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An Integrated Entropy/VIKOR Model for Customer Clustering in Targeted Marketing Model Design (Case Study: IOT Technology Services Companies)

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ABSTRACT

Today, marketing researchers are constantly trying to carefully examine consumer behavior and accordingly, provide appropriate solutions for better and more effective sales, which in turn will lead to an increase in their market share. In this regard, the purpose of this study is to investigate the role of customer clustering in the design of a targeted marketing model. The research method is applied and exploratory. The statistical population studied in the qualitative section was sales and marketing managers of companies providing Internet of Things technology services, and 15 people were selected for interviews by non-random and available methods. In the quantitative section, all the customers of the studied companies were included, and due to the unlimited nature of the society with Morgan's table, 384 people were selected as the sample size. The data collection tools in this study were interviews and questionnaires, which used the opinions of marketing experts and reliability of Cronbach's alpha to examine the validity of the questionnaire. In order to analyze the data, first decision methods such as entropy and VIKOR were used and then to analyze the results, structural equations obtained with PLS2 software were used. The results showed that the dimensions of the model in question fall into four main clusters, communicational factors, behavioral factors, individual factors and economical factors that customers are classified according to the characteristics of using the services provided, are classified in these clusters.

1 Introduction

These days, one of the most widely used management tools in managing organizations is the use of data analysis techniques. These techniques, which have been introduced under various names such as data mining, can be developed in a variety of management areas [5]. One of these areas is market management [30]. The benefits of data mining and its applications in the industry are increasing every day; because it helps business owners identify hidden information under a huge amount of data and this will allow these industries to better understand their customers in the marketplace [12]. In this context, Data mining has a variety of tools, one of the most important of which is cluster analysis [15]. Some of the most widely used data mining techniques in marketing are different clustering techniques [13]. These techniques are perfect for market segmentation and compared to traditional and intuitive methods of

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market segmentation and they can also help marketers to improve their performance more effectively [26]. Activities such as long-term planning and marketing should be planned and executed purposefully with adequate input from different client segments and their clustering and classification, so that the organization can be as productive as possible [24]. Considering that in today's dynamic world, the corporate climate has changed from product-centric to consumer-centric [4], recognizing customer behavior has become more relevant, and one of the most critical tasks for customer-centric companies is to identify and appreciate customers preferences [31]. In fact, the study of consumer behavior is a way for companies to better understand the market and identify new prospects for growth [34]. Furthermore, most companies have realized that the customer database is one of their most valuable tools [19], and most of them use this database by evaluating the consumer information in order to establish marketing strategies [35]. Research shows that in recent years, multi-criteria decision making methods have been one of the most effective strategies for assessing and selecting the most appropriate factors and alternatives [20]. Among the decision-making methods, the entropy technique is one of the most important methods for measuring the weight and importance of indicators [42].

Additionally, many decision-making strategies were introduced to rate and pick the most appropriate alternatives and the VIKOR method is one of the most important methods in this category [45]. Thanks to the fact that a range of choices can be identified as accepted responses in this method, so this approach has been used to identify and evaluate categories of customers [38]. In recent years, technologies have played an important role in improving the business environment and making it more competitive which Apart from having influence on industries [43], this has contributed to the emergence of technology-based companies that operate on the basis of information technology [29] and IOT service providers are one of those businesses. On the other hand, owing to the infancy of these companies, little work has been done in this area which means that there are multiple areas for study and research in "IOT Service Providers" and Customer clustering is one of those areas. This issue was not addressed in previous researches, and was ignored and in the present paper, given that these companies are trying to obtain more customers for growth and advancement through different methods such as clustering, therefore a combined method using entropy and VIKOR technology was then used to analyze consumers and customer clustering of Internet of Things products, which was done to select the appropriate marketing technique [1, 7, 27].

2 Preliminaries

2.1 Multi-Criteria Decision Making

The decision-making process includes the proper presentation of the goals, the evaluation of specific and potential alternatives, and the assessment of their viability, the assessment of the implications and outcomes of the application of each solution and, ultimately, its selection and implementation [48].

$$\begin{array}{c|ccc} & C_1 & \cdots & C_n \\ \hline A_1 & x_{11} & \cdots & x_{1n} \\ \vdots & \vdots & & \vdots \\ A_m & x_{m1} & \cdots & x_{mn} \end{array} \tag{1}$$

The key goal of multi-indicator decision-making is to select the most appropriate option from $A_1, \ldots, A_m$ or rank it on the basis of $c_1, \ldots, c_n$ indicators. In these cases, the material is primarily provided in the form of a matrix of decisions in the form of a (1) where $\boldsymbol{x_{ij}}$ indicates the $\boldsymbol{A_i}$ option score relative to the $\boldsymbol{c_j}$ criterion. One of the most important steps in selecting the most appropriate option for multi-criteria decision-making is the weight calculation and the importance of indicators [52]. There are a variety of methods to measure the weight of indicators, including the Shannon entropy method.

2.1.1 Shannon's Entropy Method

Entropy is a concept in information theory that refers to the amount of information that each message gets. The definition of entropy has been introduced by Claude A. Shannon. Shannon was an American mathematician and electronics engineer known as the founder of the information theory. In the entropy concept, Shannon refers to the degree of uncertainty in the received message and expresses it with a probability theory [41]. Shannon's entropy in information theory is an indicator of the uncertainty measurement represented by a distribution of probabilities. Given the weights obtained from the indicators at this stage, those indicators which are more distributed are more important than other indicators when applying Shannon's entropy technique in decision-making problems, and their impact on choosing the best choice is more significant [37]. Suppose the decision matrix is based on the (1). Consequently, this procedure has the following steps:

Step 1: Build a normalized decision matrix.

