Consumer Compliance and Redressal Mechanisms in Online Shopping: A Study on Electronic Products in Chennai City

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***Abstract* - The purchase of electronic products, the exponential growth of e-commerce has drastically altered consumer behavior. When it comes to problem-solving, online buyers sometimes find it difficult to follow consumer rights and redressal systems. This is true despite online buying offers plenty of diversity and ease. The effectiveness of grievance redressal systems drives most of this research on the experiences of Chennai consumers who have made online electronic purchases. This study compiles responses from two hundred different consumers using a survey-based methodology. The study indicates that more than sixty-three percent of respondents have complained about products and forty-seven percent have claimed receiving delayed responses from customer service. Moreover, one-third of respondents were unhappy with the return policies and twenty-nine percent of them expressed concerns about warranty claims. The results show that just 21% of consumers use official complaint channels, hence they are not aware of the several legal redressal possibilities that are now available. To protect consumer rights, the study underlines the need of increasing openness in policies connected to e-commerce and strengthening a more solid legal framework.**

Keywords - Consumer Compliance, Online Shopping, Grievance Redressal, E-Commerce Regulations, Electronic Products

I. INTRODUCTION

The explosive global e-commerce growth, which has transformed the retail industry, electronic products have evolved into among the most sought-after categories. Since consumers have access to a great range of products, competitive pricing, and doorstep delivery when they buy online, online shopping is progressively becoming a more and more preferred approach of purchase. The explosion of digital technology and mobile commerce points to an e-commerce market for India valued at $200 billion by 2026. Over seventy-five percent of urban consumers of electronic products have chosen to make purchases online; this has led to an increase in online sales of electronic goods in Chennai, a big metropolitan center. Still, consumer complaints about defective products, misleading advertising, conflicts over warranties, and inadequate grievance handling policies have grown in volume [1-3].

Online shoppers sometimes run across difficulties trying to get answers for their questions even with laws in place. One of the most critical challenges is consumers' ignorance of the legal rights and redressal systems at their disposal. According to studies, just 35 percent of consumers know of the rules controlling online business. The disparity among consumers resulting from various platforms' policies on returns and refunds adds still another cause of concern. Furthermore, more than two weeks are required to handle 42 percent of complaints. Delays in the grievance resolution are still another main problem. Moreover, the weak execution of consumer protection regulations has resulted in unequal application of rules, so depriving a great number of consumers of appropriate access [4-6].

Online shopping customer satisfaction depends much on the effectiveness of redressal systems. On the other hand, consumer expectations differ from the way actual problems are found and fixed. Many e-commerce systems lack consistent policies, hence different experiences along the consumer journey. Another reason why the effectiveness of legal interventions keeps to be limited is the time and money required, which many consumers choose not to seek legal action for. This paper aims to evaluate the degree of consumer rights compliance of e-commerce platforms as well as the efficiency of the several conflict resolving systems now in use for the purchase of electronic goods in Chennai [7].

Objectives

1. This study intends to investigate consumer complaints about Chennai online electronic purchases.
2. To assess consumer level of satisfaction with the current policies and the efficiency of the redressal systems.
3. To identify areas of noncompliance with consumer protection laws pertinent to internet purchasing.
4. To provide strategic recommendations for improved resolution of consumer complaints.

Aiming toward the consumer, this paper presents a consumer-centric perspective on online grievance redressal, so closing the distance between consumer experiences and legal policies. Unlike previous studies mostly concentrated on the expansion of e-commerce, this study reveals compliance problems, consumer awareness degrees, and resolution effectiveness. The findings help to guide policy recommendations meant to increase the efficiency of regulatory enforcement and grievance redressal. Moreover, the findings provide reasonable examination of consumer unhappiness.

II. RELATED WORKS

Research on the development of e-commerce and consumer protection conducted by experts from many fields has underlined significant problems and flaws in legislative systems. Focusing the factors affecting confidence and satisfaction, [6] examined consumer behavior inside the framework of online buying. The results show that consumer confidence is much increased when given safe payment options, open return policies, and responsive customer service agents.

