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An Association Between Product Discounts, Rating and Customer Service: An Empirical Study

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Abstract:

This study investigates the relationship between buyers' perceptions and empirical data regarding product ratings and discount percentages during e-commerce sales events. Through a mixed-methods approach combining survey analysis and real transactional data, the research reveals a significant discrepancy between consumer beliefs and actual trends. Survey results indicate that the buyers perceive a strong influence of product ratings on discount percentages. However, quantitative analysis of sales data contradicts this perception, demonstrating no statistically significant association between product ratings and discount levels. Instead, the study identifies a moderate positive correlation between customer service quality, measured by chat response time, and product ratings, suggesting that responsive support enhances customer satisfaction and, consequently, product evaluations. Additionally, the research explores three predictive models—linear regression, decision tree, and random forest—to forecast discount percentages based on historical sales patterns and consumer behavior metrics. These models provide actionable insights for e-commerce platforms to refine dynamic pricing strategies, optimize promotional campaigns, and improve overall customer experience. The findings highlight the importance of data-driven decision-making in e-commerce, as consumer intuition may not always align with actual market trends. By leveraging predictive analytics, retailers can better anticipate demand fluctuations, tailor discounts effectively, and foster greater trust through transparent pricing practices. This study contributes to the growing body of knowledge on consumer psychology and pricing optimization in digital marketplaces.

Keywords*—Buyer, Consumer, Perception, Association, Correlation, prediction, Ratings, Ship OnTime, Neural Network, SVM, XGBOOST, e-commerce.*

I. INTRODUCTION

A. Background of Study:

In the current digital age, business owners are expanding their reach by providing services online, and because of this, shopping online has become a phenomenon or a facility that has been offered to consumers by the business owners. It has become a convenient, popular, and useful approach for consumers as it enables them to select and compare a vast variety of products and goods that can be delivered or transported to their doorstep as per their convenience. For the past few decades, E-Business or online shopping has appeared as a substantial trend that has guaranteed commercial, social, marketable, and economic benefits to both consumer and seller. E-Business not only allows sellers to reach the majority of consumers irrespective of their geographical location, but it also permits buyers to shop from distant locations or any part of the world. Buyer Ratings, reviews, and delivery options have a significant influence on sales as well as on product pricing in terms of online marketplaces as ratings and reviews offer valuable insight to the potential clientele about the quality of products and their satisfactory level of product purchase which can lead to the great influence on the purchasing decision of prospect buyers [1].

Recent studies suggest that dynamic discount strategies play an important part in drawing attention during major e-commerce sales. Along with this, ratings from buyers also show trustworthiness among buyers, which can help in influencing consumers to translate it into their purchasing decision [2].

Another study suggests that delivery options such as Free Delivery and Standard Delivery influence sales performance and customer contentment [3]. In this research, we are investigating the influence and the association of product reviews/ product ratings, delivery options, and product price, and the basis of the impact, extending the study to predict product prices for the future.

In this paper, we are trying to examine how individuals' experiences, and opinions are evaluated and acknowledged as it is a crucial and fundamental phenomenon of E-commerce studies have revealed that individual opinions and reviews have a great impact on customer purchasing decisions and sales as positive ratings and reviews build trust among potential buyers which can further be translated into purchase [4]. Even though these factors primarily affect the volume of sales, they can also influence pricing strategies. For example, products with positive ratings and reviews may have higher prices due to the higher perceived value, whereas economical and competitive delivery options can support and validate premium pricing [5].

B. Purpose of Study:

There has been tremendous and incredible rapid development and growth in an online marketplace offering advanced and progressive online businesses, such as Amazon and Daraz. This research intends to identify the association and relationship between consumer reviews, ratings, and delivery options on product sales. In this study, we are also trying to identify its impact on pricing strategies. Additionally, we are trying to explore whether the data findings are according to the user perception or not. This study is also used to predict the product's future pricing based on the available historical pricing patterns reflected in the data.

C. Objectives:

This study has significant practical importance, as the outcome and findings from this study are anticipated to be beneficial for both the sellers as well as the buyers/ consumers. Sellers can gain valuable insights into how buyers perceive the association between product reviews, product price, and delivery options, which enables the seller to strategize better, as consumer behavior and perception are vital for optimizing business and marketing offerings related to the product.