This is achieved on the basis of the linear norm and the formula (2).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{2}$$

The following normalized decision matrix is created by using formula (2).

$$\begin{array}{c|ccc} & C_1 & \cdots & C_n \\ \hline A_1 & r_{11} & \cdots & r_{1n} \\ \vdots & \vdots & & \vdots \\ A_m & r_{m1} & \cdots & r_{mn} \end{array} \tag{3}$$

Step 2: Measure the variance or the degree of deviation of each indicator.

For each c_j criterion, we first determine the value of E_j, showing the sum of data concentration in the index, according to (4).

$$E_j = -\frac{1}{Ln\, m}\sum_{i=1}^{m} r_{ij} Ln(r_{ij}), \quad j = 1, \dots, n \tag{4}$$

In this case, the degree of uncertainty or the degree of variance of the c j index will be determined according to (4). The values of d_j represent the degree of dispersion of data and information in the c_j criterion and, according to the entropy method, the higher the amount, the higher the effectiveness of the c_j criterion in the options calculation, and thus the higher the index weight.

$$d_j = 1 - E_j, \quad j = 1, \dots, n \tag{5}$$

Step 3: Calculate the weight of the criteria

Using (6), d_j can be used to determine the weight of the indicators, depending on the obtained values. The w_j value shows how significant and efficient the c_j criterion is in assessing options.

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}, \quad j = 1, \dots, n \tag{6}$$

In most multi-criteria decision making, it is important to know the weight of the elements. Shannon's entropy technique is one of the methods used to determine the weight of elements. In this technique, the weight of the elements is determined based on the amount of dispersion of the values of the element.

2.1.2 VIKOR Technique

Ranking research options is very important in multi-criteria decision making models. One of the methods that deals with this category is VIKOR. The VIKOR method is a multi-criteria decision method to address a decision problem using inappropriate metrics and specific and conflicting units of measurement [42]. The aim of the VIKOR method is to concentrate on rating and selecting from a range of solutions to a problem with conflicting criteria. The results shown in the VIKOR method are a satisfactory ranking list plus one or more satisfactory solution. As one of the objectives of this research is to provide a clustering of customers, using the VIKOR method, could be helpful to achieve and provide this clustering which provides the possibility of providing more than one option, or in other words a range of options. The VIKOR method steps are as follows. The decision matrix is assumed to be in accordance with (1).

Step 1: Measure the best and worst values.

The best values of the options in the c_j criterion are shown with x_j^* and are calculated as follows:

$$x_j^* = Max_j\, x_{ij} \qquad \text{If } c_j \text{ is Benefit} \tag{7}$$
$$x_j^* = Min_j\, x_{ij} \qquad \text{If } c_j \text{ is Cost}$$

And the worst values of the options are shown in the c_j index with x_j ^ and are measured as follows:

$$x_j^- = Min_j\, x_{ij} \qquad \text{If } c_j \text{ is Benefit} \tag{8}$$
$$x_j^- = Max_j\, x_{ij} \qquad \text{If } c_j \text{ is Cost}$$

Step 2: Measure the weight of the indicator.

The weight and importance of the indicators can be calculated by methods such as entropy. Suppose the resultant weight is as follows:

$$W = (w_1, \dots, w_n)$$

Step 3: Measure the sum of utility and the sum of regrets.

The utility value of the i^{th} alternative is shown by S_i, which shows the relative distance of the i^{th} alternative from the ideal value and is defined as (9).

$$S_i = \sum_{j=1}^{n} w_j \frac{x_j^* - x_{ij}}{x_j^* - x_j^-}, \quad i = 1, \dots, m \tag{9}$$

The regret value for the i^{th} option is shown with R_i, which indicates the maximum discomfort of the i^{th} option from the distance of the ideal value and is defined as (10).

$$R_i = \max_{j=1,\dots,n} \left\{ w_j \frac{x_j^* - x_{ij}}{x_j^* - x_j^-} \right\}, \quad i = 1, \dots, m \tag{10}$$

Step 4: Measure the VIKOR Index

The VIKOR Index for the A_i alternative is indicated by Q_i. The VIKOR Index offers a comprehensive index for evaluating options in aggregate (11) by aggregating utility values and regrets.

$$Q_i = v \left[\frac{S_i - S^-}{S^* - S^-} \right] + (1 - v) \left[\frac{R_i - R^-}{R^* - R^-} \right], \quad i = 1, \dots, m \tag{11}$$

Which $R^* = \max_i R_i$ ،$R^- = \min_i R_i$ ،$S^* = \max_i S_i$ و $S^- = \min_i S_i$.

The value of parameter v plays a decisive role in (11) and this parameter is determined by the amount of agreement of the decision-making group. On this basis, the following conditions are considered:

If the agreement is too high, then v> 0.5

If the agreement is with a majority of votes, then v = 0.5

If the agreement is small, then v <0.5

The larger the v, the higher the group views.

The smaller the v, the more valuable it is to individual opinions.

Step 5: Rank the options and calculate the consensual answer set.

