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Examine of Customer Satisfaction Levels in Telecom Complaint Handling Using a Probabilistic Model

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Abstract
Artificial Intelligence empowered technologies have emerged as the future of customer service operations including handling customer complaints. While (AI) enabled systems are associated with greater efficiency, scalability and consistency; it remains unclear if these systems can help drive customer satisfaction in complaint handling operations. Previous research has mainly focused on technology adoption and operational performance; little attention has been paid to the underlying psychological and perceptual processes influencing customer experience with AI powered complaint handling processes. In an attempt to bridge this gap, the current study examines the impact of AI adaptability on customer satisfaction using multiple linear regression analysis. The study also reports the mediating effects of customer psychographics and perceived usefulness. Following a post positivist approach, quantitative data was gathered from telecom customers who recently experienced the company's (AI) enabled complaint handling system. Results indicate that complaint complexity plays a moderating role in this relationship suggesting limits to how well (AI) systems can handle high complexity service recovery episodes.
Keywords: Artificial Intelligence, AI Adaptability, Telecom Complaint Handling, Customer Satisfaction, Complaint Complexity

1. Introduction

Telecom complaints can arise due to technical faults, billing errors or connectivity issues. Number of complaints in a week follows Poisson distributions in stochastic modeling approaches The Poisson regression of complaint frequency on 134 weeks of observational data from a Telecom firm discovered its compositional causes and helped improve services. Achcar et al. (2022). Mobile technology is advancing rapidly and enormous amounts of data text, voice, graphics, video are now transmitted faster and through numerous channels than ever before. Mobile network operators are receiving an increasing number of customer complaints as their service portfolios expand and technical issues become more difficult to resolve.

Gairn Muñoz et al. (2016) reported that 28.5% of respondents experienced issues with their telecommunications services including slow service, poor coverage, incorrect billing and unauthorized charges. To effectively manage these complaints, it is important to determine their causes and provide rapid and effective resolutions. Failure to do so can result in dissatisfied customers who could switch to another service provider. Therefore, mobile network operators face the challenging task of identifying the reasons behind customer complaints and finding optimal resolutions that can lead to greater customer satisfaction overall. Customer complaint management in mobile telecommunications can be viewed as a complex decision-making problem wherein the ambiguity exists in deciding what action needs to be taken. There can be multiple reasons behind receiving a complaint, whether it is due to failure in the network or due to some faulty device customer is using. Each of this reason when categorized leads to different classification outcome. Many efforts have been made by researcher in developing various decision support system to ease the task of complaint management. Decision support systems can distinguish between genuine and non-genuine complaints Galinsky et al. (2009), automatically categorize complaint emails Casement and Van den Poel (2008) and integrate with web based platforms to map customer complaints and measure customer satisfaction Faed et al. (2014).

Ontologies that are interoperable can be used to assist in intelligently analyzing complaint-related knowledge bases and drive smart complaint handling process Lee et al. (2015). Optimization techniques such as data envelopment analysis and data mining can be used together to extract useful customers from the population of complainers Faed et al. (2014).

Overall DSSs play a vital role in intelligently automating the process complaint handling by combining human intelligence and machine learning algorithms to perform tasks. Classification ambiguity still remains to be a major challenge especially when the complaints are stated with incomplete, inaccurate or conflict information due to the customer’s lack of understanding about why the service or product failed. Many decision-making models based on fuzzy logic, rough set theory or even DST have been proposed to help alleviate ambiguity and provide better classification. Authors developed a framework for evidential reasoning that helps decision makers deal with problems where information available to them can be incomplete, conflicting, or imprecise Browne et al., 2013.

The authors also recommended a fundamental methodology for forecasting financial ratios of distressed companies using evidential reasoning based on DST Ko et al., 2017. A model based on rough set theory, referred to as evidential signal of price herds is used to help discover the features that represent price herds and predict future prices Fujita et al 2018.

They also suggested a newly developed evidentiary reasoning (ER) rule for classifying data with uncertainty. This rule is based on original evidential reasoning algorithm and uses Dempster’s rule that is an inferencing approach under DST Topcu et al, 2011. But all these research work failed to include textual information while taking a decision. Probabilistic models are best suited for telecom since the data involves randomness such complaining customers Probabilistic Bayesian Belief Networks have been used to predict churn based on complaint behaviours and have better results than conventional approaches in predicting propensity Kasigluk P et (2011).

