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ANALYZING CUSTOMER FEEDBACK FOR IMPROVED SERVICE QUALITY USING BINARY LOGISTICS REGRESSION MODEL

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Abstract

Analyzing customer feedback and management of complaint processing mechanisms has become a necessity for every firm to gain a competitive edge in business. The data reveals a lot of information about the customer and helps understanding how to improve the service quality in the firm. This can also be taken as an external method of quality control of the product through customer feedback. The present study has conducted a primary survey to validate how much does the customers' feedback helps in improving the quality of processes and the product thereby. This survey is predominantly carried out on different types of companies situated in NCR of Delhi. Through the analysis, an attempt was made to get a comprehensive score representing the aspect of market customer complaints in these companies.

Keywords: *customer complaint, service quality, binary logistics, regression analysis*

I. Introduction

In the last decade, with the advent of technology and available information, pressure has increased over the companies to improve the quality of the product and services. It has become a necessity for firms to analyze

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customer complaints and feedback to gain a competitive advantage in the market (Tsung, 2000). Analyzing trends and customer insights from the data help you retain the customers and increase the potential of new customers in the firm (Culnan, 1989; Voss et al., 2004). The data analysis helps understanding of the customer behavior and their needs to gain over the competitors in the market (Jannach et al., 2014).

A company's improvement plan in terms of profitability, productivity etc., depends on how they are able to satisfy their customers and retain them (Mittal, 2020a). This approach requires satisfying customer's implied and stated needs. While satisfying the implied needs, the company gets an edge over its competitors in retaining the customers (Fernandes and Solimun, 2018). In order to achieve this company should know the nature of the customers and their needs. Customers articulate their satisfaction/dissatisfaction through their communications–oral or written (Atulkar and Kesari, 2014). This concept is called customer complaint/ appreciation. The company's success depends on how they are redressing the customers' complaints through timely redressal, effective handling, etc. The study aims to examine the customer complaints mechanism followed in the selected firms through primary survey analysis in 38 companies located in Delhi-NCR. The study also attempts to find the significant factors that influence the customer complaint aspects

2. Literature review

Previous studies in customer feedback analysis and the improved service quality have contributed in many ways in designing the complaint mechanism and suggest to improving in delivering the quality (Jannach et al., 2014; Silva et al., 2018; et al., 2015). The concept of customer feedback analysis by the firms are more concerned with understanding the patterns and customer behavior in demanding that product (Gupta and Mittal, 2015; Mittal, 2015, 2017). Customer feedback has become the part of the supply chain that helps organizations to monitor the production process on a

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continuous basis and offer it as desired by the customers (Arora et al., 2021; Sharma and Mittal, 2012). At present, with the advent of new technologies, there have been multiple communication channels to give feedback to the companies (Bhatia and Mittal, 2019; Mittal, 2020b). However, the task of integrating the data from different formats and application becomes difficult (Chen et al., 2013). Further, the challenge is to extract all information without any loss to ensure the effective implementation of the complaint mechanism (Jukić et al., 2015).

Chang et al. (2009) used data mining techniques to understand the customer's attitude to understand their profile and needs. The study developed a growth model in an e-commerce environment. Gamon (2004) in the study used sentiment analysis and natural language processing (NLP) to classify customer feedback. Coussement and Van den Poel (2008) used text mining approach to understand the profile of the customers and assist them in the decision making which making online purchases. The system inputs the interests of the customers to predict and recommend their buying preferences accurately. Mittal (2020) study indicates the expectations of citizens' and improving quality in product and services that are posing a great challenge for the firms. The present work attempts to identify through primary survey analysis about the customer complaint mechanism of the companies in automobile and other sectors.

3. Research Methods

We have carried out a primary survey analysis of 38 companies to examine the customer complaint mechanism of the companies situated in Delhi-NCR. The study adopted purposive convenience sampling for the purpose of selection of the companies. The structured questionnaire was administered to collect the responses on the process that the companies are adopting to handle market customer complaints. The collected responses show that 79% of companies go and get regular feedback on their product's quality and 76% also use it more improvement in product

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quality and rest 21% are also improving but may be due to shortage of resources or maybe customers are not willing to fill the feedback form, they work on complaints only. The study has used the binary logistics regression model to examine the significant factors to influence the customer complaint aspects.