In the final step of the VIKOR technique, the options are divided into three groups, from small to large, based on the values of Q, R and S.

The optimal choice is to get the highest rank in all three values, otherwise the top option is the alternative with the smallest Q, so that the following two conditions are fulfilled.

Condition 1: If the A_1 and A_2 alternatives are ranked first and second among the m alternatives, the following relationship should be established:

$$Q(A_2) - Q(A_1) \geq \frac{1}{m - 1} \tag{12}$$

Condition 2: Alternative A1 must be recognized as a top rank in at least one of the R and S groups.

If the first condition is not met, a set of options will be selected as the top alternatives as follows.

$\{A_1, \dots, A_k\}$ Best Alternatives

The maximal value of k is determined according to the following relationship:

$$Q(A_k) - Q(A_1) < \frac{1}{m-1}$$

If the second condition is not met, both options A_1 and A_2 will be selected as the best option.

2.2 Marketing

Marketing is described by the American Marketing Association as: marketing is the corporate function and set of processes that are in place to develop, transfer and distribute value to consumers and maintain customer relationships in a way that leads to the creation of benefits for the organization and stakeholders [40]. According to Sergio Simeon, marketing identifies and specifies parts of the market as the most appropriate market segment for the company, and the company has the ability and capacity to provide services to them and it also designs and introduces the most suitable products and services needed for this sector [36]. In order to introduce a company properly, the aims, products, attitudes and actions of all parts of the company must be in complete harmony with each other there should be continuous participation in the field of competition and, according to Philip Cutler, marketing is a human activity that meets needs and wants through an exchange of needs and wants. Human needs and wants are the basic source and pillar of the marketing system [23]. The product is born out of human need, anything that provides or meets a need for a service may be considered a product that includes individuals, places, organizations, services and beliefs. Marketing demand requires a form of satisfaction, and demand has the capacity to meet demand [16].

2.3 Targeted Marketing

Targeted marketing has found a very broad concept in various economic, social and cultural dimensions [44]. Marketing is one of the most fundamental business principles, but marketing must be objective and effective [39]. In today's business climate, everybody is trying to draw consumers and use marketing to strengthen their position [18]. But marketing comes in many forms and the important thing is that whatever method is used, it has to be purposeful, that is, we have to define the target community and move in the same direction, because all the people in the target community are not for sale. Therefore, we need to save time and money and do marketing in the target community [11]. Targeted marketing identifies key concepts such as need, demand, commodity, exchange, equation and market. In fact, a chain ties us to the concept of market demand and efficiently marketing from there [47]. The general marketing perception is to seek out more customers [1]. The organization’s products have specific customers. A company may be faced at a particular time with a shortage of demand, insufficient demand or excessive demand for its products [26]. Companies analyze and identify the key parts of the market in targeted marketing, then pick one or more of the different parts of the market and carry out marketing campaigns in accordance with the parts selected and demanded and instead of dispersing marketing efforts around the market as a whole, the emphasis should be on the target market [54]. The three main moves towards achieving targeted marketing are as follows:

- Market segmentation

- Targeting on the Market
- Market positioning [3].

2.4 Customer Clustering

Clustering is one of the branches of unsupervised learning and is an automated process in which samples are divided into groups whose members are similar to each other called clusters [10]. A cluster is thus a set of objects in which objects are identical to each other and are not similar to objects in other clusters [32]. Simply put, data clustering means putting together homogeneous and similar data [17]. Examining customers' buying behavior, for example, can help us cluster customers. Clustering is a data-driven task without supervision [55]. No special features are used to direct the teaching process and all input characteristics are addressed in the same way [21]. Most clustering algorithms align the model with certain repetitions, and when the model becomes converging, they stop and that's when the boundaries of the groups were set [9].

2.5 Research Background

Tleis et al. [51] addressed the issue of organic food market segmentation in Lebanon. In a study, 121 questionnaires were distributed among organic food consumers in Beirut to conduct this research. By analyzing questionnaires, consumers were divided into four clusters using the K-means algorithm and appropriate marketing strategies were developed for each group. In an analysis, Fathian and Azhdari [22] have derived a pattern of customer behavior from a telecommunication company using dynamic, fuzzy clustering. In this paper, Fuzzy clustering was used to model the behavior of a group of customers during 10 months. The results of seven types of customer behavior patterns show that two of them resulted in a decline in the customer. The resulting patterns can be used to design the services optimally and prevent customer crashes. Ansari and Riasi [8] have also researched customer clustering using fuzzy tools and genetic algorithms. In this study, which was conducted on customers of the steel industry, customers were divided into two clusters using LRFM model indicators (communication length, novelty, repetition and monetary volume).

Customers of the first cluster had long term relationships, freshness and more shopping, but the monetary volume for all the data was lower than the average. In a study, Hiziroglu and Senbas [28] also analyzed customers in the automotive industry using fuzzy clustering. The purpose of this analysis was to cluster using a fuzzy C-means algorithm and compare it with traditional clustering methods. A data set of 110 customers was received from a car supplier in Turkey for this study. The findings have contributed to a more rational clustering than conventional clustering methods, allowing marketing managers to better consider their customers. Through studying the development of marketing strategies and market risk analysis using the DEMATEL approach. Gholami [25] argues that sustainability of life and sustainable income in today's environment relies on the proper application of marketing strategy techniques and consideration of risk principles in the market as a whole. The findings show that strengthening the brand, increasing domestic market share, increasing profits and focusing on different parts of the market are the most effective marketing goals and perhaps the most important factors influencing market risk are political tensions, the risk of product prices affecting demand and the risk of non-liquidity. Bose and Chen [14] identified the migration behavior of mobile phone customers using fuzzy clustering in the study. A special method was used in this paper to develop the basic C-means fuzzy clustering algorithm, using membership functions to detect how customers shift over time between clusters.