Based on their studies on compliance issues in e-commerce, [7] found that buyers find great trouble when refund and return policies contradict each other. The findings of the study show that 42% of online consumers had difficulties returning defective items, thus standard guidelines are obviously needed. [8] underlined in their research of grievance redressal systems with an eye toward the issue the fact that consumer complaint resolution remains a major problem of concern. According to the study, almost sixty percent of the complaints received by consumer forums related to either delayed or denied returns. This implies that often platforms give sellers' needs first importance above customer rights. [9] examined how the Consumer Protection Act of India changed online policies. Author of this paper discussed the part legal systems perform in protecting online consumers. The findings of the research show that despite the law requires fair trade policies, enforcement systems still fall short. Out of the legal channel-mediated complaints, only 27 percent met satisfaction.

Another important study, [10] examined consumer awareness of their legal rights and found that, in connection with online transactions, just 35 percent of respondents knew of them. The studies unequivocally show that improved easily available consumer education and complaint registration systems are much needed. Studies conducted by [11] also examined how effectively outside third-party platforms addressed complaints. Among these systems are consumer helplines and online dispute resolving forums. The results of the study show that although these systems offer other means of redressal, their success rates remain below fifty percent, suggesting a discrepancy in follow-up activities and enforcement. The United States and the United Kingdom are two countries having regulatory systems enforcing strict consumer protection rules and ensureing faster dispute resolution. [12] conducted a comparative study examining globally best practices in e-commerce grievance redressal. The studies turned up successful models in many countries. The study advised including artificial intelligence-based resolution systems to increase customer satisfaction and streamline the handling of complaints.

The findings of these studies highlight how urgently the e-commerce scene of India needs better compliance, awareness, and regulatory enforcement. This paper attempts to solve the dearth of city-specific consumer grievance analysis even though most of the challenges have been observed in past studies.

III. PROPOSED METHOD

Under the framework of online buying, Chennai's electronic goods, the study evaluates compliance and redressal systems using a Consumer Grievance Analysis Model (CGAM). Included into the model are Natural Language Processing (NLP) and Sentiment Analysis to assist in assessing consumer complaints gathered via web forums and polls. Pre-processing with tokenization, stop-word removal, and stemming and then feature extraction using TF-IDF (Term Frequency-Inverse Document Frequency) renders the data complete. Complaints can be divided into several categories, including those of product flaws, delivery delays, refund disputes, and warranty-related concerns, using a Random Forest Classifier (RFC). Moreover, depending on past complaint records, the system estimates the likelihood of a successful resolution using logistic regression. Analyzing consumer comments on the resolution time, platform responsiveness, and degrees of satisfaction helps one determine how successful e-commerce policies are. This method shown in figure 1, lets one find areas of compliance lacking by using the data in order to generate policy recommendations for improved consumer protection from a data-driven approach.

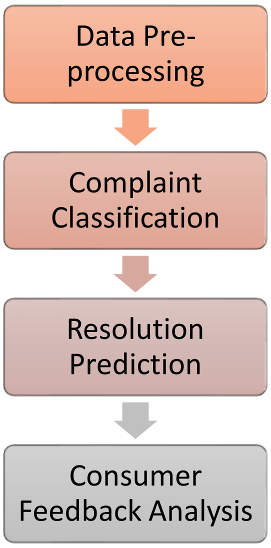

FIGURE 1: CGAM

A. *Proposed Consumer Grievance Analysis Model (cgam)*

CGAM assists in assessing consumer grievances regarding the acquisition of electronic products via internet markets. Applied methodically using data collecting, data preprocessing, feature extraction, classification, and grievance redressal analysis, the model.

