns of attribute placement for low and high loyalty segments (Farnum and Hall 2007). Vaske et al. (2009) used IPA with segmentation in their research. They segmented visitors of a biosphere reserve in Vietnam according to their preference for facility development within the reserve. Results of IPA showed that the visitors in each segments differed in their importance-performance ratings for most of the attributes (Vaske et al. 2009). Findings of mentioned research show that using IPA with market segmentation will provide more reliable and insightful results.

Segmentation first emerged in the marketing literature as an effective tool to capture consumer motives and to identify target markets. Market segmentation involves "dividing a large market, presumably with heterogeneous characteristics, preferences, and behavior, into smaller and more homogeneous segments, allowing use of different marketing strategies for each segment according to its characteristics (Hendricks et al. 2004). To set a market segmentation process in motion, one first needs to choose a set of variables that will then compose the so-called segmentation bases or criteria used to identify consumption patterns (Finisterra do Paço and Raposo 2010). Possible segmentation variables include demographic, psychographic, and behavioral characteristics of customers. In this study four demographic (age, gender, education, and income) and two behavioral characteristics (monthly expenses and length of use) and also customers' perception about performance of service attributes will be used for the purpose of market segmentation.

Clustering is commonly used for market segmentation. Clustering technique is used to identify a set of groups that both minimize within-group variation and

maximize between-group variation according to a distance or dissimilarity function (Jain and Murty 1999). Self-organizing maps (SOM) is a popular unsupervised neural network methodology for clustering problems. It can project a set of high-dimensional input data onto a low-dimensional space where the topology of the input data is preserved (Kohonen 1982). SOM can be viewed as a clustering technique that identifies clusters in a dataset without the rigid assumptions of linearity or normality of more traditional statistical techniques (Mostafa 2009). Recently, SOM applications for clustering and prediction in marketing have showed promising results as compared to the traditional statistical techniques (Mostafa 2009, 2010, 2011). Thus, SOM will be used for clustering purpose in the new framework that will provide segmentation-based IPA.
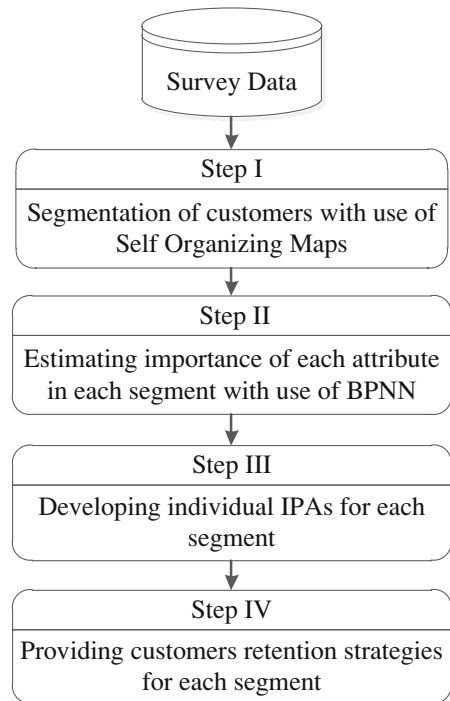
3 Proposed framework for segmentation-based IPA (SOM–BPNN–IPA)

Literature review showed that several revisions have been suggested for increasing reliability and applicability of IPA results. However, they treat the study participants (the sample) as a homogeneous group and none of them tries to integrate segmentation methods with IPA. Also, most of the IPA studies focused on developing customer acquisition strategies and maximizing customers' satisfaction. While, Customers' satisfaction does not necessarily lead to loyalty. With the purpose of acquitting these limitations, this paper proposed a new framework (SOM–BPNN–IPA) for segmentation-based IPA that used SOM for segmenting customers and BPNN (back-propagation neural network) for estimating importance of attributes based on their effects on customers loyalty. The proposed framework wills asset managers to develop customer retention strategies for distinct market segments. Figure 2 shows the four main steps of proposed framework.