This study helps sellers understand the perspective of users by shedding light on how customers perceive the relationship between product pricing and reviews, enabling sellers to tailor their strategies to better meet customer expectations and enhance their competitive edge. Sellers can also gain insights into whether delivery options correlate with product sales and ratings, and whether they also have an impact on shaping buyers' purchasing decisions or not. By analyzing and comparing data findings and buyers' perspectives, sellers can identify gaps and align their strategies which meet buyers' expectations. Likewise, buyers can have a broader perspective on how delivery options and ratings align with product pricing, which helps them make an informed purchasing decision. This study will add value effectively in an online marketplace by providing actionable insights to the seller to plan better, which helps buyers to benefit from improved quality of product, smooth delivery options, and fair pricing, which is a win-win situation in E-Business.

D. Data sets:

This research will be conducted on two different data sets. For the first part of the study, we have conducted an online survey to get an idea about consumers' preferences and perceptions related to the association between product ratings, delivery options, and product pricing, which influences buyers' purchasing decisions. For the second part of the research, the dataset of an online business named 'Daraz' has been utilized, which is available on Kaggle for research purposes to gain insights about product reviews, ratings, product pricing, and delivery options.

The outcome and results from these datasets can be compared and analyzed to understand the potential gaps of buyers' and sellers' perceptions regarding the association and actual market trends.

E. Problem Statement:

The research focuses on the perception of users regarding the association between the discount percentage and product ratings.

Hypothesis 1*:* Product discount percentage and Product Ratings are associated. Negative reviews have a great impact on the increment of discount percentage where whereas positive reviews influence the decrease of the product Discount Percentage.

Also, what is the influence of product ratings on the discount percentage?

***Hypothesis* 2:** Product Discount Percentage is influenced by online product ratings. Negative or poor reviews increase the Discount Percentage, whereas positive ratings result in a decrease in the Discount Percentage.

And lastly, what will be the discount based on a product based on the pricing pattern of that product?

***Hypothesis* 3:** Future Product price is influenced by history.

F. Research Limitations:

The focus of this study is not to identify or explore the factors that influence discount strategies but to understand or observe whether the buyer's ratings are one of the factor or not which has an influence on discount percentage during major e-commerce sales as it is suggested that ratings are one of the factors which has an impact on product sales [2].

II. LITERATURE REVIEW

In [6], the research aims to understand the correlation between logistics service ratings, delivery performance, and household e-commerce sales. It prescribes the increase in the importance of time, another factor that is under-investment by Amazon to enhance its agility. However, there has been little research done on the particular impact of delivery speed on sales. The study seeks to fill this gap through an evaluation of 157,663 customer orders on the Small platform and Cainiao logistics network through the Heckman-ordered regression model and two-step estimation method based on over fifteen million customer orders. The findings are and show that customers still anticipate delivery within two days, even though such guarantees were not explicitly made. Orders taken after this period reduce the rating, while delivery in three to two days increases the third-party provider's daily sales by 13.3 percent. Logistics performance, therefore, plays a critical role in the consumers' buying process, and the study becomes useful for e-commerce retailers, and third parties seeking ways to boost their sales and enrich customer experience [6].

The research conducted in [7] presents a new model developed through the integration of statistical analysis and machine learning methods due to interpretability- ity issues of the latter approach. The factors that underpin consumer behavior are a focus of the research when applied to 454,897 customers across JD.com, China's largest online retailer. Aware that delivery promises essentially influence the quantity, and price is the greatest in determining purchase. The research also differentiates between brand-scale and store-scale discounts and defines different success rates in terms of product type and discount size. The research concludes for JD, ways of increasing the logistics performance could reduce the Bullwhip effect created by batch ordering, hence increasing customer satisfaction and sales. The chief advantage of the hybrid model is its predictive capability, which enables organizations to make more informed decisions about sales and operations, thereby maximizing profits [7].