4. Data Analysis

We test the hypothesis that all facets are equally important using non-parametric Kruskal-wallis test. The non-parametric test is appropriate because data does not follow normality. The results of the test are presented in table 1.

Table 1: Kruskal-Wallis Test: Market customer complaint versus Facets

Facets	N	Median	Ave Rank	Weights	Z
1	38	10	92.5	92.5/48.5=1.91	2.59
2	38	5	48.5	48.5/48.5=1.00	-4.53
3	38	10	80.0	80.0/48.5=1.65	0.57
4	38	10	85.0	85.0/48.5=1.75	1.37
Overall	152		76.5		

H = 22.03, DF = 5, P <0.001

H = 29.57, DF = 5, P <0.001 (adjusted for ties)

The result shows the significance p<0.001 and confirms that sub-questions can be viewed on the same wavelength by all the companies. The test reveals that as per pre-calculated risk in market customer complaints, the companies could not view all questions in harmony. There are evidences that companies do not rate all the facets on similar levels and some seems to be more relevant compared to others. In order to give an accurate effect of each facet, the small differential effect is also taken into consideration while giving the weights for each facet and is represented as weights (see table 1). Thus, giving appropriate importance (weights calculated are shown in the above table) to all the facets, the average score of companies is

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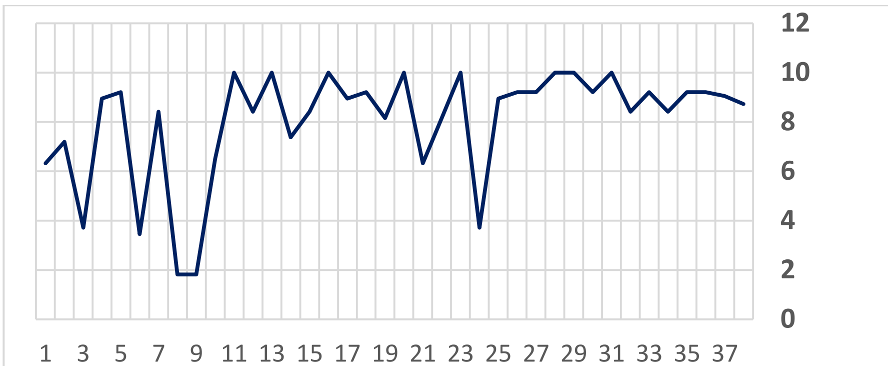
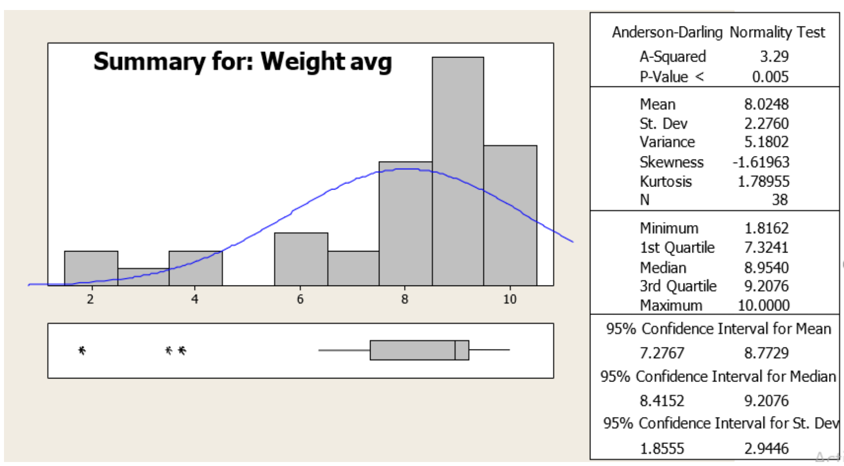
calculated based on overall performance of the companies in this aspect and is shown in a line chart presented as figure 1.

Figure 1: Line Chart showing average scores on Market Customer Complaint



The overall average of all the companies on this aspect is 8.0. It is good to observe that the companies in general are considerate of their customers, as dissatisfied customers mean rejection/rework. The normal chart shown in figure 2 exhibits its distribution, and the Anderson Darling test result shows the average data on this aspect does not follow the normal distribution.

