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CUSTOMER SATISFACTION AND PRODUCT CLUSTERING FOR GEN NEXT CUSTOMERS— A MULTIVARIATE AND SIMULATION STUDY

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Abstract *Developing marketing strategies for serving gen next customers has become vital and complex in the current times. This paper studies 'product clustering' as a marketing strategy to improve customer satisfaction of gen next customers. The relationship between product clustering and customer satisfaction is studied using multivariate statistical tools. Further, using cluster analysis techniques, customer satisfaction has been used as a criterion to develop product clusters. The complexity of product clustering has also been highlighted by conducting a Monte Carlo simulation. The paper shows that appropriate product clustering is indeed crucial in serving gen next customers better.*

Keywords: *Product Clustering, Gen next Customers, Multivariate Analysis, Simulation*

INTRODUCTION

Marketing refers to the process of understanding customer needs and satisfying them with efficiency and effectiveness (Kotler *et al.*, 2009). Marketing in the current times has attained complex proportions due to pressures of satisfying the needs of new generation (gen next) of customers (Muk, 2007; Bhatnagar, 2004). These customers have unique needs and preferences which have to be satisfied effectively for advantage. Several strategies have to be adopted with respect to marketing products and services to this class of customers. This paper focuses on one such strategy namely 'Product Clustering'. The paper explains the process of product clustering along with its advantages. It then presents the results of a study on gen next customers showing the relationship between customer satisfaction and product clustering. It also highlights the complexity of product clustering through a simulation study. The paper thus aims to show the importance of product clustering as a strategic tool essential for marketing in the current context.

PRODUCT CLUSTERING

Pepall (1990) states that, product clustering is the process of sorting goods into groups such that product similarity is high among products of the same group and low among products of different groups. The definition of product similarity is given by a characteristic measure. Goods may be grouped into clusters using the specified characteristic according to the distance criterion. The resulting pattern of product clustering describes the degree of product differentiation within the set of goods. Research has shown that product clusters can be created on the basis on a variety of criteria like customer category (Hultén, 2007), search experience (Bhatnagar, 2004), product promotion (Ziliani, 2006) and production efficiency (Magazine & Polak, 2002). For the purpose of clustering simple classification techniques or advanced statistical tools like cluster analysis can be used. Product clustering has been used in a variety of situations. These include marketing mix decisions (Kaciak & Cullen, 2006; Ziliani, 2006; Hultén, 2007; Watanapa, 2008; Sharif, 2012), after sales service (Bhatnagar, 2004), competitive strategy (Maciag *et al.*, 2007; Lin *et al.*, 2010), production planning (Magazine & Polak, 2002) and management information systems (Breur, 2007). Product clustering has several advantages. Ziliani (2006) states that product clustering helps in studying cross-elasticity of demand of products in a cluster. This can help in more efficient planning of product promotions. Clustering can provide an efficient tool to product segmentation and positioning (Lonial *et al.*, 2000). Wind and Rangaswamy (2001) opine that product clustering can help to understand consumer behaviour better by offering them appropriate combinations of products. Product clustering can also help in mapping customer needs better (Yan-hong & Guang-xing, 2009).

LITERATURE REVIEW

In this section, research literature on customer satisfaction and marketing to gen next consumers have been reviewed. Research on customer satisfaction has spanned various aspects. One category of research has dealt with identifying

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the factors that contribute to customer satisfaction. Heim and Sinha (2002) find positive correlation between product information, product selection, service quality, product availability, timeliness of delivery and customer satisfaction. Further, Bauer (2007) studied customer satisfaction as a ratio between inputs and outputs using resale value, reliability, safety, comfort, price and running costs. According to Sharif (2012), product price, product presentation and product promotion have insignificant impact on customer satisfaction. At another level research has dealt with the metrics of quantifying satisfaction. Martín-Ruiz and Rondán-Cataluña, (2008) have developed tools to quantify price fairness as a way of measuring satisfaction. Customer satisfaction and trust are closely related. Guo *et al*. (2011) have studied what price a customer is willing to pay to a trust worthy seller.

