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ABC ANALYSIS OF THE CUSTOMERS USING AXIOMATIC DESIGN AND INCOMPLETE ROUGH SET

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Abstract. Customer's recognition, classification, and selecting the target market are the most important success factors of a marketing system. ABC classification of the customers based on axiomatic design exposes the behavior of the customer in a logical way in each class. Quite often, missing data is a common occurrence and can have a significant effect on the decision- making problems. In this context, this proposed article determines the customer's behavioral rule by incomplete rough set theory. Based on the proposed axiomatic design, the managers of a firm can map the rules on designed structures. This study demonstrates to identify the customers, determine their characteristics, and facilitate the development of a marketing strategy.

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1. Introduction

In a competitive marketing environment, the management of a firm/enterprise needs to achieve the customers' satisfaction among the most important antecedents while he/she deliveries services to the customers. Customer's satisfaction leads to various effects on business management and it is known to be an indicator of a company's future income and profit [10]. Customer's satisfaction can be considered as a customer's perspectives in which his or her needs, wants, and expectations throughout the product or service life cycle have been met or surpassed, bringing about ensuring repurchase and delay uniqueness [31]. So, the management of the firms and academics in this line of researches have recognized and given interest in the importance of creating a strong customer experience and engaged customer bases such that improving customer experience and engagement is a top goal for executives [12]. Any organization seeks effective strategies for existence in the market introducing an offer of products or services that provide a certain customer value. The value created for customers and the ability to manage it have been recognized as essential elements of the business strategy of the companies [2].

Research on repetitive purchase behavior in general and customer loyalty in particular has a long tradition in marketing [6]. Even for the most successful companies, some customers can be very profitable while others actually have a negative impact on the bottom line [1]. Customers can be classified as loyal to disloyal. Consequently, customer recognition is an important issue among other important factors of marketing systems.

Keywords and phrases: ABC classification, axiomatic design, incomplete rough set.

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One way to identify the type of customers is the multiplicity of purchase and the purchase amount which are taken into account as ABC classification in this proposed model. In this case, the purchase amount is chosen as the variable for ABC analysis. Customers are ranked according to their purchase amount, and then grouped into class A, B, and C. The items classified as class A are the first 15–20% of items which accounts for 75–80% of total purchase amount. The items of class B are the next 30–40% of items, accounting for approximately 15% of total purchase amount. The items belong to class C are the rest of items, accounting for their main value of total purchase amount. The impact of satisfaction on loyalty has been the most popular subject of studies. Several studies have revealed that there exists a direct connection between satisfaction and loyalty: satisfied customers become loyal and dissatisfied customers move to another vendor [15]. The factors like as quality, price, and importance of relationship and after sales service have a positive influence on loyalty. Axiomatic design (AD) can determine these factors significantly in scientific way.

In order to check the current status of customers, previous data must be analyzed. Datasets can be roughly classified into two classes: complete and incomplete datasets. All the objects in a complete dataset have known attribute values. If at least one object in a dataset has a missing value, the dataset is incomplete. In the most real world database, incompleteness is unavoidable; hence, establishing rules from an incomplete dataset is usually more difficult than a complete dataset. Kryszkiewicz [19] proposed a rough-set approach to learn rules directly from an incomplete dataset without guessing unknown attribute values. This approach does not require completion of the system beforehand, but it chooses a template based on rough set evaluation functions and then extracts complete subsets from the incomplete information system hierarchically with the template. Then, an intermediate variable is constructed based on rough sets theories and is used to decompose incomplete information system to simplified rule sets.

Achieving segmentation of the market is one of the biggest concerns of manufacturing and trading companies. To identifying and analyzing consumer behavior, one of the most important actions of companies is the classification of customers into different behavioral groups. Therefore, this paper seeks to find out an efficient and reliable classification based on changes in customer behavior and taste by presenting the ABC classification method for customer classification and analyzing its behavior using rough theory. Finally, effective factors of the customers' satisfaction are determined based on the axiomatic design technique. In the traditional attitude of business, the process of buying and selling goods and services are done by money, but now this attitude has lost its effectiveness on the marketing. As a result, customer orientation as the core of the activities of organizations and the requirement for its survival of the cases are being emphasized. Customer behavioral purchase pattern is a function of individual and product features. Also, the axiomatic design technique while paying attention to the needs of customers breaks the system from total to details. In fact, this technique uses the reverse engineering for the first time that can be used to classify the customers.