4 Empirical study

In this section, an example case is presented to demonstrate the implementation and application of the SOM–BPNN–IPA for developing customer retention strategies. This study has chosen Hamrahe-Aval (an Iranian mobile phone operator) as a case study. Over the last few years, the mobile telecommunication market in Iran has undergone dramatic changes. This market has followed a transformation from a monopoly to a deregulated, almost open and free competitive market. At the time of this study there existed two mobile phone operators in Iran, and the third one will start its operation soon. Because of this changing dynamics, the Iranian mobile phone operators face some significant challenges. First, retaining existing customers in a high churn market has become very difficult and costly. Second, new customer acquisition is becoming more difficult than ever because potential subscribers now have more alternatives to choose from according to their perceived performance and service quality and also mobile phone operators offer charming deals to attract them. In such a competitive market, it is essential to make customer loyalty as a strategic priority.

Fig. 2 Proposed framework for segmentation-based IPA

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┌──────────────────────────┐
│       Survey Data        │
└──────────────────────────┘
             │
             ▼
┌──────────────────────────┐
│          Step I          │
│ Segmentation of customers │
│   with use of Self        │
│   Organizing Maps         │
└──────────────────────────┘
             │
             ▼
┌──────────────────────────┐
│         Step II          │
│ Estimating importance of │
│  each attribute in each  │
│   segment with use of    │
│          BPNN            │
└──────────────────────────┘
             │
             ▼
┌──────────────────────────┐
│         Step III         │
│ Developing individual    │
│    IPAs for each         │
│       segment            │
└──────────────────────────┘
             │
             ▼
┌──────────────────────────┐
│         Step IV          │
│ Providing customers      │
│ retention strategies     │
│    for each segment      │
└──────────────────────────┘
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4.1 Survey instrument

For the purpose of demonstration, data from mobile operators' subscribers were collected using a structured questionnaire. The questionnaire comprises of two parts. In the first part respondents were asked to provide information about their demographic characteristic and mobile phone usage information. The second part consists of questions about respondents satisfaction of each service attributes and also their level of loyalty. The main attributes of services within mobile telecommunication sector were extracted from existing literature and have been measured with existing and tested scales adopted from previous researches (see Table 1). Also, the loyalty scale is designed to measure both attitudinal and behavioral aspects of loyalty. Items measuring attitudinal loyalty are derived from the study undertaken by Karjaluoto et al. (2012). To measure behavioral loyalty, the scales used by Akroush et al. (2011) are utilized.

Measures were translated from English into Persian and then to insure content validity, they were assessed by three academics so that respondents would understand the questions correctly. Some items were reworded, added or deleted based on their feedback. For each item, a five-point Likert scale (Likert 1932) was used with anchors from "1 = strongly disagree" to "5 = strongly agree" for employees competency and customer service items and anchors from "1 = very poor" to "5 = very good" for the rest of the items.

Table 1 Service attributes scales used in the survey questionnaire

Scale	Source of measure	Items	Reliability
Network quality	Lim et al. (2006)	• Frequency of dropped calls • Voice quality • Coverage	0.76
Convenience	Liang et al. (2012); M. K. Kim et al. (2004)	• Number of retailers/kiosks • Methods/locations for bill payment • Ease of subscribing and changing service	0.74
Pricing plans	Lim et al. (2006)	• Offering the best plan that meets a customer's need • Ease of changing pricing plans • Delivery of information	0.89
Billing system	Lim et al. (2006)	• Provision of accurate billing • Ease of understanding • Resolving billing issues quickly	0.83
Value-added services	M. K. Kim et al. (2004)	• Variety of value-added services • Convenience in use of value-added services • Whether value-added services are up-to-date	0.87
Customer service	M. K. Kim et al. (2004)	• Variety of customer support systems • Speed of complaint processing • Ease of reporting complaint	0.85
Employees competency	Eshghi et al. (2008)	• Employees are efficient and competent • Employees are courteous, polite and respectful • Employees are willing to help	0.87

Next, a pre-test of the questionnaire was conducted with 50 respondents to confirm that the instrument and measures were clear, legible, and understandable. Based on respondents' feedback, the questionnaire was revised and finalized. Also, to assess the internal consistency (reliability) of the questionaries' items, Cronbach's alpha was calculated (Cronbach 1951).