The study of the consumer behaviour of gen next customers has become important in the current times.Marketing strategies need to be reformulated in the digital age where competitive forces use information technology effectively to their advantage (Lin *et al*., 2010). Gen next customers have unique needs and characteristics. They are easily attracted by digital media content delivered through the internet and SMS messages (Muk, 2007; Bhatnagar, 2004). According to Flavian and Gurrea (2006), digital newspapers are avidly sought by gen next customers. Duffy and Block (2007) state that behaviour of next-generation consumers suggest radical shifts in media consumption patterns.

Wind and Rangaswamy (2001) state that product clustering can give strategic advantage while serving customers. This paper attempts to study this vital aspect of marketing strategy in relation to gen next customers. The next sections explain the objectives and methodology of the study. This is followed by presentation of results and its implications. The final section attempts to simulate the results of the study in a supermarket inventory situation.

OBJECTIVES

The objectives of this paper are stated as follows:

1. To explore and understand the contours of customer satisfaction of gen next customers across product clusters
2. To appreciate the importance of customer satisfaction as an effective product clustering variable, and
3. To simulate a SKU (stock keeping units) system to understand the potential complexity of product clustering.

METHODOLOGY OF THE STUDY

This section explains the methodology of the study. The section first states the hypotheses of the study and then provides details of data collection and analysis techniques used in the study.

Hypotheses

Chang, Changchien and Huang(2006) and Wind and Rangaswamy (2001) state that with personalisation of consumer features using net based technologies, it is possible to learn about consumer behaviour patterns for delivering appropriate combinations of products and services to targeted consumers. Customer satisfaction depends on a variety of factors, which includesprice fairness, product availability, timeliness of delivery, customer support (Heim & Sinha, 2002), product assortment, product availability and excellence in customer service (Sharif, 2012). It is however not known whether customer satisfaction levels differ with product clusters. The first hypothesis stated below studies the impact of product clustering on customer satisfaction.

Hypothesis 1: There are no differences in customer satisfaction levelsamong product clusters.

If the above hypothesis is proved incorrect then it implies that marketers must use product clustering seriously as a part of their strategy.

The second hypothesis extends the relationship between customer satisfaction and product clustering. While product clusters have been created on the basis on a variety of criteria like customer category (Hultén, 2007), search experience (Bhatnagar, 2004), demand elasticity (Ziliani, 2006) and production efficiency (Magazine & Polak, 2002), research has not focussed on using customer satisfaction as a product clustering variable. The second hypothesis studies this aspect of the relationship between product clustering and customer satisfaction.

Hypothesis 2: Customer satisfaction level is avariable for creating product clusters.

If customer satisfaction is indeed an effective variable in creating product clusters, then marketing professionals must understand the complexity of creating product clusters using customer satisfaction levels.

Data collection

Data of customer satisfaction levels were collected across 17 assorted products and services used by gen next customers. For every product or service, customer satisfaction levels were collected from 20 gen next customers randomly, totally leading to 340 customer satisfaction numerical values. The customer satisfaction value was collected on a ten point scale between ‘1’ and ‘10’ with ‘1’ representing lowest satisfaction value and ‘10’ representing highest satisfaction value. The list of the products and services used in the study is given in Appendix 1.

Data analysis

The data collected were subjected to three levels of analysis. In the first level, in order to examine the first hypothesis, the products and services used for the study were clustered based on the following criteria. These criteria are based on extant research literature on factors affecting customer satisfaction (Heim & Sinha, 2002; Bauer, 2007; Sharif, 2012):

- Branding
- Price range
- Product category
- Usage rate
- Product loyalty
- Product promotion
- Demand elasticity
- Luxury perception
- Purchase comparison
- Peer opinion during purchase decision
- Purchase speed, and
- Purchase frequency

The customer satisfaction coefficients in each product cluster were subjected to Multivariate Analysis of Variance (MANOVA). The following statistical tests were conducted to analyse whether the customer satisfaction levels among the product clusters in each classification criteria were similar.