The results of this study led to the identification of two groups of customers that have demonstrated migratory behavior over time. The results helped mobile service providers learn how to spot customer behavior changes and recognize features that affect customer migration. In an article using a fuzzy C-means algorithm and a TOPSIS method, Azadnia et al. [9] measured the importance of consumer life-time. In this study, the fuzzy hierarchical analysis was used to weigh the RFM model variables. Upon measuring, clustering was done using the FCM algorithm.

According to the results, the customers were divided into three clusters and the lifetime value of each cluster was ranked according to the TOPSIS method. Tarokh and Sharifian [50] also divided bank customers into clusters using genetic algorithms and data mining techniques. Ali Heydari Biyouki and Khademi Zare [6] categorized banks' credit customers with the help of decision-making and data analysis techniques, including food industry companies, the pharmaceutical industry, electrical appliances, the automotive industry, base metals, gypsum and cement, machinery and equipment, manufacturing, telecommunications, glass and crystal, and the mining industry. All used a combined data mining model and a multi-indicator decision-making model, VIKOR, to cluster households and examined the importance of using the proposed model in the Statistic Center of Iran. Izadikhah and Shamsi [33] evaluated and categorized the legal clients of the National Bank of Arak with the help of multi-criteria decision-making methods and data envelopment analysis, as well as information on the assessment and ranking and interpretation of credit risk provided by the three major credit rating agencies Fitch, Modiz and Standard and Purz.

As a result of the novelty of the Internet of Things technology industry in Iran and, of course, in the world, no research has been identified which explores the relationship between marketing and customer behavior analysis in this industry by analyzing previous studies and much of the work has been conducted on the technical issues and ecology and infrastructure of this industry, It can therefore be said that current research has been praised by the Information Technology Research Institute, which conducts research on the Internet of Things industry, for creating interdisciplinary communication in the field of marketing management and information technology in the field of novelty and innovation in research. The result of this research can therefore be a new achievement in the literature on the Internet of Things Marketing and Industry, which, in turn, will lead to many practical benefits for this fledgling industry in the country.

3 Methodology

According to the goals sought, the present work is part of applied research and, in terms of the study process, is part of descriptive and exploratory research. The statistical population is divided into two parts, the qualitative section of sales and marketing managers of companies providing Internet of Things (IOT) services, this has led to new findings and in a small part has included all customers of the studied companies, which due to the unlimited community with Morgan table 384 people were selected as the sample size.

Data collection tools were used in the qualitative section of the interview and in the quantitative part of the closed questionnaire, which covers all aspects of the sample influenced by the identification of customer clusters, with a 5-point Likert scale (I totally agree = 5, I agree = 4, I have no opinion = 3, I disagree = 2 and I absolutely disagree = 1) Variables were measured.

Table 1: Factors and initial customer clustering

Factors	A_1:Customer Loyalty	A_2:Communication factors	A_3:customer relation management	A_4:Behavioral factors	A_5:Customer satisfaction
Sub Factors	1. Easy access to the product 2. Meet customer expectations 3. customer services 4. Appreciate the customer 5. Reputation 6. Develop customer relationships 7. Special offers 8. Giving the customer a chance to make decisions 9. Considering market conditions 10. Pay attention to statistics, figures and research results 11. Easy access to the product 12. Meet customer expectations 13. customer services 14. Appreciate the customer 15. Reputation 16. Develop customer relationships 17. Special offers 18. Giving the customer a chance to make decisions 19. Considering market conditions 20. Pay attention to statistics, figures and research results	1. Service usage 2. Revisit rate 3. The extent of communication with the company 4. Suggestions 5. Shopping rate 6. Service usage 7. Revisit rate 8. The extent of communication with the company 9. Suggestions 10. Shopping rate	1. Service and communication channels 2. Supportive technologies 3. Employee knowledge and awareness 4. Organizational communication and culture 5. Customer management process 6. Service and communication channels 7. Supportive technologies 8. Employee knowledge and awareness 9. Organizational communication and culture Customer management process	1. Quality 2. Recommend others 3. Service functions 4. Shopping experience 5. Advertising 6. Service support 7. Quality 8. Recommend others 9. Service functions 10. Shopping experience 11. Advertising 12. Service support	1. Compliance with expectations 2. Variety of products 3. Ease of purchase 4. after sales services 5. Compliance with expectations 6. Variety of products 7. Ease of purchase 8. after sales services

Table 1: Continue

Factors	A_6:Economical Factors	A_7:Factors affecting the non-purchase of customers	A_8:Customer experience management	A_9:Individual factors	
Sub Factors	1. Service prices 2. Income level 3. Job 4. Sales discounts 5. selling the credit leasing	1. Foot 2. Shift 3. New communications 4. Better choice or alternative goods 5. Dissatisfaction with product quality Improper behavior	1. Associated with advertising 2. solve problems 3. Promise Brand Support	1. Age 2. Gender 3. Level of education Modern lifestyle	

Cronbach's alpha was used to evaluate the validity of the marketing and reliability experts' questionnaire, which was 0.86 and confirmed. In order to analyze the data, the content analysis approach was used in the qualitative part and structural equations were used in the small part and all analyzes were performed using PLS2 software.