2. The related literature

2.1. Customer loyalty

The importance of customer loyalty has been recognized in marketing literature for many years [20]. There are many different approaches to customer loyalty. Theories of behavioral loyalty were dominating until 1970 considering loyalty as the function of the share of total purchases [4, 9] and function of buying frequency or buying [28, 30] or function of buying probability [14, 22, 32]. These approaches looked at brand loyalty in terms of outcomes (repeat purchase behavior) rather than reasons until the year 1969 while the two-dimensional concept of brand loyalty stated that loyalty should be evaluated with both behavioral and attitudinal criteria. But, contemporary researches consider and accent the psychological (mostly attitudinal and emotional) factor of loyalty pattern [3, 7, 17, 23, 26]. There are also approaches comparing loyalty with marriage [8, 16, 21]. As shown in Figure 1 the factors which measure the dimensions of the customer loyalty are high sales and profit margins, training and employment of employees, employee satisfaction and competence, superior service delivery, and customer satisfaction which are adapted from previous studies.

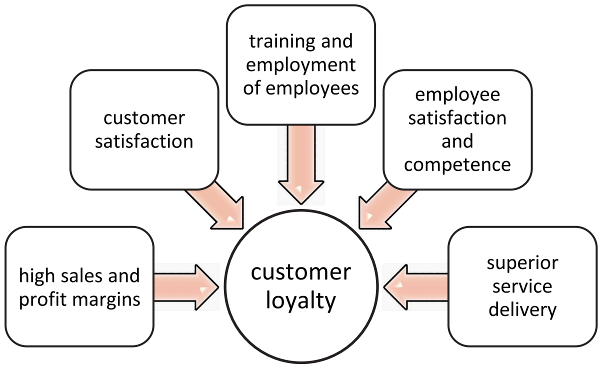

FIGURE 1. Dimensions of the customer's loyalty.

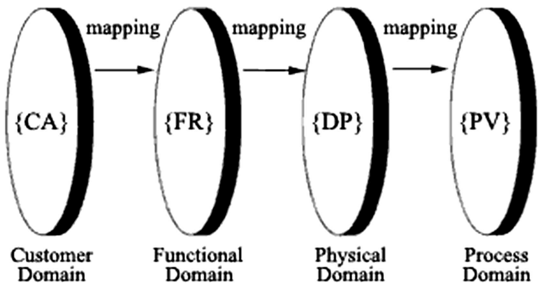

FIGURE 2. Concept of domains.

2.2. Axiomatic design

The methodology [2] of axiomatic design theory (AD) is a structured way to formulate a design due to its focus on how different requirements interact [24]. The concept of axiomatic design introduced by Suh [29] refers to a set of scientific principles. AD helps the formulation of design of goals which is to be carried out in a hierarchical structure covering all the required information. This approach is observed in several different areas ranging from product design and improvement to the process design and improvement [18]. Although the first AD implementations are related to the product design [29], today it is also used in areas related to systems design. There are four domains in design world as shown in Figure 2. The relationship between the two adjacent domains is "what we want to achieve" and "how to achieve". The "what" is represented by the domain on the left and the "how" are represented by the domain on the right. The specific characteristics of CAs (customer domain), FRs (functional domain), DPs (physical domain), and PVs (process domain) depend on the specific nature or goals of the software and the "what"/"how" relationship of the domains (Fig. 2).

2.3. Incomplete rough set

The rough set theory is an important mathematical tool to deal with imprecise, inconsistent, incomplete information, and knowledge [25]. Originated from the simple information model, the basic idea of the rough set theory can be divided into two parts. The first part is to form concepts and rules through the classification of relational database. And, the second part is to discovery knowledge through the classification of the equivalence relation and classification for the approximation of the target [33].

In the last 30 years, the development of rough set theory has achieved a significant outcome in the theoretical as well as applied researches. In recent years, an increasing number of academic activities on rough sets have been done. The range of academic conferences throughout the world promote the development of rough set theory [33]. Rough set theory is a useful mathematic tool for dealing with vague and uncertain information and it has been applied successfully in many fields of classical rough set model based on equivalence relation or partition which can only deal with complete and symbolic (or nominal) datasets, whereas datasets with numerical attribute values more common in real world are beyond its scope [5]. An incomplete information system is an information system with some missing values [11]. Samant and Sarkar [27] introduced fuzzy rough relation on a set and they proved that collection of the relations is closed under different binary compositions.

There are some simple preprocessing methods handling these systems of which missing values can be deleted or filled with some values and then the incomplete information system is transformed to a complete one [13]. The contribution of the existing literature is given in Table 1.

3. The model

Datasets can be roughly classified into two classes: complete and incomplete datasets.

A complete decision system is a 4-tuple $S=\langle U, AT\cup d, V, f\rangle$, where U is the universe; AT is a non-empty finite set of conditional attributes, d is a decision attribute where $AT\cap d=\emptyset$; V is regarded as the domain of all attributes; $\forall\, x\in U$, $f(x,a)$ denotes the value that x holds on a $(a\in AT\cup d)$.