Table 1 shows service attribute scale items used in the survey questionnaire with their reliability and source of the measures. The Cronbach's alphas of our scales ranged from 0.74 to 0.89, which were all higher than the recommended value of 0.7. The internal consistency reliability (Cronbach's alpha) of loyalty scale was also tested and it meets the respective 0.70 thresholds.

4.2 Sample

The population for the study is focused on mobile users in Iran at Yazd province. The sample was collected from subscribers that used Hamrahe-Aval operator services for at least six month. A convenience sampling method was used to select the respondents. So that, the interviewers randomly selected passers-by, asked them to take part in the study and to complete the standardized, self-administered

questionnaire. A total of 640 initial responses have been received. In order to insure the accuracy of the survey results, respondents that had used the service for less than six months, used the same answer for all questions and those that had too many missing answers were excluded. Thus, the final sample consisted of 617 respondents, resulting in a response rate of 96.4 %.

5 Data analysis and results

5.1 Sample profile

Table 2 summarizes the descriptive statistics of the sample. Among the respondents, 73.4 % were male and 26.6 % were female. As it can be seen in Table 3, the sample is rather skewed toward young and medium educated users having monthly income lower than 10 million Rials. Also, some information about respondents' mobile phone usage is presented in Table 2.

5.2 Step 1: segmentation with use of SOM

The network of SOM usually consists of two layers of neurons: input layer and output layer. Although, the neurons on input layer are fully connected to the neurons on output layer, the neurons on each layer have no connection to the neurons in that layer. The SOM is trained based on an unsupervised training algorithm where no target output is provided and the network evolves until convergence. After training the network, output neurons will self-organize to an ordered map and neurons with similar weights are placed together. They are connected to adjacent neurons by a neighborhood relation, dictating the topology of the map (Mostafa 2010).

There are many software packages available for analyzing SOM models. This study have used Viscovery SOMine version 5.0 that applies artificial intelligence techniques to automatically find the efficient SOM clusters. Most authors use the unified distance matrix to visualize the cluster structure of SOM. However, this method does not give crisp boundaries to the clusters (Mostafa 2009, 2010, 2011). SOMine software applies a hierarchical cluster analysis with a Ward linkage method (called SOM-Ward Cluster) to the SOM to clearly delineate the edges of each cluster.

Survey dataset including demographic and behavioral data together with customers' perception of performance of each service attribute were used for training the SOM network and visualizing each market segment. The sequential learning algorithm was used to train the SOM and the number of neurons in output layer was chosen to be 2000. Moreover, "automatic map format" was selected as the desired map format in which the map ratio is derived automatically through the training process. Consequently, the resulting map size became equal to 49 × 39. Training schedule was set to "accurate." This setting corresponds to internal schedules for the training process. A higher accuracy means more iteration steps and hence, a longer training time. Tension level was set to 0.5 for the resulting map. The tension reflects the rigidity of the map. A larger tension makes a smoother map, which is less specific at the nodes.

Table 2 Sample profile

Measure	Items	Frequency	Percentage (%)
Gender	Male	453	73.4
	Female	164	26.6
Age (year)	<20	42	6.8
	21–25	170	27.6
	26–30	210	34.0
	31–40	128	20.7
	>41	67	10.9
Education	Diploma degree or lower	86	13.9
	Associate degree	62	10.0
	Bachelor's degree	215	34.8
	Master's degree	232	37.6
	D.C.	22	3.6
Income (rials)	>5 million	63	10.2
	5–10 million	278	45.1
	10–20 million	198	32.1
	20 million	74	12.0
Monthly expenses	<150,000 rials	75	12.2
	150,000–250,000	163	26.4
	250,000–400,000	209	33.9
	400,000–700,000	109	17.7
	>700,000 rials	55	8.9
Length of use (year)	<1	48	7.8
	2–4	117	19.0
	5–7	221	35.8
	8–10	141	22.9
	>11	80	13.0

The SOM cluster results are shown in Fig. 3. This two-dimensional hexagonal grid shows clear division of the input pattern into three clusters. Each cluster represents a market segment.