The authors in [8] investigate the effects of consumers' remarks on quality and cost approaches to e-markets. The authors use game-theoretical modeling to examine cooperative and non-cooperative behavior between contesting firms. One of the considerations is the ability to use dual-element dynamic strategies where organizations can vary both quality and price to reach better financial results. The study outlines a sequential reaction wherein firms first enhance product quality and reduce prices, influenced by the use of online reviews. Over time, there is a decline in the quality of products to enhance the prices required for maximum returns. The results of this study, therefore, have implications for understanding the role of strategy concerning customer perceptions of product usefulness and appropriateness [8].

The empirical study in [9] that compares the Tokopedia e-commerce consumers in Jambi City has found that qualitative online consumer reviews have an intention to decide. However, quantitative ratings were considered as less effective, which signifies that qualitative information about the customer experience has more value than simple statistics. Similar to other surveys that were conducted and analyzed by multiple linear regression, this also confirms that reviews significantly influence the behavior of consumers [9]. Consequently, within the research, positive online customer reviews significantly boost sales for micro-businesses, illustrating the general impact the customer reviews elicit on sales and trust. Finally, based on 390 research studies employing the PRISMA Model. This research has integrated the data and synthesis that suggest that favorable reviews win the confidence of the agents of demand and sales in multiple sectors. These studies highlight the need and value of maintaining high-quality feedback mechanisms for the survival and growth of clients [9].

In [10], the authors aim to explain how online consumer ratings affect prices established by firms with a special outlook on product customization. This research notes the absence of knowledge of the variation of such impacts, depending on the level of customization, and attempts to fill the gap by using a dynamic modeling framework [10]. To address these questions, the research adopts a two-period dynamic model that explores the price and profit effects of products grouped according to the degree of customization as being niche, neutral, or mainstream. Here, it is also important to note that the study starts with the assumption that the consumer has not been informed about the real worth of a product. After the initial consumption phase, consumers provide online ratings, which drive the second-period consumers' consumption decisions and consequently affect firms' prices [10].

In [11], the authors explore the mobile interaction between sales performance and counterfeit products and fraudulent signals. The study also focuses on the problem of low-quality legislation, as an insufficient regulation of counterfeit products and fraud leads to a violation of market and consumers' confidence [11]. The research fills a void left in the literature concerning the impact of fraudulent signals in e-commerce over the long term. The authors, using data capture technology on e-commerce sites, examine how these signals affect sales in different competitive environments [11].

The research in [12] focuses on the importance of the price factor in online purchases, highlighting the drawbacks of existing research and enunciating new approaches. Thus, it emphasizes that, in addition to price, the users see the concept of 'comparison prices', i.e., the past prices of the same item, prices of similar products, prices on selling platforms other than the present ones, etc. except the present price of the product [12]. To fill these gaps, the authors propose the implementation of the price competitiveness metric, which estimates how favorable an item's price is these comparison prices. This approach is accomplished with the creation of the Price Competitiveness- aware Network (PCNet). Compared with PCNet, ModNet is designed to identify multiple forms of price competitiveness, and it is equipped with actual national statistics, which help improve its estimation capabilities as well as its interpretation [12].

The authors in [13], focus on pricing transparency in consumer decision-making, which conveys that an effective pricing strategy should be developed out of the existing competition features of the online environment [13]. The study examines dynamic pricing as one of the dynamic strategies for increasing gains and revenues. Contrary to the basic strategies that aim at disseminating the research by providing the lowest possible prices, the study underlines the significance of choosing the "correct price" to achieve optimization. The framework is mainly built specifically for inventory-based e-commerce firms, though it can be easily extended to wider online marketplaces beyond inventory-based e-commerce firms [13].

The authors in [14] discuss the significance of dynamic price setting in the current fast-growing e-business environment. Such approaches are recommended for use in organizations to boost revenue and sustain viability since conventional cost-setting techniques cannot adapt to shift occurrences in the market [14]. The study focuses on the multi-disciplinary area of applying machine learning and business intelligence for dynamic pricing. It acknowledges the absence of literature in determining how these sophisticated technologies can be applied to e-commerce pricing. Pricing strategies of many firms remain reactive, despite the availability of more scientific techniques, thus calling for adaptation in the online environment [14]. Conclusions derived from the research show that there is a strong positive correlation between BI systems enhanced with ML and the capacity of a company to price goods correctly and within the shortest time possible due to changes in the market. SVM, being an adaptive model, enables refinement of the price decision, hence the proposition of utilizing a synergy of ML and BI in dramatically changing the e-commerce strategies [14].