When precise values of some objects on the condition attributes are not known in a decision system, the system is called an incomplete decision system and is still denoted without confusion by $S=\langle U, AT\cup d, V, f\rangle$. Here, $V=V_{AT}\cup V_d\cup\{*\}$, the special symbol "*" is used to indicate the unknown value. We assume here that the unknown value is just "missed", but it does exist.

Definition 3.1. Let S be an incomplete decision system, $A\subseteq AT$, the dominance relation in terms of A is defined as:

$$R^E(A)=\{(x,y)\in U_2\colon \forall a\in A, f(x,a)\geq f(y,a)\vee f(x,a)=*\vee f(y,a)=*\}. \tag{3.1}$$

$\forall(x,\ y)\in R^E(A)$, x dominates y on A possibly because existence of unknown values. $R^E(A)$ is reflexive, but not necessarily symmetric and transitive. By $R^E(A)$, we can define the following two sets for each $x\ \in U$: $R_A^{+E}(x)=\{y\ \in U\colon (y,\ x)\in R^E(A)\}$, $R_A^{-E}(x)=\{y\in U\colon (x,y)\in R^E(A)\}$.

Moreover, assume that decision attribute d makes a partition of U into a finite number of classes.

Let $\mathbf{CL}=\{CLt,\ t\in N\}$, $N=\{1,2,\ldots,n\}$, be a set of these classes those are ordered, that is $t_1>t_2$ $\forall t_1$, $t_2\in N$ and the objects from CLt_1 are preferred to the objects from CLt_2. The approximated sets are to be an upward union and a downward union of classes such that $CL_t^{\geq}=\cup_{t'\geq t}CLt'$, $CL_t^{\leq}=\cup_{t'\leq t}CLt'$, $t,\ t'\in N$.

Definition 3.2. Let S be an incomplete decision system, $A\subseteq AT$, $t\in N$, the lower and upper approximations of $CL_t^{\geq}$ in terms of the dominance relation $R^E(A)$ are defined as

$$\underline{A}_E(CL_t^{\geq})=\{x\in\cup : R_A^{+E}(x)\subseteq CL_t^{\geq}\},\qquad \overline{A}_E(CL_t^{\geq})=\{x\in U : R_A^{-E}(x)\cap CL_t^{\geq}\neq\emptyset\}.$$

The lower and upper approximations of $CL_t^{\leq}$ are defined as:

$$\underline{A}_E(CL_t^{\leq})=\{x\in\cup : R_A^{-E}(x)\subseteq CL_t^{\leq}\},\qquad \overline{A}_E(CL_t^{\leq})=\{x\in U : R_A^{+E}(x)\cap CL_t^{\leq}\neq\emptyset\}.$$

By above approximations, the boundary regions of $CL_t^{\geq}$ and $CL_t^{\leq}$ are

$$Bnd_A^E(CL_t^{\geq})=\overline{A}_E(CL_t^{\geq})-\underline{A}_E(CL_t^{\geq}),\qquad Bnd_A^E(CL_t^{\leq})=\overline{A}_E(CL_t^{\leq})-\underline{A}_E(CL_t^{\leq}).$$

TABLE 1. Contribution of previous literature.

Authors' names	Techniques	Field of application
Cepeda-Carrion *et al.* [2]	Dynamic capability and knowledge management processes	Creation of customer value
Grewal *et al.* [12]	Conscious capitalism	Customer engagement
Lee and Wong [20]	E-service quality models and relationship quality theories	Customer loyalty
Forozia *et al.* [10]	Random sampling method	Customer satisfaction in hospitality industry
Usta *et al.* [31]	Multiple stepwise regression analysis	Hotel customers' satisfaction
Cabiró [1]	Pareto's principle	Customers classification
Diamantopoulos *et al.* [6]	Marketing models and marketing research methods	Marketing management
Heskett *et al.* [15]	Service profit chain	Customer loyalty and satisfaction
Kabadurmuş and Durmuşoğlu [18]	Axiomatic design principles	Design of pull/Kanban production control systems
Cunningham [4]	Logit model	Brand loyalty
Farley [9]	Calculus technique	Brand loyalty
Tucker [30]	Empirical methods	Brand loyalty
Sheth [28]	Factor analytical model	Brand loyalty
Harary and Lipstein [14]	Markov model	Brand loyalty
McConnell [22]	Factorial design	Brand loyalty
Wernerfelt [32]	Calculus technique	Brand loyalty and market equilibrium
Jacoby and Kyner [17]	Calculus technique	Brand loyalty
Oliver [23]	Calculus technique	Customer loyalty
Chaudhuri [3]	Model of attitudes, habit	Brand quality
Djupe [7]	Empirical methods	Brand loyalty and political loyalties
Reichheld [26]	Survey questionnaire method	Customer loyalty
Hofmeyr and Rice [16]	Conversion model	Brand loyalty
Lewitt [21]	Theory of supply and demand presumes	Relationship management
Dwyer *et al.* [8]	Marketing theory and practice	Relationship management
Ómarsdóttir *et al.* [24]	Axiomatic design	Robotics
Pawlak [25]	Rough set theory	Computer science
Zhang *et al.* [33]	Rough set theory	Information technology
Dai [5]	Incomplete rough set theory	Data characterized with numerical attributes
Greco *et al.* [11]	Rough set analysis	Decision making
Grzymala-Busse [13]	Rough set strategies	Decision making
Suh [29]	Axiomatic design	Mechanical engineering
Samanta and Sarkar [27]	Fuzzy-rough sets	Information engineering
Kryszkiewicz [19]	Rough set theory	Classification and decision making
Our present article	Axiomatic design and incomplete rough set theory	Classification of customers