4 Findings

Initially, the demographic findings of the clients were examined, and the results showed that 55 of them were female and 329 were male, 211 had a bachelor's degree, 88 had a master's degree, and 85 had a doctorate. Also, 48 of them were between 20 and 30 years old, 197 people between 30 and 40 years old and 139 people over 40 years old, which shows that most of the customers of the companies are men and people with bachelor's degree and between 30 and 30 years old. They are 40 years old. A review of the literature led us to the initial clustering for customers according to Table 1. Sub-factors are identified as sub-factors in Table 1. In order to achieve the main factors, and therefore the main clustering of customers, in order to identify consumer behavior and thus find appropriate solutions for better and more efficient sales and increase market share, it is necessary to evaluate the factors on the basis of targeted indicators. In this respect, when examining the literature, the following indicators were established for the analysis and evaluation of the key factors.

C 1: Reduction of the costs of attracting new customers

C 2: Reducing the sensitivity of the customer to changes and prices

C 3: Benefits of the value of the life of the customer

C 4: Positive performance by increasing predictive power

C 5: Raise the barriers to entry for potential competitors

It is clear that the above factors are evaluated on the basis of qualitative and verbal values. The opinions of 15 people from sales and marketing managers of companies providing Internet services of Things Internet technology were therefore received as qualitative variables. The allocation of quantitative values is based on the spectrum set out in Table 2.

Table 2: Convert qualitative variables to quantitative

Very Strong	Strong	Moderate	weak	Very Weak	The importance as quantitative variables
9	7	5	3	1	**The importance as qualitative variables**

Table 3 summarizes the average opinion of the 15 experts in the table. This decision matrix table poses the question of evaluating and identifying the most relevant variables.

Table 3: Results of Evaluation

Criteria						
C5: Raise the barriers to entry for potential competitors	C4: Positive performance by increasing predictive power	C3: Benefits of the value of the life of the customer	C2: Reducing the sensitivity of the customer to changes and prices	C1: Reduction of the costs of attracting new customers		**Factors**
5.089	4.933	3.878	5.689	5.311	Customer Loyalty	
5.933	5.656	7.333	6.833	7.044	Communicational factors	
5.178	5.622	3.378	5.589	4.956	customer relation management	
6.822	6.400	7.100	6.900	7.333	Behavioral factors	
4.778	4.900	4.067	5.444	5.333	Customer satisfaction	
6.611	6.344	7.956	7.422	7.078	Economical Factors	
5.222	5.144	5.489	5.667	4.967	Factors affecting the non-purchase of customers	
4.889	4.700	3.767	6.100	5.233	Customer experience management	
6.867	6.744	7.267	6.489	7.033	Individual factors	

In order to determine the weight and importance of the indicators, the entropy method has been used and the steps taken to implement it have been taken as follows. The normalized decision matrix in the form of Table 4 is obtained by applying the linear norm and using relation (2). The uncertainty of each indicator, E_j, as well as the amount of data scattering by index, d_j, are shown in Table 4. It can be seen that the highest distribution is related to the Customer Life Value Benefit Index, and we expect the most weight for this index. The final weight of the indicators is also specified in the last row of Table 4, and it can be seen that the highest weight and the greatest impact on the assessment and classification of the customer are the 'benefits of the value of the life of the customer. Now, in order to rank and select a set of agreed options and identify the main clusters, the Vikor method is used, the implementation steps of which are as follows. The best and worst values for each index are calculated according to Table 5 and are based on the relations (7 and 8). The weights of the indicators are calculated using the entropy method, as shown in Table 4. Thus, the weight of the indicators is as follows.

$w_1 = 0.155$ ، $w_2 = 0.065$ ، $w_3 = 0.574$ ، $w_4 = 0.091$ و $w_5 = 0.115$

The value of usefulness and regret for each alternative is obtained according to Equations (9 and 10) and can be found in Table 6. The best and worst value of usefulness and regret is also given in this table.

Table 4: Entropy Process

C5: Raise the barriers to entry for potential competitors	C4: Positive performance by increasing predictive power	C3: Benefits of the value of the life of the customer	C2: Reducing the sensitivity of the customer to changes and prices	C1: Reduction of the costs of attracting new customers	
0.099	0.098	0.077	0.101	0.098	**Customer Loyalty**
0.115	0.112	0.146	0.122	0.130	**Communication factors**
0.101	0.111	0.067	0.100	0.091	**customer relation management**
0.133	0.127	0.141	0.123	0.135	**Behavioral factors**
0.093	0.097	0.081	0.097	0.098	**Customer satisfaction**
0.129	0.126	0.158	0.132	0.130	**Economical Factors**
0.102	0.102	0.109	0.101	0.091	**Factors affecting the non-purchase of customers**
0.095	0.093	0.075	0.109	0.096	**Customer experience management**
0.134	0.134	0.145	0.116	0.130	**Individual factors**
0.995	0.996	0.978	0.997	0.994	E_j
0.005	0.004	0.022	0.003	0.006	d_j
0.115	0.091	0.574	0.065	0.155	w_j

In the second cluster, there are customers whose factors have influenced their buying behavior. According to experts, these customers are affected by the nature of services, advice from others, business features, shopping experience, advertisement and service support, and seek to purchase from the services of companies. In the third cluster, which is called individual factors, features such as age, gender, education level and modern lifestyle have played a major role in the purchase of customers, and the results of demographic studies have also shown that all customers have a university education and that's why they've chosen a modern lifestyle, and most men are middle-aged.