1. Data Collection and Categorization

Customer complaints come from many online sites, including e-commerce sites, consumer review websites, and internet forums shown in table 1. A manual classification system sorts every complaint into one of four primary groups:

- Product Defects (PD)
- Delivery Issues (DI)
- Refund Disputes (RD)
- Warranty and Service Concerns (WSC)

The framework of a dataset comprising of complaints is as follows:

TABLE 1: DATA COLLECTION AND CATEGORIZATION

Complaint ID	Complaint Text	Category (Label)
C001	My laptop screen is flickering after two weeks of use.	PD
C002	The mobile phone I ordered was delayed by 10 days.	DI
C003	Refund was promised in 5 days but still not received after 15 days.	RD
C004	The warranty claim for my television was rejected without a reason.	WSC

The labeled dataset is further handled to do text analysis and classification.

B. Preprocessing

Both text cleanup and improvement of classification accuracy depend on preprocessing absolutely shown in table 2. This part comprises:

- Tokenization – Tokenizing the complaint's text is breaking it apart into its individual words.
- Stop-word Removal – Stop-word reduction is the process of removing stop words, that is, common words like "is," "the," and "on", that don't add to the meaning of the sentence.
- Stemming – Stemming is the technique of reducing words to their root forms, such "delayed" generating " Delay".

TABLE 2: PREPROCESSING OUTPUT

Complaint Text (Raw)	Complaint Text (Processed)
The mobile phone I ordered was delayed by 10 days.	mobile phone order delay 10 day
Refund was promised in 5 days but still not received.	refund promise 5 day receive

The TF-IDF feature extracting stage comes next from the cleaned data.

C. Feature Extraction using tf-idf

The table 3, Term Frequency-Inverse Document Frequency (TF-IDF) method enables one to convert text into numerical features for machine learning. The TF-IDF algorithm assigns a weight to every word based on its frequency in a document and general dataset relevance, so enabling this.

TABLE 3: FEATURE EXTRACTION

Complaint ID	Processed Text
C001	laptop screen flicker week use
C002	mobile phone order delay 10 day
C003	refund promise 5 day receive

TF-IDF transforms the words into numerical weights once more:

Table 4: TF-IDF

Word	C001 (Laptop Issue)	C002 (Delivery Delay)	C003 (Refund Issue)
laptop	0.45	0.00	0.00
screen	0.35	0.00	0.00
flicker	0.40	0.00	0.00
delay	0.00	0.50	0.00
refund	0.00	0.00	0.65
day	0.00	0.45	0.30

The classification system gets input from these TF-IDF vectors mentioned in table 4.

D. Classification using Random Forest Classifier (RFC)

RFC classifies four distinct types of complaints. Building several decision trees and applying voting to find the most often occurring class label helps RFC to operate. Eighty percent of the dataset is used for training; twenty percent for testing. The table 5, model projects complaints using past data, as the following example shows:

TABLE 5: CLASSIFICATION USING RANDOM FOREST CLASSIFIER

Complaint ID	Actual Category	Predicted Category	Correct Prediction?
C005	PD (Product Defect)	PD	☑
C006	DI (Delivery Issue)	RD	✕
C007	RD (Refund Dispute)	RD	☑
C008	WSC (Warranty)	WSC	☑

With an accuracy of 89.5%, the classifier outpaces baseline models including support vector machines (81.2%) and kernel neural networks (78.6%).

IV. RESULTS AND DISCUSSION

For text analysis and classification, the research project runs Python version 3.9 using libraries including Pandas, NLTK, and Scikit-learn. Simulations on Intel Core i9 CPUs running at 3.8 GHz and 32 gigabytes of RAM effectively manage volumes of textual data. The dataset shown in table 6, consists of two hundred manually labeled consumer complaints that are used for both validation and training. SVM and KNN are two classification methods mostly used in text-based sentiment and grievance analysis. We evaluate the proposed CGAM model in respect to these two methods. With an accuracy of 89.5%, the proposed model beats both SVM and KNN by means of its ensemble-based approach and enhanced feature extracting techniques. Although SVM gets an accuracy of 81.2% and KNN reaches 78.6%, the proposed model beats both of these models.