TABLE 2. Decomposition level 1.

	DP_1	DP_2	DP_3	DP_4	DP_5
FR_1	X	0	0	0	0
FR_2	0	X	0	0	0
FR_3	0	0	X	0	0
FR_4	0	0	0	X	0
FR_5	0	0	0	0	X

Similar to the definition of accuracy of approximation in Pawlak's rough set model [25], the accuracies of approximations of unions of decision classes are $\alpha^E_{CL_t^{\geq}} = \frac{|\underline{A_E}(CL_t^{\geq})|}{|\overline{A_E}(CL_t^{\geq})|}$ and $\alpha^E_{CL_t^{\leq}} = \frac{|\underline{A_E}(CL_t^{\leq})|}{|\overline{A_E}(CL_t^{\leq})|}$, respectively, where $|T|$ is the cardinal number of set T. The ratio

$$\gamma_A^E\left(CL\right) = \frac{\left|U - \left(\left(\cup Bnd_A^E\left(CL_t^{\geq}\right)\right) \cup \left(\cup Bnd_A^E\left(CL_t^{\leq}\right)\right)\right)\right|}{|U|},$$

denotes the quality of approximation of the partition **CL** in terms of $R^E(A)$ or briefly, quality of sorting. This ratio expresses the relation between all the A-correctly classified objects and all the objects.

3.1. Design of customer classification using AD principles

A successful design approach should begin with a definition of what we want to achieve and end with a clear description of how we will achieve them. The main functional requirement (FR) at the higher level expresses what the vessel should do. In this work, the following has been selected as the highest FR:

FR_0 = presence in the competitive environment.

The following DP is selected to satisfy the FR provided above:

DP_0 = customer retention and customer loyalty.

The following lower FRs set is described as below:

FR_1 = providing a convenient location.
FR_2 = reduce customers costs.
FR_3 = respect to the customer.
FR_4 = presenting high-quality products.
FR_5 = perfect after-sales service.

The following DPs are selected to satisfy the FR provided above:

DP_1 = equipping the shop with a convenient materials.
DP_2 = understanding customer's uselessness.
DP_3 = staff training.
DP_4 = identifying high-quality products.
DP_5 = strengthen after-sales services section.

The corresponding design matrix provides the relationships between the FR and DP elements (Tab. 2).

The design given in Figure 2 is an uncoupled design and satisfies the independence axiom completely. It shows that customer retention and customer loyalty can be done in five independent ways.

TABLE 3. Decomposition level 2.

	DP_{11}	DP_{12}	DP_{21}	DP_{31}	DP_{32}	DP_{41}	DP_{42}	DP_{51}	DP_{52}
FR_{11}	X	O	0	0	0	0	0	0	0
FR_{12}	0	X	0	0	0	0	0	0	0
FR_{21}	0	0	X	0	0	0	X	0	0
FR_{31}	0	0	0	X	X	0	0	0	0
FR_{32}	0	0	X	X	X	0	0	0	0
FR_{41}	0	0	0	0	0	X	0	0	0
FR_{42}	0	0	0	0	0	0	X	0	0
FR_{51}	0	0	0	0	0	0	0	X	0
FR_{52}	0	0	0	0	0	0	0	0	X

Level 2 includes decomposition to identify suitable location using professional experts considering the real needs of the customer, staff training, identifying new products. Regarding this matter, we can decompose FRs mentioned above into the terms as follows:

FR_{11} = placing in a quick and easy access location.
FR_{12} = equipping with parking, elevator, etc.
FR_{21} = setting up counseling sessions with customers.
FR_{31} = learning how to deal respectfully with customers.
FR_{32} = learning how to help and guide customers.
FR_{41} = identifying all the global markets.
FR_{42} = identifying the fake products.
FR_{51} = training specialists in the field of after-sales service.
FR_{52} = accelerating the provision of after-sales service.