Table 3 summarizes the mean of service attribute performance in each cluster and also in overall sample. This information will be used for developing IPA matrixes for each segment.

When the SOM produces visual images of each cluster, not only the mean of each cluster is calculated but also other aspects such as which variables make the cluster different from others (Mostafa 2011). For nominal and categorical variables this comparison will be made for each category (value) of variables. Figure 4 presents a variable-wise importance analysis of demographic and behavioral variables within each cluster. Practitioners could use this information for developing marketing and
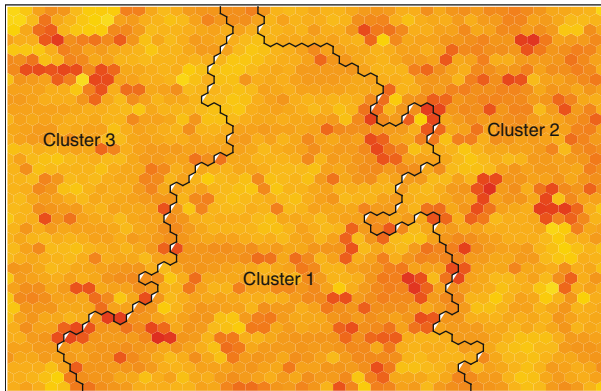
Fig. 3 SOM-Ward Clusters

Table 3 Mean of service attributes performance in each cluster

| Cluster	Freq. %	Network quality	Convenience	Pricing plans	Billing system	Value services	Customer service	Employee competency	Loyalty
Cluster 1	34.52	4.04	3.73	2.96	3.67	3.18	3.02	3.31	3.24
Cluster 2	36.30	3.58	3.24	2.27	3.33	2.58	2.36	2.82	2.66
Cluster 3	29.17	4.37	4.23	3.55	4.22	3.76	3.49	3.86	3.90
Overall Sample	100	3.99	3.73	2.92	3.74	3.01	2.95	3.33	3.26

positioning strategies based on individual characteristics of customers in each market segments.

5.3 Step 2: attribute importance estimating with use of BPNN

This study uses NeuroSolutions six software to build the BPNN prediction model for each segments' customers' loyalty. The BPNN model is modeled as one input layer, one hidden layer, and one output layer. The seven attributes are the neurons in input layer and customers' loyalty is the only neuron in the output layer. The activation function used in hidden layer and output layer is a hyperbolic tangent function. The values for learning rate and momentum are both 0.7 and decrease as training proceeds. The learning terminative rule is a cross-validation procedure suggested by Smith (1993) to avoid overfitting. The data from each segment is assigned 70 % into the train case, 15 % into the test case, and 15 % into the validation case.

The number of neurons in the hidden layer is crucial to BPNN model performance. No precise formula exists for determining the number of neurons in the hidden layer (Deng et al. 2008a, b). In order to determine the number of hidden layers' neurons, some experimental networks with different number of hidden neurons were performed separately for dataset as to each market segment. The mean