Figure 2: Normality check for frequency distribution of Market Customer Complaint



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As the data distributions are asymmetric, median scores are appropriate for the presentation of data. The median score of market customer complaints is 8.95. The median score says that 50% of company's score is less than 8.95. Looking at a scale of 1-10 this score is very healthy. It means companies value their customers. All companies, irrespective of the type of product, age, turnover, and employees strength of a company, are scoring quite high on this aspect. To see whether all industries may be ranked equally on this aspect, or they are significantly different, Wilcoxon-signed rank test is applied. The results of the test are shown in table 2.

Table 2: Wilcoxon signed rank CI: Wt. Avg

N	Est. median	Achieved confidence	Confidence interval	
			Upper	Lower
38	8.68	95.0	7.77	9.08

The above test gives the estimated median of 8.68 with 95% C.I. (7.77, 9.08). A sensitivity test has been carried out for the 95% C. I. region based on median score of the market customer complaints. The results of the test in this region are presented in table 3.

Table 3: Wilcoxon signed rank test: Wt. Avg

Test of median	N	Wilcoxon statistic	p-value	Ext. Median
Median <8.68	38	371.0	0.506	8.685
Median<9.00	38	268.0	0.070	8.685

The results confirm that that the population median is not statistically different from 8.68 (p>0.05). The test shows that the median at the current level of 8.68 is insignificant. Hence we tested for a higher value at 9.00. The results were found significant and can be treated as an internal benchmark on this aspect.

Incidentally, the average scores of perceptions of the customers' satisfaction was lower in non-automobile (7.0) comparing to the automobile

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companies (8.76). The difference in averages is due to the strong competitive environment for auto-companies. It can also be observed that the non-automobile companies in general are not scoring differentially low. As there are some electronic components manufacturing and some garment companies who are also scoring high on this external quality control method of customer feedback.

Even though quality consciousness and need to satisfy customer's requirement are the two important paradigms for any company, the reasons exhibited by the companies who are having score of 9 and above on market customer complaint were studied and it is found that these reasons could be attributed to type of company, age, turnover, and the employee strength.

4.1 Binary Logistic Regression Analysis: Market Customer Complaint

The study has established a mathematical model to find out the influence of different factors to improve the customer complaint aspects. As the outcome parameter is binary (0' performance below median score, 1' performance at and above median score), we have used the binary logistic regression model to examine the effects of multiple explanatory variables. The general form of the empirical relationship can be represented as:

$$z = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \ldots + \alpha_k x_k + error$$

where x_1 denotes the type of company, x_2 denotes the age, x_3 denotes the turnover, and x_4 denotes the employee strength.

Table 4: Results of Binary logistic regression at median level (8.68)

Variable	**Value count**			
Response binary	1	21		
	0	17		
Total		38		
Logistic Regression Table				

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Predictor	Coef	SE Coef	Z	P
Constant	-1.20602	1.27089	-0.95	0.343
x_1	0.334811	0.425945	0.79	0.432
x_2	-0.328378	0.432523	-0.76	0.448
x_3	0.147755	0.402146	0.37	0.713
x_4	0.455709	0.491099	0.93	0.353
Log-Likelihood = -24.210				
Test that all slopes are zero: G = 3.837, DF = 4, P-Value = 0.428				
Measures of Association:(Between the Response Variable and Predicted Probabilities)				
Pairs	Number	Percent		
Concordant	230	64.4		
Discordant	119	33.3		
Ties	8	2.2		
Total	357	100.0		

The above analysis done on binary logistic regression shows moderate concordance of 64.4%. The p-value = 0.43 for the model predicts model is insignificant. It can be seen that one of the regressor coefficients X2 is having negative sign implying inverse propensity of these factors with a response, since the factor is not significant parameter as indicated by p= 0.45 the corresponding variable is dropped. With the remaining factors rerun of the analysis with different combination was made. It was found that none of the variables showed significance. The above analysis shows that companies at the median level of 8.68, have no significant propensity to the response, on improvement, from median level of 8.68 (level 0) to next higher level (level 1). It shows companies as a whole are very considerate of customer satisfaction irrespective of the nature of product, age, turnover, and employees strength of a company.

To further identify the significant factors at the benchmark level of 9.0, binary logistic analysis has been carried out and shows that x1, x2, x4 are

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insignificant and hence dropped from the analysis. The final results are shown table 4.