In satisfying the FRs defined above, we move from the functional domain to the physical domain. The following DPs are in response to the FRs listed above:

DP_{11} = away from traffic area.
DP_{12} = using the proportional space to business.
DP_{21} = using consultants or training employees who can advise customers.
DP_{31} = establishing customer-oriented training courses.
DP_{32} = training the young staffs by professional experts.
DP_{41} = constant updating the information about new products which are offered to the global market.
DP_{42} = recognition superseded, and high-quality products that reduce customer costs.
DP_{51} = organize training courses for after-sales service staff.
DP_{52} = using the appropriate number of staff in the after-sales service department.

The design matrix for this level is shown in Table 3.

The design (Tab. 3) at this level is a decoupled design obtained by consulting the training employees who can advise the customers. Establishment of customer-oriented training courses, the younger and more patient staff, recognition superseded and high-quality products which reduce customer costs are the most important factors to maintain the goodwill of the customers.

In Table 4, it is observed that customer's maintenance has been decomposed to three levels. Suitable location, reduce customers costs, respect to customers, and many other factors have been regarded in the decomposition process. On the other hand, regarding Table 4, several DPs affect FR_{32} to encourage customers to other parts of the shop. This means that the strategy of persuading customers has a great importance. Nowadays, many retailers have found the importance of this strategy. If we look carefully at complete matrix, we will find it coupled.

TABLE 4. Complete design matrix in the competitive environment.

			DP0= retaining the customers and customer loyalty								
			DP_1= Considering customer welfare dimensions materials		DP_2= Removing customer's uselessness	DP_3= Staff training		DP_4= Identifying the real needs of customers		DP_5= Strengthening the infrastructure of the after sales service sector	
			DP_{11}= Locating in the customer access center	DP_{12}= Using appropriate customer's welfare equipment	DP_{21}= Modifying the processes	DP_{31}= Holding customer behavioral encounter training sessions	DP_{32}= Holding customer scientific and specialized encounter training sessions	DP_{41}= Surveying to identify actual needs	DP_{42}= Surveying to identify potential needs	DP_{51}= Establishing active agencies in the area of providing after-sales services	DP_{52}= Mechanizing after-sales service
FR_0 = Presence in the competitive environment	FR_1= Providing a convenient location	FR_{11}= Consider the location dimension	x	0	0	0	0	0	0	0	0
		FR_{12}= Consider the equipment dimension	0	x	0	0	0	0	0	0	0
	FR_2= Reducing customer costs	FR_{21}= Reviewing the processes	0	0	x	0	0	0	0	0	0
	FR_3= Gaining customer satisfaction	FR_{31}= Behavioral training of employees in dealing with customers	0	0	0	x	0	0	0	0	0
		FR_{32}= Scientific and specialized training for staff in providing customer services	0	0	0	0	x	0	0	0	0
	FR_4= presenting high-quality products	FR_{41}= Identify actual customer needs	0	0	0	0	0	x	0	0	0
		FR_{42}= Identify potential customer needs	0	0	0	0	0	0	x	0	0
	FR_5= Presenting perfect after-sales service	FR_{51}= Increase after-sales service	0	0	0	0	0	0	0	X	0
		FR_{52}= Accelerating the provision of after-sales service	x	x	0	0	x	0	0	0	X