Table 1 illustrates the overall gap analysis issues and the factors relevant for the research.

Table 1: Gap Analysis and Relevance to Research

Gaps	Relevance to research
Limited exploration of the relationship between product ratings and price strategies (including discount percentages in e-commerce platforms.	The research aims to bridge this gap by analyzing how product ratings influence discount percentages and other price strategies in the context of e-commerce sales.
Lack of studies that correlate consumer perception of price strategies (such as discounts) with actual sales data.	Study compares consumer perceptions with real data to validate whether these perceptions align with the actual sales patterns observed on e-commerce platforms.
No clear prediction models for discount percentages based on consumer behavior and product ratings.	Compare predictive models for discount percentages, using findings from consumer behavior analysis and real data to forecast future pricing strategies in e-commerce.

III. Research Methodology

In this section, a research methodology has been discussed:

Phase I: At the initial stage, the survey has been conducted to understand the buyer's perspective regarding the Ratings, Delivery Preference (Free Delivery vs. standard Delivery), Discounts, and On-Time Shipping. A survey has also been conducted to understand consumers' point of view regarding the association between Ratings and discount %. For this purpose, a questionnaire has been formed.

Phase II: The Second part of this research was conducted to analyze the records of real data regarding the ratings, discount %, On-Time Shipping, and Delivery Options.

Phase III: The following step was to compare the readings of the buyer's perspective and the readings from real data. For this purpose, a 'Daraz 11.11 sale' dataset has been utilized, which is available on "Kaggle" [17].

Phase IV: The last stage of this research is to predict the discount. Figure 1 shows the workflow of the research.

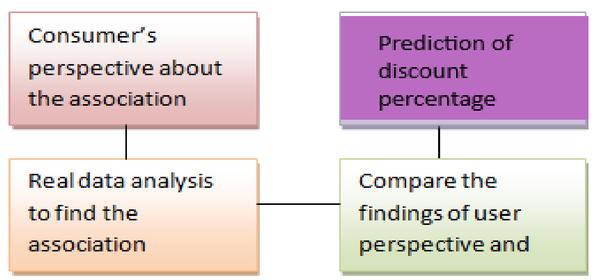

Figure 1:Workflow of the research.

IV. RESEARCH DESIGN

To study the findings and analyze the research problem effectively, the following approach has been used.

A. Quantitative Approach:

For this research, a questionnaire has been formed to get the perspective of buyers or consumers. The questionnaire was more of the form of multiple-choice, Likert scale ranking, or ranked-choice preferences, which can be quantified while analyzing the data. Along with it, 'Daraz 11.11 sale' data is also available in numerical form, hence quantitative approach has been used [17].

B. Predictive Approach:

This approach has been utilized to predict the discount % for future purposes.

i. Data Collection:

Data has been collected and gathered into two phases.

Phase 1: For analyzing online buyers' perspectives, the link to the online questionnaire has been circulated via email and WhatsApp messages. Along with it, posting has been done on various social media platforms.

Phase 2: For the real data sets findings, a dataset of 'Daraz 11.11 sale' was downloaded through 'Kaggle' and has been utilized for comparison and prediction purposes.

ii. Data Sets:

The following section provides the information regarding the two different data sets which has been used for investigating the buyers' perspective and then would be utilized to compare it with real data findings. The information regarding data sets is as follows:

A. Buyer's Perspective Online Questionnaire:

i. **Population:** For data gathering, the Target Audience is those who shop online during sales and is limited to Karachi, Pakistan.

ii. **Sample Size:** The Sample Size of the record is 426.

iii. **Sampling Procedure:** A Random sampling method has been used while recording the buyer's perspective to avoid biased views.

iv. **Questionnaire Development:** As the research approach is quantitative, questions were formed in the form of a Ranked choice, Likert Scale, ranging from 1 to 5, where 1 represents 'Not Important' and 5 represents Extremely Important. Some multiple-choice and Ranked questions were also developed.