Table 4: Results of Binary logistic regression at median level (9.00)

Variable	**Value count**			
Response binary	1	21		
	0	17		
Total		38		
Logistic Regression Table				
Predictor	Coef	SE Coef	Z	P
Constant	-1.79746	0.898516	-2.00	0.045
x_3	0.605685	0.312376	1.94	0.053
Log-Likelihood = -22.528				
Test that all slopes are zero: G = 4.182, DF = 4, P-Value = 0.041				
Measures of Association:(Between the Response Variable and Predicted Probabilities)				
Pairs	Number	Percent		
Concordant	205	57.4		
Discordant	76	21.3		
Ties	76	21.3		
Total	357	100.0		

The model shows concordance of 57.4% is low but is more than double of discordance, as in 21.3% cases there is tie. Also, as the model as well as factor X3, turnover of company shows high significance, taking the coefficients of factor X3, the predicted response model may be given by the following relationship:

$$Y = -1.8 + 0.61 * X_3$$

Through the model we are trying to develop a policy oriented approach for a Company to move up from benchmark median level of 9.0 (level ‘0’) which is going to be primary target for all the companies for survival. A scatter plot depicts the above relation graphically (see figure 3).

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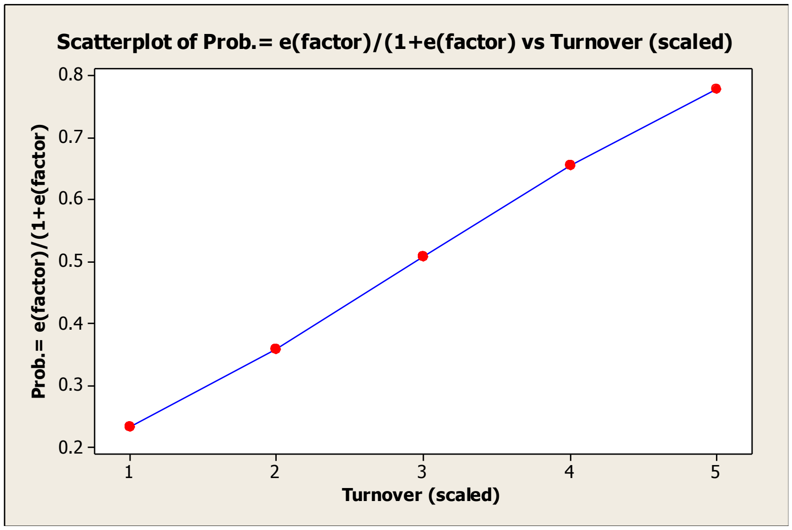
Figure 3: Scatter plot- Turnover Vs Propensity to improve



The exact probabilities are worked out for different combinations, using exponential distribution and represented as: Predictive Prob.= eY/(1+ eY)

Table 4: Predictive Probabilities

X_3 (Turnover) in crores	Prob. to improve
Less than 32	0.233259
32-108	0.358933
108- 276	0.507499
276- 812	0.654753
Greater than 812	0.777300

5. Conclusions

The study findings have resulted in the following inferences on response model: Customer Complaint Aspect at benchmark level:

- The small-scale company with a turnover <32 Cr. (scale 1) has a very low probability of 23% to move up, from score of 9.0 (from defined quality level '0' to '1').
- The medium-scale company with a turnover between 32-108 Cr. (scale 2) has also low probability of 36% to move up, from score of 9.0.

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- The large scale company with a turnover between 108-276 Cr. (scale 3) has a probability of 51% to move up, from a benchmark quality score of 9.0.
- The company with a turnover between 276-812 Cr (scale 4) has moderate probability of 65% to move up, from benchmark quality score of 9.0.
- The big companies with a turnover scale of five (>812 cr.) has a high probability of 78% to move up, from benchmark quality score of 9.0 (from defined quality level '0' to '1').

The reasons behind these results maybe are, it is uneconomical for small and medium scale company and hence they believe as when a complaint comes, they will resolve the problem for which they are ready to follow any strategy, even of replacement of the product. It is felt that in general, there is no standard department to handle customer complaints through proper analysis and interpretation of the data, situation, etc.

Customer feedback and complaints are imperative for quality improvement. Customers have a role in improving the product quality as a stakeholder, so it may be considered as a win-win situation for both company and the end product user if this linkage is strengthened.

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