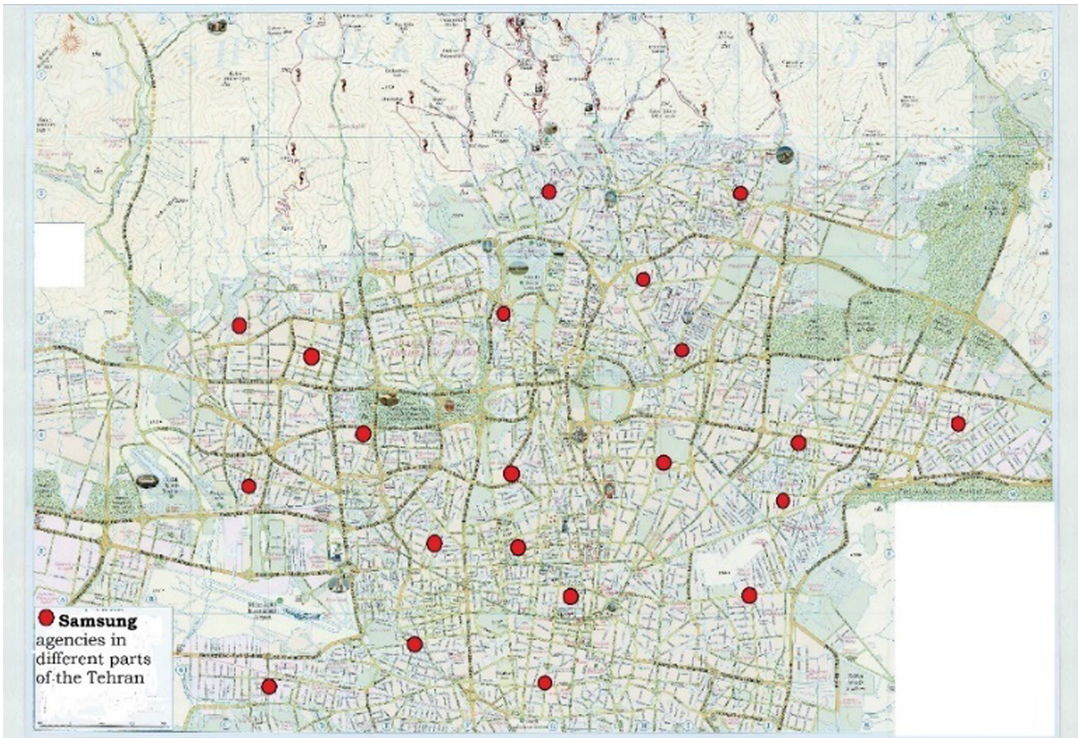

Figure 3. Samsung agencies indifferent parts of Tehran.

4. Illustration

Over 70 years, Samsung has been dedicated to making a better world through diverse businesses which span advanced technology, semiconductors, skyscraper and plant construction, petrochemicals, fashion, medicine, finance, hotels, and more. Our target company Samsung Electronics leads the global market in high-tech electronics manufacturing and digital media (Fig. 3).

The main goal of this paper is to identify the different kinds of customers of Samsung mobile phone, and classifying them into 3 groups according to the purchase amount in order to give them appropriate products and services from the point of view of axiomatic design. The questionnaires are distributed in the number of centers in different parts of Tehran city which is shown in Table 5 having questionnaires filled by 5579 customers.

The customers have responded to the questionnaire which are given in Table 6.

Table 5 contains many variables that results in very time consuming to perform calculations. Therefore, in order to reduce the large volume of data, we summarize the data in Table 7 and perform calculations according to this table. This table details 10 questionnaires evaluated by means of four attributes.

Where a_1: earning; a_2: quality; a_3: after sale services; d: purchase amount.

The components of the data table are:

$U = \{x_1, x_2, \ldots, x_{10}\}$ is the universe;
$AT = \{a_1, a_2, a_3\}$ is the set of all condition attributes, d is the decision attribute;
$Va_1 = Va_2 = Va_3 = \{\text{High, Medium, Low}\}$ where "High" > "Medium" > "Low";
$V_d = \{\text{High, Medium, Low}\}$ where "High" > "Medium" > "Low".

Thus, the decision d determines the following partition on the universe:

Table 5. A summary of customers' reports.

Perceptual information related to customer loyalty (extracted from axiomatic design)					Personal information related to the purchase (extracted from the database)					Customer
Conditional variables					Decision variable	Conditional variables				
Customer costs	After sale services	Courtesy of staff	Store location	Quality	Purchase amount ($)	Education	Earning ($)	Age	Gender	
*	M	M	M	H	1220	H	2300	*	F	X1
L	M	*	L	L	560	L	1230	35	F	X2
M	M	L	*	*	650	M	2850	27	M	X3
M	L	M	H	H	480	*	900	33	F	X4
L	L	M	M	L	300	H	1000	46	*	X5
M	L	M	*	H	420	B	1350	*	M	X6
*	L	M	H	L	100	H	*	38	M	X7
*	M	*	M	L	850	*	2400	47	F	X8
L	M	L	*	*	910	H	1250	43	F	X9
H	M	*	M	M	930	M	1700	*	M	X10
…	…	…	…	…	…	…	…	…	…	…
M	M	*	L	*	900	H	1300	*	F	X5579

Table 6. Guide table for respondents.

Gender	Female (F)	Male (M)	–
Age	20–30 (L)	31–40 (M)	41–50 (H)
Earning	$1500–2500 (H)	$1000–1500 (M)	$800–1000 (L)
Education	Master and above (H)	College (M)	High school and below (L)
Quality	High (H)	Medium (M)	Low (L)
Store location	Excellent (H)	Good (M)	Bad (L)
Courtesy of staffs	Excellent (H)	Good (M)	Bad (L)
After sale services	High (H)	Medium (M)	Low (L)
Reduce customer costs	High (H)	Medium (M)	Low (L)
Purchase amount	More than $1000 (H)	Between $500 and $1000 (M)	Less than $500 (L)

Table 7. A summary of customers' reports from 10 sample question papers.

(U)	(a_1)	(a_2)	(a_3)	(d)
X_1	H	H	M	H
X_2	M	L	M	M
X_3	H	*	M	M
X_4	L	H	L	L
X_5	L	L	L	L
X_6	M	H	L	L
X_7	*	L	M	L
X_8	H	L	L	M
X_9	M	*	L	M
X_{10}	H	M	M	M

TABLE 8. Rules table.