Table 5: The best and the worst values

C5	C4	C3	C2	C1	
6.867	6.744	7.956	7.422	7.333	$\boldsymbol{x}^*$
4.778	4.700	3.378	5.444	4.956	$\boldsymbol{x}^-$

Table 6: The amount of utility and the amount of regret for each option

Title	Symbol	$\boldsymbol{S_i}$	$\boldsymbol{R_i}$
Customer Loyalty	A_1	0.8785	0.5113
Communicational factors	A_2	0.2161	0.0780
customer relation management	A_3	0.9321	0.5740
Behavioral factors	A_4	0.1422	0.1072
Customer satisfaction	A_5	0.8801	0.4876
Economical Factors	A_6	0.0485	0.0178
Factors affecting the non-purchase of customers	A_7	0.6829	0.3093
Customer experience management	A_8	0.9054	0.5253
Individual factors	A_9	0.1365	0.0863
	S^*	0.9321	
	S^-	0.0485	
		R^*	0.5740
		R^-	0.0178

In Table 7, the value of the VIKOR index is determined on the basis of the various values of the agreement parameter v. The reason for this is to select a range of accepted choices and to choose the correct customer cluster. It can be shown that option A 6 was the best option in all values of v. For v = 0.1, option A 2 rows second, and for the rest of values v, option A 9 rows second. Table 8 shows that different sets of satisfactory options are identified as superior responses based on the VIKOR method for different values of v.

Since there was no priority in this analysis, and according to the managers, to follow a particular strategy for choosing the full weight of group desirability, a total of four factors listed in the accepted sets of Table 8, i.e. A6: economic factors, A9: human factors, A4: behavioral factors and A2: communication factors were chosen as the final factors for further analysis. The results have therefore shown that marketing managers of Internet service providers have considered 4 main customer clusters, which include 1-communication factors, 2-behavioral factors, 3-individual factors and 4-economic factors, most of the customers of these companies have had its factors. According to experts, customers are divided into four clusters which any person in the first cluster because of communication factors are called "loyal customers. “Such customers also attempt to communicate with companies by using the product, the amount of the return, the amount of customer contact, the number of sales and the purchase amount, those people want to have a strategic relationship with businesses, because they rely on Internet of Things technology for their work.

Table 7: VIKOR index for various value of v

Rank	Mean	$v = 1.0$	$v = 0.9$	$v = 0.8$	$v = 0.7$	$v = 0.6$	$v = 0.5$	$v = 0.4$	$v = 0.3$	$v = 0.2$	$v = 0.1$	
7	0.9159	0.9394	0.9342	0.9290	0.9238	0.9186	0.9133	0.9081	0.9029	0.8977	0.8925	A1
4	0.1530	0.1897	0.1816	0.1734	0.1653	0.1571	0.1490	0.1408	0.1327	0.1245	0.1164	A2
9	1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	A3
3	0.1307	0.1061	0.1115	0.1170	0.1225	0.1280	0.1335	0.1389	0.1444	0.1499	0.1554	A4
6	0.8977	0.9412	0.9315	0.9219	0.9122	0.9026	0.8929	0.8833	0.8736	0.8640	0.8543	A5
1	0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	A6
5	0.6307	0.7180	0.6986	0.6792	0.6598	0.6404	0.6210	0.6016	0.5822	0.5628	0.5435	A7
8	0.94397	0.9699	0.9641	0.9584	0.9526	0.9468	0.9411	0.9353	0.9296	0.9238	0.9181	A8
2	0.1102	0.0997	0.1020	0.1044	0.1067	0.1091	0.1115	0.1138	0.1162	0.1186	0.1209	A9

Table 8: Satisfactory set for various value of v

$v = 1.0$	$v = 0.9$	$v = 0.8$	$v = 0.7$	$v = 0.6$	$v = 0.5$	$v = 0.4$	$v = 0.3$	$v = 0.2$	$v = 0.1$	**various value of v**
{A6,A9,A4}	{A6,A9,A4}	{A6,A9,A4}	{A6,A9,A4}	{A6,A9}	{A6,A9}	{A6,A9}	{A6,A9}	{A6,A9,A2}	{A6,A2,A9}	**Satisfactory set**

Table 9: Descriptive findings of clusters

Standard Deviation	**Mean**	**Main Clusters**
0.376	4.22	**Communicational factors**
0.433	3.98	**Behavioral factors**
0.651	4.15	**Individual factors**
0.768	3.77	**Economical factors**

With regard to the fourth cluster, it can be said that economic factors play an important role in selling services to such customers, including service prices, income levels, employment, sales discounts, credit sales and installment sales. If the above requirements are met, these customers will purchase the services.