The data was recorded through a questionnaire about the following variables.

a. Demographic Data: such as gender and name.

b. Online Shopping Context: Information regarding whether they shop online and how often they shop during sales.

c. Behavioral Analysis: whether the check ratings before purchasing and what they consider regarding the ratings, discounts, On-Time Shipping, and delivery options.

d.Perception Regarding Ratings and Discount %: such as whether a positive or negative rating influences the discount % during sales or not.

A. Daraz 11.11 Sale Data:

Instrument Variable Information: 'Daraz 11. 11 sales data, which has been downloaded for this study, has the following information:

- Total Number of Ratings.
- Seller's positive Rating Percentage.
- Original Price of Product.
- Discounted Price of Product.
- Discount percentage offered for the product during sales.
- Category of product.
- Delivery Type (Free Delivery or Standard Delivery).
- On-Time Shipping: percentage of the product shipped on time.
- Flagship Store: Whether the product is offered by a flagship store or not.

B. Data Pre-Processing:

To make sure that the findings or the data analysis results are accurate or to improve the precision and accuracy of algorithms, data cleaning is required [15]. The data that is gathered may have some missing values, duplicated records, and inconsistent records, which require some actions to be performed on the data so that the outcome of the Investigation or study is reliable.

i. Data Cleaning:

Initially, duplicate data and the records with empty or missing values have been removed to make the data reliable and consistent [16].

ii. Converting Data into Numerical Form:

To investigate the perspective of the Buyer, we have collected the responses through a questionnaire which has some multiple-choice questions, yes no questions, Ranked ranked-choice questions which need to be converted into a numeric format to run the statistical analysis.

iii. Data Integration:

Data downloaded from Kaggle has multiple files of product categories in which variables were different, having inconsistency of format, which required being transformed into a single format, such as converting percentages into a float value, as some records have integer values and some have decimal point values.

V. RESULTS AND DISCUSSION

The subsequent step is to analyze the collected data. This step is a crucial part of the research as it helps to understand or examine the data and interpret the results properly. The reason for examining the data is to draw conclusions that can hold significant importance and can further be utilized in real-life scenarios while making decisions.

A. Buyer Perspective Analysis:

This section provides information regarding the buyer's perspective.

i. Reliability Analysis using Cronbach's Alpha:

Cronbach's Alpha is widely used to check whether the items/ variables are consistent and examine the connected factors in an instrument or questionnaire before proceeding with further analyses, as it determines the research reliability factor. Table 2 indicates that the Cronbach's Alpha value is 0.721, which shows that the reliability aspect of the analysis is higher.

Table 2: Reliability Analysis

Reliability Statistics	
Cronbach's Alpha	**N of Items**
.721	7

B. *Data Analysis:*

Table 3,4, and Figure 2 depict that a total of 407 entries were collected through the questionnaire, out of which 240 records, which is 59.0 percent of the survey, were filled out by the female respondents, whereas 167 records, which make up 41 percent of the data, were collected from male respondents.

Table 3: Gender-wise Breakdown

Gender					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	**Male**	167	41.0	41.0	41.0
	Female	240	59.0	59.0	100.0
	Total	407	100.0	100.0	

Table 4: Shopped Online Statistics

Shopped_Online_During_Sales Cross Tabulation				
Gender		**Shopped_Online_During_Sales**		**Total**
		Yes	No	
Male	Count	140	27	167
	% of Total	34.4%	6.6%	41.0%
Female	Count	210	30	240
	% of Total	51.6	7.4%	59.0%
Total	Count	350	57	407
	% of Total	86.0%	14.0%	100.0%

Table 5. shows that 46.4 percent or 29.5 percent are female respondents whereas 17 percent are respondents who think higher ratings are associated with higher discounts where as there is another section of respondents which is 47.7 percent out of which 24.1 percent are male responders and 23.6 percent are female responders who perceive that positive rating means lesser discounts whereas only 5.9 percent of the entire sample size which belongs to female responders only who perceive that there is no association between positive ratings and discounts.