No.			Class
1	If age (Y) & earning (M) & education (H) & quality (H) & after sale services (M) & location (M)	→ purchase amount (H)	A
2	If age (M) & earning (H) & education (M) & quality (H) & after sale services (L) & location (H)	→ purchase amount (L)	C
3	If age (L) & earning (L) & education (M) & quality (L) & after sale services (H) & location (L)	→ purchase amount (M)	B
4	If age (H) & earning (H) & education (M) & quality (H) & after sale services (H) & location (M)	→ purchase amount (M)	B
5	If age (M) & earning (M) & education (L) & quality (M) & after sale services (L) & location (H)	→ purchase amount (L)	C
6	If age (L) & earning (H) & education (M) & quality (H) & after sale services (L) & location (N)	→ purchase amount (H)	A

$\mathbf{CL} = \{CL_1,\ CL_2,\ CL_3\}$, $CL_1 = \{x \in U:\ f(x,\ d) = \text{Low}\} = \{x_4,\ x_5,\ x_6,\ x_7\}$, $CL_2 = \{x \in U:\ f(x,\ d) = \text{Medium}\} = \{x_2,\ x_3,\ x_8,\ x_9,\ x_{10}\}$, $CL_3 = \{x \in U: f(x,\ d) = \text{High}\} = \{x_1\}$.

By the expanded dominance relation, we obtain:

$\underline{AT}_E\ (CL_1^{\leq}) = \{x_4, x_5\}$, $\overline{AT}_E(CL_1^{\leq}) = \{x_3, x_4, x_5, x_7, x_9\}$, $Bnd_{AT}^{E}(CL_1^{\leq}) = \{x_3, x_7, x_9\}$,
$\underline{AT}_E\ (CL_2^{\leq}) = \{x_2, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}\}$, $\overline{AT}_E(CL_2^{\leq}) = U$, $Bnd_{AT}^{E}(CL_2^{\leq}) = \{x_1, x_3\}$,
$\underline{AT}_E\ (CL_3^{\geq}) = \emptyset$, $\overline{AT}_E\ (CL_3^{\geq}) = \{x_1, x_3\}$, $Bnd_{AT}^{E}(CL_3^{\geq}) = \{x_1, x_3\}$,
$\underline{AT}_E\ (CL_2^{\geq}) = \{x_1, x_2, x_3, x_8, x_{10}\}$, $\overline{AT}_E\ (CL_2^{\geq}) = \{x_1, x_2, x_3, x_7, x_8, x_9, x_{10}\}$, $Bnd_{AT}^{E}(CL_2^{\geq}) = \{x_7, x_9\}$.

5. Rule generation

The decision rules are expressions of the form "if (conditions), then (consequence)" that represent a form of dependency between condition criteria and the decision criterion. More exactly, the decision rules say that if some condition attributes have given values, then some decision attributes have other given values.

A set of rules are established in Table 8.

The "minimum cover rules" (*i.e.*, where the set does not contain any redundant rules), and these rules are certain such that there are a total of 18 rules generated from the data. The reduced rule set contains 18 rules in which 3 rules have the maximum strength. In rough set, we have to translate data of the decision table to meaningful rules as follow:

- *Rule 1:* Class A customers: if (age = Y), (earning = H), (education = H), (quality = H), (after sales-service = M), and (store location = N) then (purchase amount = H).

Form preliminary review of the rules given in Table 8 about the category A, it can be concluded that, if the age, income, education, product quality, after-sales service, and store location are key factors, then the answer to the ultimate question is the purchase amount which will be more than of $1000. According to final answer, it can be ensured that the customers purchase amount is being affected to the quality of products. Moreover, if we want to keep this category, of customers, we should strengthen the quality of products. Customers in rows 1 and 6 of Table 8 are examples of this group. Mechanisms to strengthen the quality of the products are shown in Figure 4.

- *Rule 2:* Class B customers: if (age = O), (earning = H), (education = H), (quality = M), (after sales-service = M), and (store location = L) then (purchase amount = M).

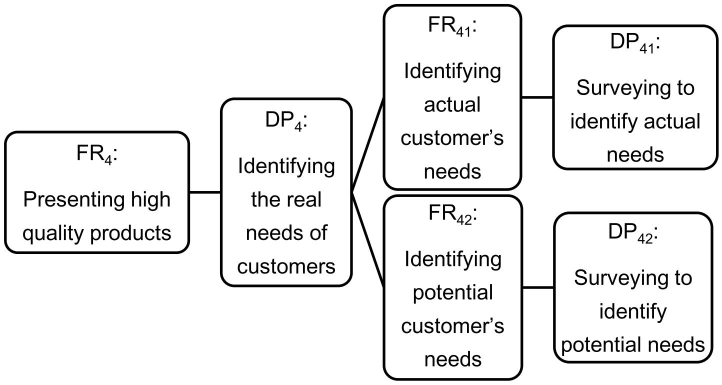

Figure 4. The most important factor for the customers belong to the category A.