- Pillai's Trace
- Wilks' Lambda
- Roy's Largest Root

To analyse the second hypothesis, the customer satisfaction coefficients were subjected to a K-means cluster analysis to identify clusters based on customer satisfaction levels. In the third stage to study the third objective, the cluster analysis results were used to perform a Monte Carlo simulation to understand the dynamics of a stock-keeping units (SKU) environment in a supermarket.

In the next sections the results of the study are presented and analysed.

RESULTS

Customer Satisfaction Level Differences in Product Clusters

Table 1 presents the results of the various MANOVA tests studying customer satisfaction differences in various product clusters.

Table 1: Customer Satisfaction Level Differences in Product Clusters

Clustering Criteria	Manova p-values of customer satisfaction level differences			Remarks
	Pillai's Trace	Wilks' Lambda	Roy's Largest Root	
Branding	0.06	0.03*	0.00*	sig
Price range	0.07	0.00*	0.00*	sig
Product category	0.15	0.03*	0.00*	sig
Usage rate	0.00*	0.02*	0.00*	sig
Product loyalty	0.41	0.01*	0.00*	sig
Product promotion	0.05*	0.03*	0.00*	sig
Demand elasticity	0.05*	0.06	0.00*	sig
Luxury perception	0.00*	0.03*	0.00*	sig
Purchase comparison	0.50	0.17	0.01*	not sig
Peer opinion	0.23	0.14	0.01*	not sig
Purchase speed	0.34	0.15	0.01*	not sig
Purchase frequency	0.07	0.12	0.00*	not sig

NOTE: * represents value significant at 95% significance level. The remarks column shows significance for the criteria if atleast two of the test results are significant.

Clustering Using Customer Satisfaction Levels

The customer satisfaction levels of all the selected products were classified using cluster analysis in SPSS software. Using the K-means clustering technique, three clusters were created of the products and services selected. Table 2 provides details of the clusters created.

Table 2: Product Clusters Created Using Customer Satisfaction Levels

Cluster	No of elements in the cluster	Cluster Mean	Cluster Standard Deviation	Cluster Coefficient of Variation (%)	Cluster Name
1	1	4.03	3.16	79	Unstable low satisfaction products cluster
2	4	5.99	2.20	37	Intermediate satisfaction products cluster
3	12	7.55	1.55	20	Steady high satisfaction products cluster

The next section analyses and interprets the results presented in this section.

ANALYSIS OF RESULTS

An analysis of Table 1 shows that customer satisfaction levels vary for certain product clustering criteria and does not vary for certain criteria. The criteria for which customer satisfaction levels are significantly different are branding, price range, product category, usage rate, product loyalty, product promotion, demand elasticity and luxury perception. The criteria for customer level differences among product clusters are not significantly different are purchase comparison, peer opinion, purchase speed and purchase frequency. The number of clustering criteria for which customer satisfaction levels are significantly different is more than the number of criteria for which satisfaction levels are not significantly different. This leads to not accepting Hypothesis 1, which stated that there are no differences in customer satisfaction levels in product clusters.

Table 2 shows the clusters that can be created based on customer satisfaction levels. It is important to note that customer satisfaction creates products clusters among two different criteria:

- Mean customer satisfaction level
- Variation in customer satisfaction level.

These variables can be combined to create the following matrix (Table 3) of product clusters. The matrix also shows the product clusters identified by the study using the customer satisfaction coefficients.

The product clusters highlighted in the above matrix prove that customer satisfaction is indeed an effective criterion in creating product clusters. Thus Hypothesis 2 of the study which stated that customer satisfaction is a variable in creating product clusters is proved.

The above result also has useful implications for marketers while serving gen next customers. It is not only necessary to identify the customer satisfaction levels of products among gen next customers, but it is also important to identify the variation in customer satisfaction levels. As the study shows, both mean and variation are useful variables in clustering products. When steady satisfaction productsare clustered with intermediate or unstable satisfaction products, customers can get confused which can in turn affect serving gen next customers effectively. Progressive concerns have used these clustering variables in bundling products effectively. For example, Zhaofeng (2003) shows that how automobile companies have clustered services like insurance, financing and maintenance along with their main products to effective marketing to gen next customers.