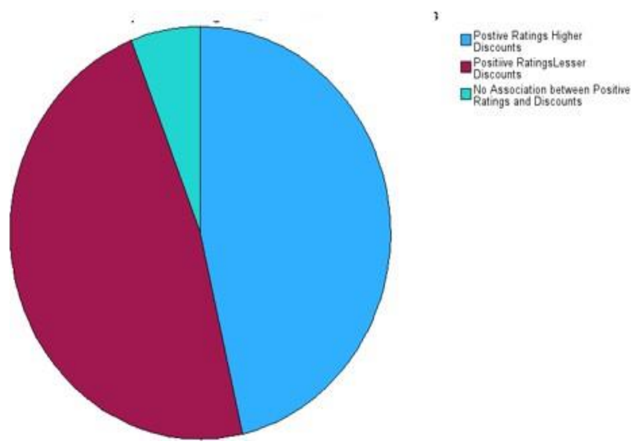

Figure 2: Buyer's perception of Positive Rating influence during sales on discount

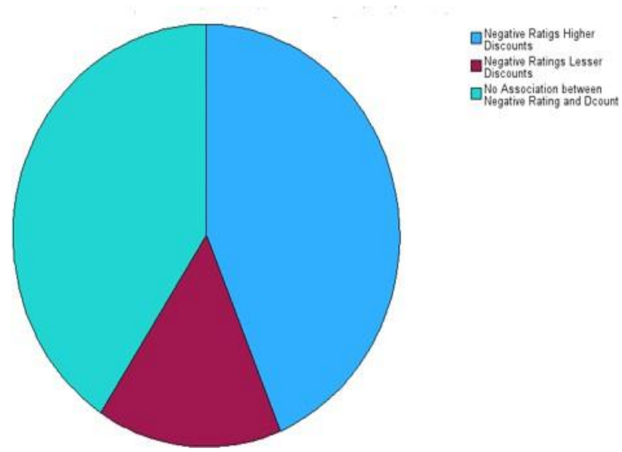

Figure 3: Buyer's perception of Negative Rating influence during sales on discount

Table 5: Buyer's Perception of Negative Rating Influence During Sales on Discount

Negative Rating Influence on Discount% % during Sales					
		Negative Ratings Higher Discounts	**Negative Ratings Lesser Discounts**	**No Association between Negative rating and Discounts**	**Total**
Male	Count	82	39	46	167
	% within negative rating influence discount % during sales	46.1%	61.9%	27.7%	41.0%
	% of Total	20.1%	9.6%	11.3%	41.0%
Female	Count	96	24	120	240
	% within negative rating influence discount % during sales	53.9%	38.1%	72.3%	59.0%
	% of Total	23.6%	5.9%	29.5%	59.0%
Total	Count	178	63	166	407
	% within negative rating influence discount % during sales	100.0%	100.0%	100.0%	100.0%
	% of Total	43.7%	15.5%	40.8%	100.0%

Table 5 and Figure 3 suggests that 43.7 percent respondents out of which 20.1 percent are male respondents whereas 23.6 percent are female respondent who think negative ratings are associated with higher discounts where as there is another section of respondents which is 15.5 percent out of which 9.6 percent are male respondents and 5.9 percent are female respondents who perceive that negative rating means lesser discounts whereas 40.8 % of entire sample size out of which 29.5 percent female respondents and 11.3 percent male respondents perceive that there is no association between negative ratings and discounts.

A. Daraz 11.11 Sale Data Set Analysis:

Table 6 suggests that the 'Daraz 11.11 sale' data sets have 12907 records, which suggests that 1156422 items were sold during the sale. Whereas Table 7 explores that there are a total of 10 categories in the entire record, and besides each category total number of sold products is mentioned alongside it.

Table 6: Daraz 11.11 Sales Dataset Descriptive Analysis

Descriptive statistics				
	N	Minimum	Maximum	Sum
Number of products to be sold	12907	19.00	2495.45	1156422
Valid n (listwise)	12907			

Table 7: Daraz 11.11 Sales Dataset Categories

Category	No. Of Products Sold
Automotive & Motorbike	70,906.46
Electronic Accessories	114,299.10
Electronics Devices	105,877.63
Groceries	69,078.94
Health & Beauty	71,381.17
Men's & Boys' Fashion	114,656.12
Mother & Baby	254,283.42
Sports & Outdoors	89,162.10
TV & Home Appliances	107,237.51
Watches, Bags, Jewellery	159,540.27

Correlation: For analyzing the association between the discount percentage and the product ratings, we have chosen the Pearson correlation. Along with the correlation analysis, we are also interested in the two-tailed test between the product's discount price with respective positive ratings because it examines the probability of the association in both directions. Following are a few evidence correlation matrices in which we have examined the finding of the association between the product Discount percentages concerning Ratings.