Fig. 4 Overall characteristics of customers in each cluster
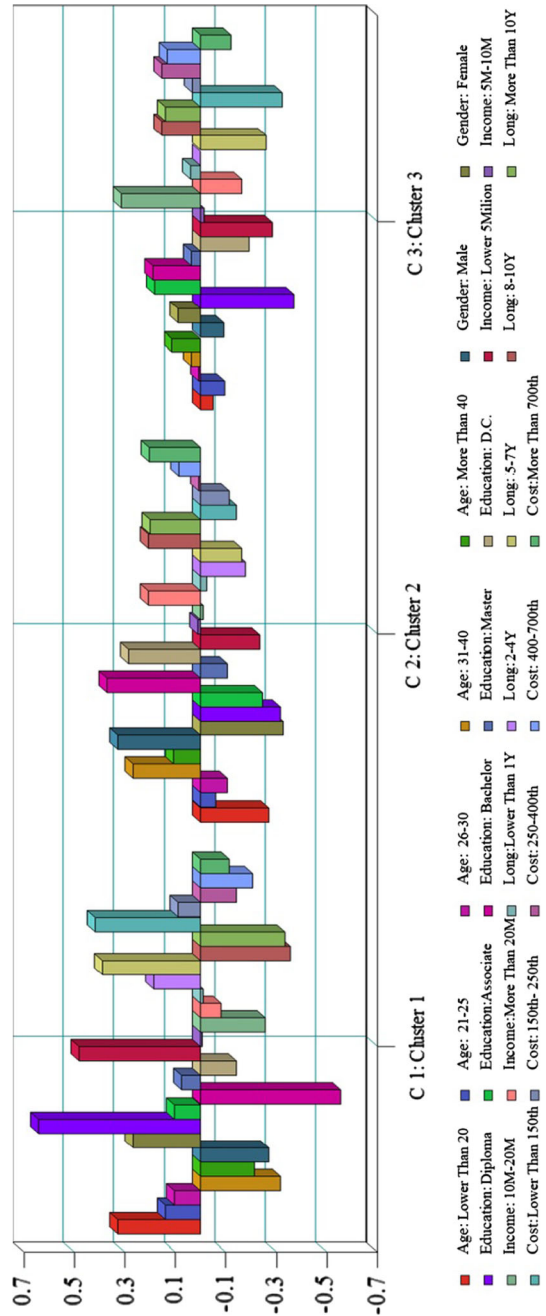
absolute error (MAE), mean squared error (MSE), and R2 will be considered as the benchmark to evaluate performance of networks with different structure. Table 4 shows the structure of outperform network for each market segment.

Table 4 Best-performing networks for market segments' dataset

Market segment	Structure	MAE	MSE	R2
Segment 1	7–4–1	0.41	0.27	0.73
Segment 2	7–5–1	0.53	0.38	0.64
Segment 3	7–12–1	0.35	0.18	0.61
Overall sample	7–7–1	0.55	0.43	0.66

Table 5 Importance of service attribute in each market segment

No.	Service attributes	Segment 1	Segment 2	Segment 3	Overall sample
1	Network quality	0.03	0.37	0.23	0.18
2	Convenience	0.07	0.22	0.17	0.13
3	Pricing plans	0.16	0.14	0.20	0.15
4	Billing system	0.12	0.08	0.27	0.09
5	Added-value services	0.14	0.45	0.19	0.28
6	Customer support	0.31	0.17	0.45	0.24
7	Employee competency	0.006	0.13	0.20	0.11

The sensitivity analysis of BPNN model is employed in this study for acquiring the implicitly derived importance of each service attribute in each market segment. So that, after training the network each input variable was modified from its minimum value to its maximum value while keeping other inputs unchanged. The impact of this change on the output was then monitored. Importance of each attribute estimated based on the changes of output. Table 5 presents the results of the sensitivity analysis for each market segment and also for overall sample.

First of all, it is evident from Table 5 that service attributes have different importance in predicting customers' loyalty in different segment. For example, in segment 1, customer support is the most important factors in developing customers' loyalty. Added-value services and network quality are the most effective factors on customers' loyalty in segment 2.

5.4 Step 3: developing individual IPA matrixes for each market segment

According to research framework, after calculating the importance and performance of service attributes in each market segment, it is time to develop individual IPA matrixes for each segment. Martilla and James (1977) prescribed that the crosshairs of the IPA matrix must be placed at the mean values of the observed (reported) importance and performance ratings. Then, position of each attribute on matrixes will be determined considering its performance (see the Table 3) and importance (see the Table 5). Figure 5 presents IPA matrixes for three identified market segments.