Probabilistic models represent uncertainty in data using probability theory. In telecom we can use probabilistic models to predict probability of customer satisfaction based on wait time, resolution time and empathy shown by agents. This is different from deterministic models since it allows us to use probability distributions such as poisson distribution for arrivals of complains or Bayesian distribution to update our beliefs of customer satisfaction after a service has been resolved. Structural Equation Modeling approaches were used in COVID telecom research to establish relationship between service quality, customer expectations and loyalty. But remember, Telecom complaints also involves a lot of randomness; more complains during peak hours, inconsistency in the way every agent handles calls and noisy customer sentiments. Probabilistic models account for this randomness using stochastic processes.

2. Literature Review

Montes et al. (2026) evaluated the impact of service quality on analytical laboratories competitiveness by analyzing the effect of the gradual implementation of a quality management system based on ISO 9001: 2015 standard on customer satisfaction, in a chemical analysis laboratory located in Lima. Employing a pre-experimental longitudinal study design, customer satisfaction was monthly measured through a SERVQUAL based questionnaire.

The quantitative information was statistically described using measures of central tendency and variability, Student's t-test for related samples, and Poisson regression for complaints. The results showed statistically significant differences $p < .05$ in all SERVQUAL dimensions before and after QMS implementation, increasing from 50% to 85% in credibility and from 45% to 80% in personalized service. Moreover, overall customer satisfaction showed a significant increase from 46% to 97%. Results also showed an improvement in documentary compliance, from 33% to 98%, and the monthly number of complaints tended to decrease considerably.

The study concluded that integrating customer satisfaction measurement processes with QMS requirements allows a significant improvement in perceived service quality delivered by chemical laboratories. Sinha et al. (2026) aimed to address the growing challenge of customer churn prediction in one of the highly competitive industries, the telecommunication industry by comparing the performance of various machine learning models using 21 attributes of customers.

The performance of Support Vector Machines, Random Forest, Logistic Regression and hybrid multimodal approach based on Artificial Neural Networks was compared using metrics such as accuracy, precision, recall and F1-score. Results indicated that hybrid ANN-based model outperformed the other models achieving an accuracy of 85%. Traditional machine learning models such as Random Forest and Logistic Regression also showed good performance. Feature selection was crucial for the optimal performance of the models. The study concluded that use of advanced and hybrid machine learning models can allow telecom industries to identify customers at-risk of churning and assist in strategizing customer retention schemes to improve business productivity.

Yin et al. (2025) aimed at addressing the growing concerns of effectively managing large volumes of complicated customer complaints in the telecommunication industry by utilizing artificial intelligence and data mining techniques to predict customer satisfaction. Following the Cross Industry Standard Process for Data Mining framework, authors analyzed 4500 real customer complaints to derive features which impacts customer satisfaction and built a fine-tuned BERT model to predict satisfaction levels of telecom customers. Authors achieved excellent results with precision, recall and F1-scores all exceeding 99%, indicating superior performance of the model. Study concluded that data driven and intelligent models can help telecom industries better understand their customers complaints and allow them to improve CX through proactive decision-making.

Batticon et al. (2025) address the increasing significance of customer retention in Brazil one of the many competitive markets for Internet service providers by developing predictive models of customer churn utilizing complaint data customers filed with Brazil's national regulatory authority. Authors made use of natural language processing and machine learning techniques to include textual complaint data. Results indicated that including textual complaint data significantly improved recall of churn predictions and helped in better identification of customers at-risk. Furthermore, authors used interpretability methods such as Integrated Gradients to highlight key terms associated with churn. Study concluded that use of such textual data in conjunction with advanced analytical methods can help businesses in effectively strategizing retention measures.

Ribeiro et al. (2024) explored what factors influenced customers to switch from their current telecommunication operator in one of the most cut-throat industries where service bundles are concerned. Authors collected data from 3,004 customers of a Portuguese telecom operator. Covariance-based structural equation modeling and logistic regression were performed to identify factors that contributed to customer loyalty and churn. Results indicated that among all the services, internet service, TV service and contact center were positively influencing customer loyalty the most while landline service was statistically insignificant in influencing customer loyalty. Furthermore, positive relationship was found between customer loyalty and churn indicating how important customer loyalty is in retaining customers. Authors recommended telecom operators to focus on factors that increase customer experience to reduce customer churn.

Javed et al. (2024) proposed an advanced statistical EWMA based model to detect small shifts in process mean. They also illustrate the effectiveness of proposed model using Monte Carlo simulations and a practical data example. Although this paper is widely used in process monitoring but these advanced statistics can help in improving predictive modeling and helps asses model performances.