As it is necessary to cluster steady high satisfaction products together, it is essential to understand the complexity of such product clustering for the purpose of creating and executing marketing strategy. This complexity is explained through a simulation study in the next section.

SIMULATION OF PRODUCT CLUSTERING IN A STOCK KEEPING UNITS (SKU) SYSTEM

Simulation refers to the process of modelling a real system based on key inputs and variables. Monte Carlo simulation is a mathematical modelling process of real system using the probabilities of key variables (Rust & Verhoef, 2005). A retail store or a supermarket maintains a stock keeping unit (SKU) inventory system. This study shows that products can be clustered based on customer satisfaction levels for marketing effectiveness. The key input variables in the simulation model are mean customer satisfaction level and variation in customer satisfaction level. As shown in Table 3 both mean and variation can be low, intermediate or high.

Table 3: Matrix of Product Clusters based on Customer Satisfaction Levels

Variation in customer satisfaction levels	**High**	Unstable low satisfaction products cluster		
	Intermediate		Intermediate satisfaction products cluster	
	Low			Steady high satisfaction products cluster
		Low	**Intermediate**	**High**
		Mean customer satisfaction levels		

These can be combined to create product clusters of which steady high satisfaction product clusters are strategically the most efficient.

In the first stage of the simulation, random values of mean and standard deviation of customer satisfaction levels were generated for each SKU. These values were classified as low, intermediate or high based on the actual values of mean customer satisfaction and its standard deviation derived in this study as shown in Table 2. The products were then clustered and the number of products in the steady high satisfaction product cluster was identified for various SKU levels ranging from 100 units to 25000 units. This is shown in Table 4.

Table 4: Number of Products in the Steady High Satisfaction Cluster based on Monte Carlo Simulation

SKU LEVEL	NUMBER OF PRODUCTS
100	20
1000	210
5000	1076
10000	2166
25000	5359

The complexity of product clustering is shown in Table 4. While in a small store with around 100 SKU's there are 20 products in the steady high satisfaction cluster, in a super market with 25000 SKU's this number increases to more than 5000. Clustering so many products would be a great challenge to marketers. Yet attempting this challenge would be highly fruitful to marketing professionals.

CONCLUSIONS

This paper has explained the importance of product clustering as a strategic tool for marketers in serving gen next customers. The paper has also highlighted the complexity of product clustering to create steady high satisfaction product clusters. The main conclusions of this study are:

- Branded products must be clustered together and differentiated from unbranded products. Clustering branded and unbranded products together can confuse gen next customers, which can reduce customer satisfaction.
- High priced products should not be clustered with low priced products.
- Products of similar use must be clustered together.
- Products of similar usage rate must be bundled together.
- Products which evoke high customer loyalty should not be clustered with products which evoke low customer loyalty.
- Products which are promoted heavily should not be mixed with less promoted products.
- Products which are inelastic in demand and which are elastic in demand must be clustered separately.
- Finally, luxury products should not be clustered with non-luxury products.

The results of this study therefore have important implications for marketing professionals for improving their efficiency in satisfying the needs of gen next customers.

DEDICATION: The author humbly dedicates the paper to Bhagavan Sri Sathya Sai Baba, The Revered Founder Chancellor of Sri Sathya Sai Institute of Higher Learning, Prasanthinilayam, India.

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The above details are absolutely important. Please do not ignore them. These details were provided in the supplementary file at the time of submission.

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APPENDIX 1

LIST OF PRODUCTS AND SERVICES INCLUDED IN THE STUDY

Table 5: Branded Products

Mirunafruit drink
Oreo biscuits
BSNL – ITC cards
Techno Tip pen
Reynolds pen
Tirumalachocolate lassi

Table 6: Unbranded Products and services

Hair dressing and Saloon services
Laundry services
Tea time snacks – Samosa and Kachori
Soft drinks
Stationary and note book
Track pants
Body sprays
Newspaper
Birthday cards
Potato chips