5.5 Step 4: providing customer retention strategies

In this step customer retention strategies will be developed proportional to plotted IPA matrixes and characteristics of customers in each market segment (based on
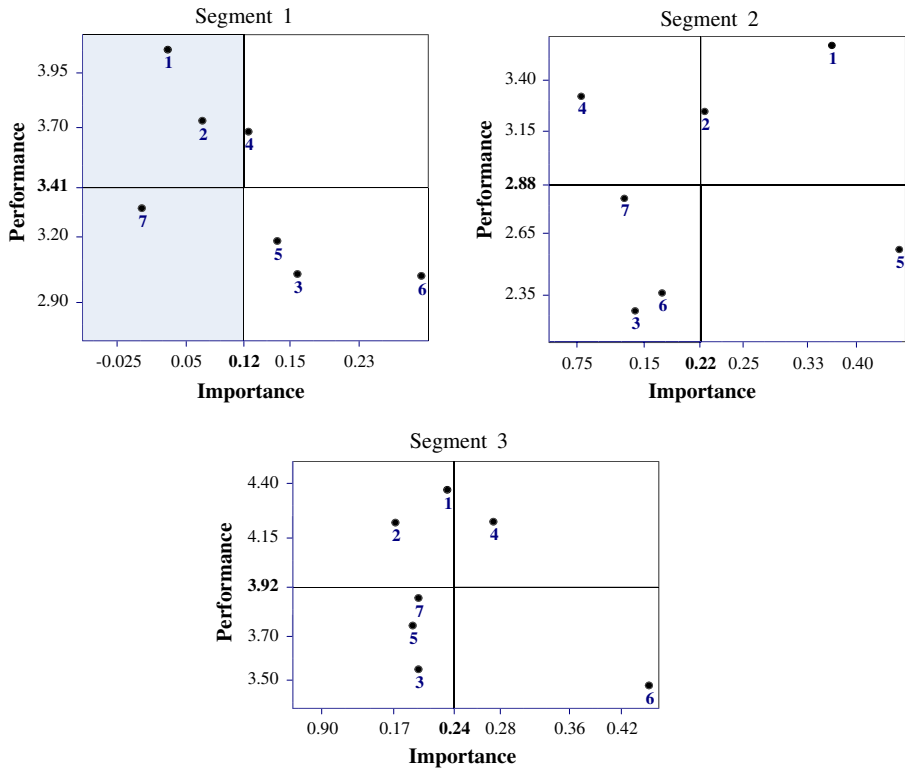
Fig. 5 IPA matrixes for each market segment
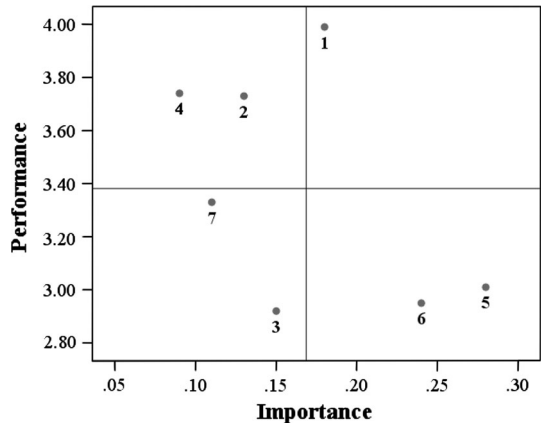
Fig. 6 Conventional BPNN-
IPA map

Fig. 4). Then, the results of our proposed framework (SOM–BPNN–IPA) will be compared with the results of a conventional BPNN-based IPA approach (Fig. 6).

Segment 1: This segment mainly consists of young people (aged lower than 30), and is the segment that includes younger female customers with low educational

levels (diploma and associate degree) and income (lower than five million rials). Compare to other segments, this segment consist of subscribers with low monthly expense (lower than 250th rials) and subscription long between 2 and 7 years.

To enhance loyalty of customers in this market segment, Hamrahe-Aval (selected Telecommunication Company for case study) should concentrate on service attributes 6, 3, and 5. Customer support is the key driver of this segments loyalty but Hamrahe-Aval has a low performance in this attribute from the perspective of customers in this segment. Employee competency is an attribute with low priority. Network quality and convenience can be viewed as arias of overkilled in this market segments. These two attribute have low priority in customers' loyalty and resources to these attributes would be better employed elsewhere.

Segment 2: This segment includes customers from the higher age groups, and those with higher educational levels than the other segments. Most of the individuals in this market segment are male subscribers with high level of income (more than 20 Million Rials), monthly expense (more than 400th rials), and subscription long (more than 8 year).