Achcar et al. (2022) empirically studied the effects of telecommunications service quality on customer loyalty by taking into account the mediating role of customer satisfaction during the COVID-19 pandemic. Survey data from 384 Telecom customers in Egypt were used to perform regression analysis and structural equation modeling to validate the hypothesized relationships. Results revealed a significant positive relationship between service quality dimensions and customer satisfaction. Service quality was also found to have a significant positive relationship with customer loyalty. Customer satisfaction was seen to fully mediate the relationship between service quality and customer loyalty. Authors concluded that service quality should be improved to create stronger customer satisfaction which in-turn helps in creating customer loyalty. This study is significant as it was conducted during the COVID-19 pandemic.

3. Research Methodology

The primary objective of this research study is to examine how artificial intelligence adaptability affects customer satisfaction levels during telecom complaint handling. Furthermore, the study also looks at perceived usefulness and customer psychographics as mediators and complaint complexity as a moderator. To attain the goals stated above, a quantitative approach and theory-oriented research design was employed.

3.1 Research Questions

In order to meet the objectives and provide answers to the hypotheses stated above. We have formulated our research questions to focus on different yet specific aspects of AI adaptability, customer perception towards AI and the effectiveness of AI based complaint handling in Telecom sector.

3.1.1 RQ: How does changes in Artificial Intelligence Adaptability Index impact customer satisfaction scores in Telecom complaint handling processes?"
Rationale: The research question aims to measure the direct impact of AI adaptability on customer satisfaction"

3.1.2 RQ: How does Artificial Intelligence Adaptability Index impact customer psychographic response to automated complaint resolution processes?"
Rationale: This research question would help us understand the impact of AI Adaptability on how customer perceive these AI bots.
3.1.3 RQ: How does changes in Artificial Intelligence Adaptability Index impact users' perceived usefulness of AI enabled telecom service?
Rationale: In this research question we aim to see the effect of AI Adaptability on how useful customers think these AI tools are.
3.1.4 RQ: How does Customer Attitude toward Hybrid Interaction (CAHI) impact Customer Satisfaction (CS) in AI mediated telecom complaint handling process?
Rationale: This question would help us know the extent to which effective customer handling impacts their satisfaction levels.
3.1.5 RQ: How does Customer Attitude toward Hybrid Interaction (CAHI) impact Customer Psychographics (CP) when it comes to AI driven customer service?
Rationale: This research question would allow us to understand how AI based complaint affect customer personality.
With research questions defined, a questionnaire was designed to collect data from respondents. Prior to data collection, a pilot study was conducted in which the questionnaire was administered to a few users to test the instrument. This helped us identify possible errors and ambiguities in the questions. Modifications and corrections were made to the questionnaire to rectify the issues and finalize it. After data was gathered, descriptive statistics was used to describe and present the data. Prior to analyzing the data, the dataset was cleaned for any errors, missing values and outliers. Data was then segmented into useful formats for statistical testing and analysis. Linear regression analysis was used to obtain estimates of how artificial intelligence impacted customer satisfaction levels. AI adaptability was measured using questions pertaining to service quality, response time and system efficiency.

4. Problem Statement

Artificial Intelligence (AI) adaptability has an impact on customer satisfaction levels in Telecom complaint handling process. To what extent does implementing AI tools that are adaptable to customer complaints help improve end customer experience during service recovery? Also, does perceived usefulness of these AI tools impact how customer rate their satisfaction levels?

4.1 Data Analysis & Conclusion

Data was collected using questionnaire method. The first step in analyzing data is presenting it. Ensuring that data is complete, consistent and reliable is an important step in statistical analysis. During data screening we observed many missing observations. Since all our variables were qualitative in nature; mode was used to replace missing observations. Data reliability was checked using Cronbach's alpha which was found to be 0.937 indicating high reliability among all our variables.

4.2 Split half reliability

Subsequently we went on to calculate split half Cronbach's alpha since our dataset had 48 items. Dataset was split into two equal halves and reliability was measured using spearman's boot prophecy formula.