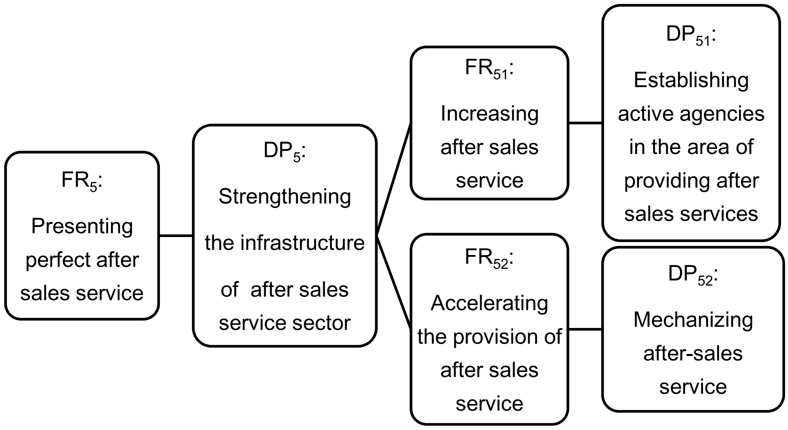

Figure 5. The most important factor for the customers belong to the category B.

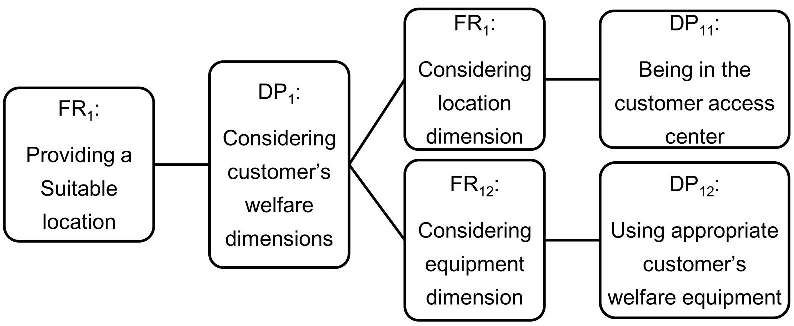

Figure 6. The most important factor for the customers belong to the category C.

In the category B, a preliminary review of the rules by considering the age, income, education, product quality, after-sales service, and store locations as key factors suggests that the customers purchase amount will be between \$500 and \$1000. The purchase amount of this category is more affected by after sale services. Customers in rows 3 and 4 of Table 8 are examples of this group. In order to keep this category we should consider the factors which are shown in Figure 5.

- *Rule 3:* Class C customers: if (age = M), (earning = L), (education = H), (quality = M), (after sales-service = L), and (store location = H) then (purchase amount = L).

In category C, taking into account the age, income, education, product quality, after-sales service and store locations as key factors, the purchased amount will be less than $500. In such situation, the purchased amount is more affected by storage location. Customers in rows 2 and 5 of Table 8 are examples of this group. For category C, we can use the guidelines presented in Figure 6.

6. Managerial implication

The management of a firm/enterprise may use the proposed approach to identify the factors and barriers of satisfaction at different stages of decision making because customer's satisfaction or dissatisfaction varies in different times and places. It also suggests the managers of the company's to design loyalty programs such as applying reciprocity policies like cash discounts and fixed discount levels according to each customer groups (classes A, B, and C) and their purchases amount in order to maintain and adapt to different groups of customers.

7. Conclusion

This paper deals with the customer classification. When describing real classification problem, it is possible to express its description by using a natural language. The proposed model illustrates the usefulness of the classification approach as an operational tool for the prediction of customer behavior. An illustrative example (Samsung mobile phones customers) has been employed to show the validity of this classification. It is found virtually in all cases that the proposed prediction in the model takes the form of decision rules. This article generalizes and enhances the well-known ABC customer grouping approach by offering integrated automated and optimized solutions. On the basis of the above stated facts, it can be claimed that the proposed classification is functional, relatively successful compared with other methods. Since these findings extend the derived rules which are supported by real examples which describe only the most relevant attributes/criteria. This study therefore indicates the main advantage of the customer classification such that it considers all categories of customers and it tries to attract more customers. Like previous researches, a comprehensive approach along with providing a solution for maintaining and increasing the loyalty of each of the different classes of customers, this research seeks to classify the customers and present an appropriate solution for each group of the customers simultaneously. As far as the authors' knowledge goes, the use of axiomatic design as a new and flexible method for classifying customers is introduced in this literature for the first time.

Since there are many successful mathematical methods recently proposed such as fuzzy data mining, fuzzy rough set theory, and nature-based computation techniques, it would be interesting to apply these approaches in ABC analysis. In future, the existing model may be extended incorporating other variables which are absent in this model as the complex processes of segmentation and analysis of customer behavior.

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