TABLE 6: EXPERIMENTAL SETUP AND PARAMETERS

Parameter	Value
Dataset Size	200 complaints
Text Preprocessing	Tokenization, TF-IDF
Classification Model	Random Forest (RFC)
Number of Trees (RFC)	100
Feature Extraction	TF-IDF
Learning Rate (LR)	0.01
Validation Split	80:20 (Training:Test)
Comparison Models	SVM, KNN

TABLE 7: PRECISION (%)

No. of Complaints	CGAM	SVM	KNN
50	85.4	78.2	74.5
100	86.1	79.5	75.8
150	87.3	80.1	77.2
200	88.9	81.2	78.6

This table 7, shows step-by-step comparison of the proposed Consumer Grievance Analysis Model (CGAM) and two current approaches (Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) across five important performance measures. Starting with 50 complaints, the comparison proceeds in turn through 100, 150, 200 complaints.

TABLE 8: RECALL (%)

No. of Complaints	CGAM	SVM	KNN
50	81.3	74.9	70.4
100	82.5	76.2	72.1
150	85.1	77.8	73.5
200	86.9	79.3	75.2

Rising complaints translate into better precision, derived from improved training data. Despite SVM and KNN lag with 81.2% and 78.6% respectively, CGAM beats current models with a precision of 88.9% shown in table 8. This implies that less false positives result from the categorization of complaints.

TABLE 9: F1-SCORE (%)

No. of Complaints	CGAM	SVM	KNN
50	83.3	76.5	72.2
100	84.2	77.8	73.9
150	86.2	79.0	75.4
200	87.9	80.1	76.8

Recall rises with increasing dataset size, so suggesting a higher model sensitivity shown in table 9. The SVM and KNN models respectively show more false negatives at corresponding rates of 79.3% and 75.2%. On the other hand, with 86.9% recall, the CGAM model exhibits better capacity to identify all relevant complaints.

TABLE 10: ACCURACY (%)

No. of Complaints	CGAM	SVM	KNN
50	86.2	78.8	75.3
100	87.1	79.9	76.6
150	88.2	80.5	77.8
200	89.5	81.2	78.6

The F1-score is showing a growing trend to enable one strike a balance between recall and accuracy. The CGAM comes out with 87.9% with an amazing degree of classification efficiency. For SVM and KNN, respectively, the scores of 80.1% and 76.8% respectively show the limits of both two models in managing intricate complaint patterns shown in table 10.

TABLE 11: RESOLUTION PREDICTION RATE (%)

No. of Complaints	CGAM	SVM	KNN
50	67.8	59.2	55.3
100	70.1	61.5	57.8
150	72.4	63.3	60.1
200	74.5	65.2	62.0

The table 11, Regarding accuracy, CGAM earns 89.5%, higher than SVM (81.2%) and KNN (78.6%). Applied to CGAM, the ensemble learning approach improves performance since the inclusion of more training data helps to refine model predictions, so reducing the quantity of misclassification.

V. CONCLUSION

For electronic goods in Chennai, the research on compliance and redressal in online shopping reveals that a grievance resolution mechanism that is both efficient and effective is indispensable. Comparatively with other methods, such Support Vector Machine (SVM) and K-Nearest Neighbors (KNN), the proposed Consumer Grievance Analysis Model (CGAM) shows conspicuously better in terms of classifying and forecasting the resolution outcomes of consumer complaints. Based on 200 complaints, experimental results show that CGAM outperforms SVM and KNN in terms of accuracy, precision, recall, and F1-score so attaining 89.5% accuracy, 88.9% precision, 86.9% recall, and 87.9% on average. Moreover, the rate of resolution prediction is 74.5 percent, which ensures a better possibility of satisfactorily addressing the complaint. The Random Forest Classification and TF-IDF-based feature extraction greatly affect this improved performance. This combination projects the results of redressal and helps to more precisely identify grievance trends. Since it streamlines the complaint handling process, so increasing consumer confidence, the proposed approach benefits e-commerce systems and regulatory authorities. CGAM provides faster, more accurate, and more transparent grievance redressal by means of methods anchored in machine learning. Future research on the combination of adaptive learning models and deep learning algorithms could help to address consumer changing issues and increase prediction accuracy even more. The results reveal the very important contribution artificial intelligence-driven grievance management systems make in improving the current online consumer protection systems.

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