4.3 Transformation and Assessment of Variable

Before performing any detailed analysis, we first observed the nature of all our variables. It was found that all variables were qualitative in nature. However, all the statistical methods mentioned in methodology section are only applicable to quantitative variables. Therefore, there is a need of transformation of variables. shows the positive and linear relationship between Customer Satisfaction and Artificial Intelligence Adaptability Index. It can be concluded from the figure that Organization which effectively uses Artificial Intelligence Adaptability Index in their complaint handling process tend to have higher customer satisfaction levels. The basic structure of the model is that:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \epsilon$$

Y = Customer satisfaction level.

β_0 = Intercept starting value when all independent = 0.

X_1= Artificial intelligence Adaptability Index.

β_1 = showing the impact of Artificial Intelligence Adaptability on satisfaction.

X_2= Customer Attitude toward Hybridge Interaction.

β_2 = Indicate the impact of Customer Attitude toward Hybridge Interaction on Customer satisfaction.

X_3= Artificial Intelligence Driven Communication value.

β_3 = explore impact of Artificial Intelligence Driven Communication value on Customer satisfaction.

X_4= Perceived Usefulness of Artificial Intelligence Systems.

β_4 = Highlight the influence of Perceived Usefulness of Artificial Intelligence Systems on Customer satisfaction.

X_5= Customer Psychographics

β_5 = Estimate the influence of Customer Psychographics on Customer satisfaction.

X_6 = Complexity of Complaint

β_6= show the impact of Complexity of Complaint on Customer satisfaction.

ε = Error term (unexplained variation)

Before applying the model to the dataset, the relationship between the variables is examined using a scatter diagram. This graphical tool helps in identifying the direction and strength of the association between the variables. It also provides a preliminary view of whether a linear relationship exists, which is important for regression analysis.

3.2 Asses the Relationship among the variables by Graphical Presentation

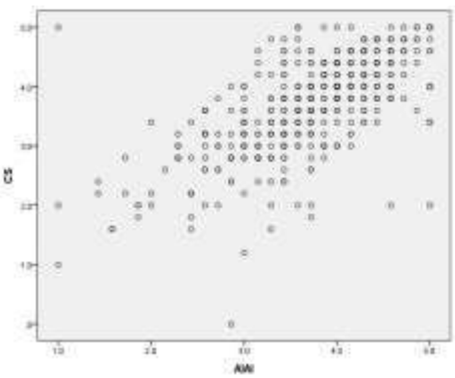

Figure 1

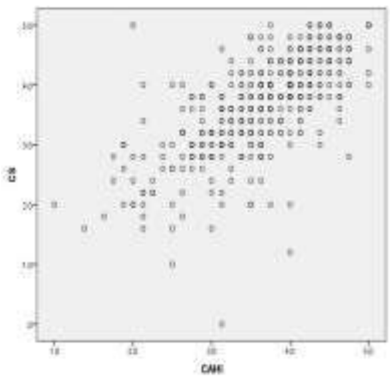

Figure 2

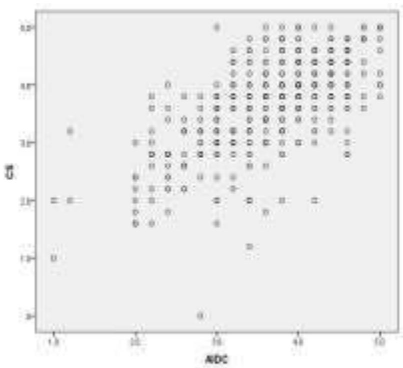

Figure 3

Figure 1: show the positive and linear relation between Customer Satisfaction and Artificial Intelligence Adaptability Index. Organization that efficiently utilized AIAI tend to achieve higher customer satisfaction.

Figure 2: The scatter plot demonstrates a positive association between Customer Attitude toward Hybrid Interaction and Customer Satisfaction. The upward trend suggests that customers with more favorable attitudes toward hybrid service models tend to report higher satisfaction levels. Although the relationship appears moderately strong, some dispersion indicates that additional variables may also influence customer satisfaction.

Figure 3: This graph Indicate the positive and linear relationship between Customer Satisfaction (dependent variable) and AI -Driven Communication value (Independent Variable). Organization which effectively uses AI -Driven Communication value in their complaint handling process tend to have higher customer satisfaction levels.