Table 8: Correlation between Discount and Positive Rating

Correlation between Discount and Positive Ratings			
		Discount	**Positive Seller Ratings**
Discount	Pearson Correlation	1	-,010
	Sig. (2-tailed)		258
	N	12907	12907
Positive Seller Ratings	Pearson Correlation	-010	1
	Sig. (2-tailed)	258	
	N	12907	12907

Table 8 correlation matrix suggests that the correlation coefficient value is -0.010 between Discount percent and positive ratings, which indicates that there is a very weak negative correlation, and practically the impact of this association is very minimal and can be negligible. Whereas the two-tailed significance value is 0.258, which is greater than 0.05, we can simply say that there is not enough statistically significant evidence and the correlation appeared to be by chance. The sample size N is 12907, making the result more reliable.

Table 9: Correlation between Discount and Total Number of Ratings

Correlation between Discount and Total Number Ratings			
		Discount	***Number of Ratings***
Discount	Pearson Correlation	1	.055
	Sig. (2-tailed)		<.001
	N	12907	12907
Number of Ratings	Pearson Correlation	.055	1
	Sig. (2-tailed)	<.001	
	N	12907	12907

Table 9 shows a correlation matrix that suggests that the correlation coefficient value is 0.055 between Discount percentage and number of ratings, which indicates that there is a very weak positive correlation, and practically the impact of this association is very minimal and can be negligible. Whereas a two-tailed significant value is less than 0.001, confirming the association is very weak. The sample size N is 12,907, making the result more reliable.

Table 10: Correlation between Chat Response and Positive Ratings

Correlation between Chat Response Rate and Positive Ratings	**Positive Seller Ratings**	**Chat Response Rate**
Positive Seller Ratings		
Pearson Correlation	1	.347**
Sig. (2-tailed)	<.001	<.001
N	12907	12907
Chat Response Rate		
Pearson Correlation	.347	1
Sig. (2-tailed)	<.001	
N	12907	12907

Table 10 suggests that there is a moderate positive correlation between chat response rate and Positive seller ratings, and the 2-tailed p-value confirms that it holds a significant value.

Table 11: Correlation between Ship On-Time and Positive Ratings

Correlation between Ship On-Time and Positive Ratings	**Ship On Time**	**Positive Seller Ratings**
Ship On Time		
Pearson Correlation	1	-.028**
Sig. (2-tailed)	.001	.001
N	12907	12907
Positive Seller Ratings		
Pearson Correlation	-.028**	1
Sig. (2-tailed)	.001	
N	12907	12907

Table 11 matrix revealed that there is a weak negative correlation between Positive Seller Ratings and Ship On-Time where whereas it is statistically significant, as the p-value is 0.001.

B. Comparing Buyer Perception and Daraz 11.11. Sales dataset findings:

There are approximately. 94% of buyers think that positive ratings have an impact on discounts % whereas real data analysis suggests that there is a very weak correlation between the two factors. This research has identified that among various factors, such as Ship On-Time, Delivery Type, Discount% has a weak correlation with positive ratings whereas chat response has a moderate association which has translated in positive ratings. We can conclude that chat response, i.e., customer service, plays one of the important factors that translate into positive ratings.

C. Price Forecasting using Neural Network, XGBOOST, and SVM:

The following section will explore Neural Network, XGBOOST, and SVM accuracy for discount percentage prediction.