Table 10: Ecstatic factor analysis

Medium extracted variance	The load factor	Sub Clusters	Main Clusters
0.673	0.783	Service usage	**Communicational factors**
	0.791	Revisit rate	
	0.811	The extent of communication with the company	
	0.701	Suggestions	
	0.743	Shopping rate	
0.655	0.891	Quality	**Behavioral factors**
	0.755	Advise others	
	0.716	Service functions	
	0.734	Shopping experience	
	0.793	Advertising	
	0.831	Service support	
0.690	0.740	Age	**Individual factors**
	0.794	Sex	
	0.843	Level of education	
	0.729	Modern lifestyle	
0.761	0.732	Service prices	**Economical factors**
	0.766	Income level	
	0.825	Job	
	0.866	Sales discounts	
	0.840	selling the credit	
	0.748	Leasing	

In this situation, both the main and sub-clusters that were implemented in the marketing model should be considered as methods for sales promotion. Furthermore, in order to verify the results obtained from the opinions of the introduced experts, it is necessary to know from the customers ' opinions how much these established factors have influenced their buying behavior, which was given to them in the form of a closed questionnaire. After the data are collected and analyzed, the results are as follows: The descriptive observations of the identified clusters were initially analyzed. The findings indicate that customers with all of the characteristics described gave high scores. According to the Likert range, the scores are above 2.5, which is higher than the demanded average. In this regard, the average communication factors (4.22) and the highest score and the average economic factors (3.77) have the lowest score, showing that the main cluster of communication factors will play an important role in targeted marketing and other behavioral and individual factors averages can be found in Table 9. In this portion, the exploratory factor analysis method was used to determine the load factor for each of the main clusters and within the clusters identified, the results of which are as described in Table 10. According to the aforementioned table, all operating loads under clusters are above 0.70 and the average extracted variance is over 0.50. As a consequence, we can see the strong influence of each element on the desired model. The cyclic redundancy check index and the coefficient of determination are used to evaluate the quality of the model. Positive numbers indicate the appropriate quality of the model. The coefficient of determination is the primary criterion for evaluating the structural model. This index shows how much of the dependent variable changes are made by independent variables. Table 11 shows that 79% of targeted marketing changes are identified by sub-clusters and the main clusters are predicted. If the cyclic consistency test index is greater than zero, the observed values are well reconstructed and the model is capable of forecasting. In this study, this index is above zero for the target marketing variable.

Table 11: Models to check the quality of the model

Redundancy	**The coefficient of determination**	**Model**
0.711	0.790	**Targeted marketing model**

The Furnell-Locker test was used to investigate divergent validity for model dimensions. The findings obtained for the measurements of the research model are shown in Table 12. Table 12 shows that the structures are completely separate, meaning that the instantaneous drop values for each hidden variable are greater than their dimension of correlation with the other hidden reflective dimensions of the model.

Table 12: Fornell Locker Index for Diagnostic or Divergent Narrative Index

4	**3**	**2**	**1**	**Clusters**	**No.**
			0.67	**Communicational factors**	**1**
		0.80	0.611	**Behavioral factors**	**2**
	0.82	0.421	0.654	**Individual factors**	**3**
0.87	0.563	0.391	0.433	**Economical factors**	**4**

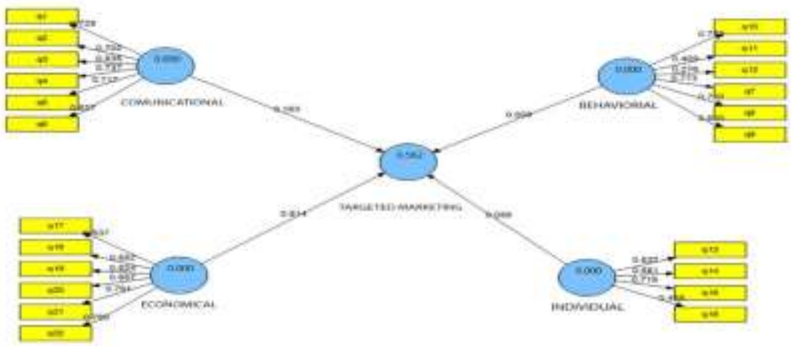

Fig. 1: Model in standard mode

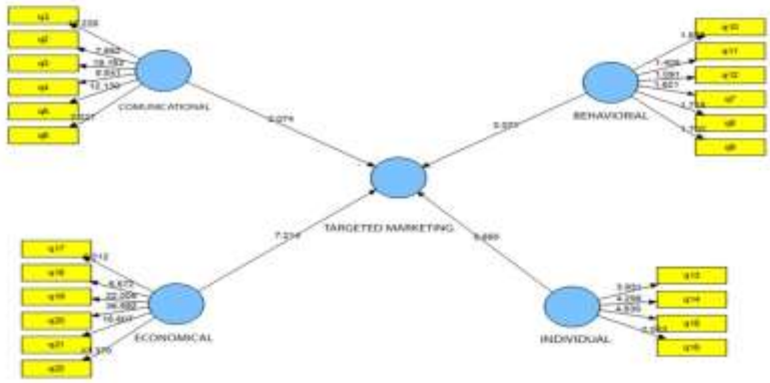

Fig. 2: Model in meaningful mode

In this section, given that it has been determined what the concept model is, the sample size is appropriate and all the dimensions identified on the model are effective, the model will be quantified using a partial square technique and a t-bootstrapping test and the results are shown in Fig. 1 and Fig. 2.