Based on IPA matrix plotted for this segment, added-value services is the most important factors in customers' loyalty but Hamrahe-Aval is evaluated low in performing this attribute. Thus, managers should concentrate on this service attribute to enhance this segment loyalty. Pricing plans, customer support, and employees competency are attributes of low priority. Their poor performance is apparently not a problem, as they are relatively unimportant in enhancing customers' loyalty. Network quality evaluated high in satisfaction and also is very important in forming customers' loyalty and the management's job in this market segment is to insure that the company keeps up the good work.

Segment 3: compared to other segments, this is the one that groups together those customers with moderate educational level (associate and bachelor degree) and income (between 10 and 20 million rials). Also this segment composed of subscribers with moderate monthly expense (between 250 and 700th rials) and long subscription time.

To enhance loyalty of customers in this market segment, managers of Hamrahe-Aval should concentrate on improving customer support because it is the most effective factor on customers' loyalty but ranked very low in performance. Added-value service, employees' competency and pricing plans are of low priority. Billing system is relatively unimportant to the customers of this segment but the company performs very well in this service attribute according to opinion of this customer groups. Management might wish to reallocate resources to somewhere more important.

In order to do a contrastive analysis, a conventional BPNN-based IPA matrix can be drawn according to the performance and importance of service attributes in overall sample, as shown in Fig. 6.

According to Fig. 6, service attributes including added-value services and customer support are located in quadrant 4 with the managerial recommendation being "concentrate here." However the results of segmentation-based IPA indicated that added-value services are not an improvement priority in segment 3, similarly is not customer support in segment 2. Pricing plan is located in quadrant 3 in the

conventional BPNN–IPA matrix and is the minor strength attribute for improving customer loyalty. However, according to Fig. 5, pricing plan is an improvement priority to enhance loyalty of customers in segment 1. As another inconsistency, based on conventional IPA matrix, billing system is located in quadrant 1 with the managerial recommendation being "possible overkill." It means that managers can decide to redirect business resource to other attributes that require resources (those in quadrant 4). However, according to segmentation-based IPA matrixes, pricing plan is a competitive advantage in term of customers' loyalty in segment 1 and especially in segment 3. Therefore, the management scheme action is "keep up the good work".

6 Conclusions and limitations

The primary purpose of this study was to demonstrate how IPA can be used with market segmentation to develop customer retention strategies for different market segments. For this purpose, a new framework based on data mining approach has been proposed that used SOM for customers segmentation and BPNN for estimating importance of attributes. Then, an example case was presented to demonstrate the implementation and application of the proposed framework (SOM–BPNN–IPA) in developing customer retention strategies.

The retention strategies that developed based on the proposed framework in comparison with those concluded from a conventional BPNN–IPA approach indicated that without segmentation, importance-performance analysis can lead to misleading conclusions. Managers must note that traditional IPA approach did not consider heterogeneity in customers' preferences and characteristics. Thus, the information acquired by traditional IPA can cause managers to take incorrect actions when attempting to improve service quality and customers loyalty. Accordingly, the new segmentation-based IPA framework presented in this paper could increase reliability and applicability of IPA results compared with traditional approach.

The major characteristics of the proposed framework in this paper are summarized as follows:

1- Service attributes importance is calculated based on their effect on customers' loyalty to develop customer retention strategies.
2- A back-propagation neural network (BPNN) is employed to implicity drive the importance of service attributes to overcome the drawbacks of statistic methods. Also, different importance ratings are calculated for same service attributes in different market segments.
3- Customers' segmentation is incorporated into IPA to consider the issue of heterogeneity sample. Thus, individual IPA matrixes are developed for each market segments based on importance and performance ratings of service attributes in that segment.

Finally, it is important to note a number of limitations associated with the proposed framework and the empirical study presented in this study:

- First, the IPA framework presented in this paper uses derived measures of service attribute importance based on BPNN method. This method needs a sufficiently large number of observations (sample size) for training the network and to avoid overfitting.
- Second, while the proposed IPA framework in this study is applicable to any service business, the paper does not claim any external validity for the results of the empirical study. Our objective was merely to demonstrate proposed framework using a real world case.

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