i. ***Support Vector Machine:*** For the SVM model, 70 percent of the data is used for training, while 30 percent is used for testing. The Accuracy is as follows:

```
Train R2 Score: 0.217495448991621
Test R2 Score: 0.2091332182365725
Train MSE: 351.66356307133907
Test MSE: 367.72420799794645
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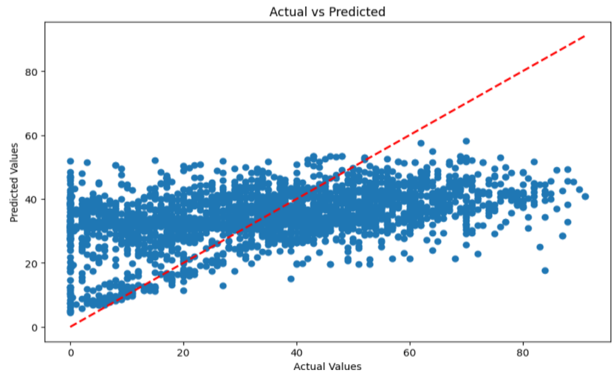

Figure 4: Buyer's perception of Negative Rating influence during sales on discount.

The model's performance showed a Train R^2 of 0.2175 and a Test R^2 of 0.2091, indicating limited predictive power, as also indicated from Figure 4.

ii. ***Neural Network****:* For the Neural Network model, 70 percent of the data is used for training, while 30 percent is used for testing. The Accuracy is as follows:

```
R^2 Score (Train): 0.9430
R^2 Score (Test): 0.9386
Mean Squared Error (Train): 25.6385
Mean Squared Error (Test): 28.5624
```

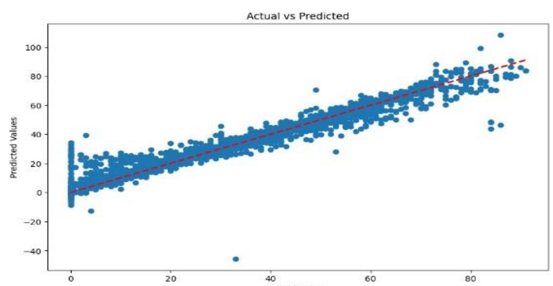

Figure 5: Buyer's perception of Negative Rating influence during sales on discount.

The above values show that the Neural Network model performs really well on training and test data, as shown in Figure 5.

2) *XGBOOST:* For the XGBoost Model, 70 percent of the data is used for training, while 30 percent is used for testing. The Accuracy is as follows:

```
Model Evaluation Metrics:
Train R2 Score: 0.9966427389566042
Test R2 Score: 0.9892681052393152
Train MSE: 1.5087789319049323
Test MSE: 4.989939636092362
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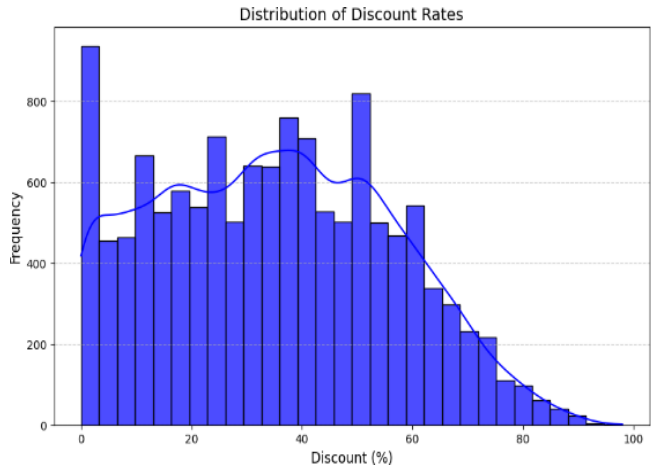

Figure 6: Actual Vs Predicted using XGBoost.

The above values, as shown in Figure 6, show that the XGBoost model performs well on training and test data.

VI. Conclusion

This research aims to analyze consumers' perceptions regarding the influence of product ratings and discount percentages during e-commerce sales. A real data analysis is then conducted to determine whether the consumer's perceptions align with the findings of the real data. After analyzing all the work we have come across that 94 percent of consumers think that the product's positive ratings influence the increase and the deduction of the discount percentage. In contrast, real data analysis says that there is no association between product ratings and discount percentages. Still, we have analyzed that chat response/ customer service is one of the factors that has a moderate association with product ratings and product price. This research also explores three different predicted models based on the identification of a discount percentage for future use.

VII. Future Work

Future work can be done on identifying the factors that have an effect on discount percentage, as we have evaluated that positive ratings are not one of them. We can also identify the seller's perspective regarding the ratings and set the discount percentage in order to analyze the gap between buyer and seller perception.

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