The findings of the above figure demonstrate that all of the obtained coefficients are positive for model dimensions and all of the obtained "t" values is more than 1.96 in Table Z, it can be inferred that the model is significant and the findings can be cited. Goodness of fit index including: GFI, AGFI, and RMSEA is used to fit the model. The values obtained in Table 13 indicate that model results are reliable. Since both the GFI and AGFI indexes are estimated to be higher than the target, and this figure is higher than the minimum of 0.90. Also, the ratio of the squared chai to the degree of freedom (X2 / df) has shown a good value. The RMSEA error criterion is also estimated to be 0.03, which is less than the permissible limit of 0.08. Based on the estimates given, it can be inferred that the model evaluated in the target community has reasonably good and acceptable fit. The results of the research model show, therefore, that the model used in present study was well-suited.

Table 13: Statistics related to the goodness of model fit

Fitting Criteria	Symbol	Criterion	Research values	The result of fitting
Divide the χ square by the degree of freedom	X^2/df	≤3	1.34	**Good Fitting**
The root of the mean squared error estimates	RMSEA	≤0.08	0.03	**Good Fitting**
Good fit index	GFI	≥0.9	0.94	**Good Fitting**
Adjusted fitness index	AGFI	≥0.9	0.91	**Good Fitting**
Comparative fit index	CFI	≥0.9	0.95	**Good Fitting**
Incremental fitness index	IFI	≥0.9	0.93	**Good Fitting**
Soft fit index	NFI	≥0.9	0.92	**Good Fitting**
Non-soft fit index	NNFI	≥0.9	0.96	**Good Fitting**
The coefficient of determination	R2	≥0.67	0.76	**Good Fitting**

5 Discussion and Conclusion

Nowadays, with increasing market competition and changing approaches from mass marketing to customer-based marketing, customer relationship management is the most important strategy for customer retention, market survival and decision-making on how to best allocate resources. In the other hand, data is currently perceived to be the beating heart of the business operations of most businesses and is developed in all industries, such as the Internet of Things, through interactions in information and communication technology networks, irrespective of the micro and macro category of industry. There is a need for a tool to process the stored data and to provide information to users. In this respect, many organizations are using data mining to better navigate all aspects of customer relationships. In this regard, the objective of the present study was to highlight the role of customer clustering in the design of a targeted marketing model. In order to do this, different categories of customers were evaluated in the first phase, with the help of entropy and VIKOR decision-making techniques, and four categories were selected as a consensual response set. These results showed that the model had four main clusters, including: communicational factors, behavioral factors, individual factors and economical factors, which customers were categorized in one of these clusters according to their characteristics.

The cluster of connectivity factors has shown that the customers of this cluster are trying to establish a strategic alliance with companies due to the business dependency of these customers on IOT services. These individuals have also made a lot of transactions and are considered to be a kind of strategic and loyal customer of the company. The findings of this cluster are consistent with the results of Ansari, Riasi[8], Telis et al.[51], Tone et al.[52] studies, because they have demonstrated that there are customers in companies that have a long-term relationship with industries due to the strategic need for the services or goods of a business. In this respect, it is suggested that managers of IOT technology providers seek to provide the necessary support to these customers in the form of the delivery of relevant facilities and after-sales services in order to maintain them. Such consumers can also be regarded as profitable customers of the company and can be considered the main cluster for the organization. With respect to the cluster of behavioral variables, it can be said that this cluster of consumers pays a great deal of attention to the quality of services and the behavior of these customers is affected by the advice of others or by the experience of shopping and advertising. The results of this cluster are consistent with the results of the research carried out by Hiziroglu and Senbas [28], Azadnia et al. [9], Sohrabi and Khanlari [49]. They found that the quality of service played an important role in the buying behavior of the customer. With regard to these observations, it can be said that, owing to the applicability of services, efficiency is a concern for these consumers, and they pay no to costs and attention it is suggested that the managers of such companies try to determine the amount of quality requested by customers by conducting a survey of this cluster of customers and in a way, defining quality from a customer's point of view, which increases and perpetuates such customers within organizations. Regarding the cluster of individual factors, it can be said that such customers try to use Internet of Things technologies due to their modern lifestyle and university education, and in fact, most of these customers were men who tend to be using this technology rather than women because of their greater involvement in jobs. The results of this cluster are consistent with the results of Rezaei and Elmi [46], Bose and Chen [14], Torkestani et al. [53], which showed that lifestyle can stimulate customer buying behavior.

Using information and communication technology, customers are now turning to the use of such techniques and this has a huge effect on their buying behavior. Therefore, it is recommended that managers of the companies studied try to make this group of customers more loyal by providing luxury services. And, on the other hand, they must employ people who interact with these customers who have a high level of technical knowledge of the company's services, which increases the impact on these customers. As far as the cluster of economic factors is concerned, it can be said that this cluster of customers often pays attention to the price of services or to the terms of sales that are important to them. The results of this cluster are consistent with the results of the research conducted by Fathian and Ajdari [22], Gholami [25], Agah et al.[2]. which found that price and sales could increase the customer's motivation to buy. As far as these results are concerned, it can be said that there are many customers who are trying to buy online services, first want to figure out the price of the services and then buy them, or want to buy them on credit and installments. Therefore, it is suggested that the managers of the surveyed companies try to make less profit in selling services to these customers or, by converting these customers into strategic customers, they can sell the services on installments and credit while receiving the requisite guarantees. At the end, it is worth noting that each study has certain limitations, and the generalization of findings to other companies and the intrinsic limitations of the questionnaire were the most significant limitations of this research. For the future, researchers will also be able to use other approaches, such as system dynamics, modeling and decision-making, to classify consumer clusters.

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