Figure 4

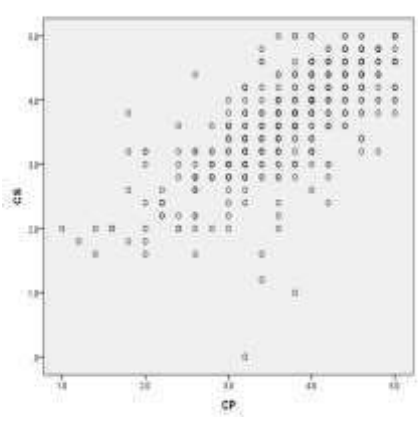

Figure 5

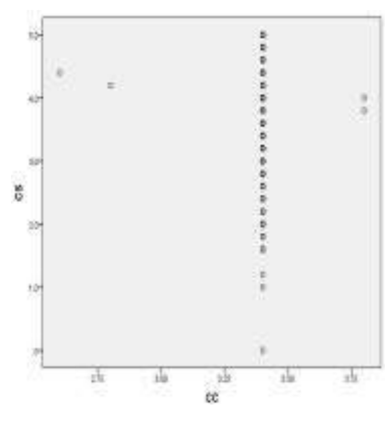

Figure 6

Figure 4: Explore the relationship between Customer Satisfaction and Perceived Usefulness of AI Systems which indicate the positive and linear relationship among the both variable.
Figure 5: Highlight clear increasing trend between Customer Satisfaction and Customer Psychographics**.** Which mean Customer Satisfaction increase with Customer Psychographics.
Figure 6: vertical alignment suggests that Complexity of Complaint is categorical variable that has been coded numerically while Complexity of Complaint appears to be a more continuous measure. Because the points are mostly clustered in a single vertical line, there is **no clear linear correlation** between the two variables shown in this specific dataset and to transformation is required for applied the multiple linear regression model.

Table 1: Estimated Regression Coefficients, Standard Errors, t-values, and Significance Levels

Model	B	Std. Error	T-test	Significance
Intercept	1.341	1.329	1.009	0.313
AIAI	0.104	0.049	2.119	0.035
CAHI	0.148	0.053	2.812	0.005
AIDC	0.092	0.046	1.982	0.048
PU	0.336	0.048	7.047	0.000
CP	0.287	0.045	6.313	0.000
CC	-0.339	0.389	-0.913	0.357

The intercept, β = 1.341, p = 0.313 is not statistically significant, indicating no meaningful baseline effect when all predictors are zero.
AIAI, β = 0.104, p = 0.035) has a positive and significant effect, suggesting it contributes modestly to the dependent variable.
CAHI, β = 0.148, p = 0.005 and
AIDC, β = 0.092, p = 0.048 are also significant, indicating both variables positively influence the outcome.
PU, β = 0.336, p = 0.000 and
CP, β = 0.287, p = 0.000 are highly significant, showing they are the strongest predictors in the model.
CC, β = -0.339, p = 0.357 is not significant and has a negative coefficient, suggesting no reliable effect on the dependent variable

Table 2: The significance of Multiple Regression Model

Model	Sum of Squares	d.f	Mean Square	F- Test
Regression	191.470	6	31.912	160.326
Residual	94.545	475	0.199	
Total	286.015	481		

The ANOVA results show that the regression model is highly significant and fits the data well.
The regression sum of squares (191.470) indicates that a substantial proportion of the total variation in the dependent variable is explained by the predictors included in the model. In contrast, the residual sum of squares (94.545) represents relatively small unexplained variation, showing that the model has

low prediction error compared to the explained variation. The F-statistic value of 160.326 with degrees of freedom (6, 475) is highly significant, indicating that the overall regression model is statistically meaningful. Since the model is significant ($p < 0.001$, as implied by the large F-value), the null hypothesis that all regression coefficients are equal to zero is rejected. Overall, these results confirm that the independent variables jointly have a strong and significant effect on the dependent variable, demonstrating good explanatory power of the model.

Conclusion

Since P-value associated with F statistic is less than $\alpha = 0.05$, we can conclude that our model is significant. Hence null hypothesis is rejected. There are a total of 476 observations included in our analysis. As seen from above results, all regression coefficients are significant suggesting that all independent variables have significant effect on customer satisfaction. R squared value of 0.669 indicates that 66.9% of the variation in customer satisfaction is explained by the model and remaining 33.1% is explained by predictors not included in the model. The Regression sum of squares (191.470) is much larger than the residual sum of squares (94.545) which indicates an excellent model with low prediction error. Standardized coefficients can be used to determine which independent variables has the greatest effect on customer satisfaction. Here CI telco has the highest absolute value of beta coefficients suggesting that it has the highest positive impact on customer satisfaction level. Adjusted R squared value of 0.662 is very close to R squared value which suggests that our model has no insignificant predictors.

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