

Research on the Influence of Discount on Consumers' Purchase Attractiveness and Coping Strategies -- Taking Consumers Aged 26-35 as an Example

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Abstract. Promotions are the driving force of consumption for E-commerce platforms, such as the “Double Eleven” shopping carnival in China, in which major e-commerce platforms participate, which has been setting new records for its volume over the past decade. Statistics from the People’s Bank of China (PBOC) show that online payment services exceeded ¥1.4 trillion in the shopping frenzy in 2019 (PBOC, 2019). The same is true in other parts of the world. For example, “Prime Day” in the United States is equivalently attractive for American shoppers. In addition to policy support and market dividends, discounting is an important stimulus for shopping campaigns to achieve such brilliant results. In order to make the discounts more attractive to consumers, merchants continue to push the boundaries of the traditional discounts, adding “direct discount”, “quantity discount”, “bundle discount”, “coupon discount”, and other diversified means of discounts. In recent years, the discount method of stacking multiple discounts together is becoming increasingly popular, and merchants often choose more than one discount at the same time, forming a multiple discount scheme. This paper studies how exactly multiple discounts affect consumers’ purchasing decisions. In particular, this paper explores the impact of multiple discount schemes on consumers’ purchase intentions through ordinary least-squared (OLS) linear regression and difference-in-difference (DID) techniques. The conclusion reached shows that the most effective discount strategies are quantity discounts and coupon discounts, giving an insight to online platform merchants on a potential way of boosting sales.

Keywords: Discount; Consumers’ purchase attractiveness; Coping strategies.

1. Introduction

1.1 Research background

The value of studying discount strategies cannot be overstated. As a shopping platform, it is desirable to determine which strategy works best to attract more users to engage in shopping campaigns, increasing user loyalty and the platform’s attractiveness for merchants to sell their products. As a merchant or seller, it is natural to determine the optimal way of operating their business. If a product wants to open up in the market quickly, it must promote a way to accumulate popularity quickly. On the other hand, Taobao’s homogenization in products is becoming more prevalent, meaning that buyers can choose a comparable product from more than one store. Hence, promotions can help to seize a part of the advantage of the business but also firm up the decision of consumers to buy goods from a certain store, effectively shortening the consumer’s consumption cycle. Moreover, suppose the promotions do a good job in inviting the customer to experience the product while ensuring product quality, cost-effectiveness, and good services. In that case, the ensuing is a variety of praise. After accumulating a certain amount, the store’s reputation and rating will greatly help when the more purchase records, the easier it will be to sell goods in the future. The excellent promotion also helps with inventory control. For any retail business, there is no concept of zero inventory. Under normal circumstances, each product order and store digestion can’t be an exact

match. As long as the product is on the shelves of the stores, there will be unstable situations, namely out-of-stock products and excessive in-stock products. Promotion is a way to force the lagging goods and elegantly cut inventory.

1.2 Literature review

Prior work of related study compares how consumers react to discounts and promotions from various perspectives.

Wang Xin, Xiao Chunqiu, and Zhu Hong conducted similar research in their paper. *A discount added is an obstacle created: the impact of multiple discounts on consumer decisions*. This study had three major findings: First, consumers generally dislike complex multi-discount campaigns and prefer simple, straightforward single discounts. Multiple discounts increase the cognitive resources required for shopping, thus creating an impression of insincerity and reducing purchases. Therefore, merchants should consider reducing the cognitive effort required by consumers when setting up promotional programs to improve the purchasing experience and enhance consumer satisfaction. Second, with increasingly sophisticated artificial intelligence and recommendation system algorithms, online shopping platforms can profile consumers based on their past shopping preferences, such as promotion attention and shopping decision time, and then choose to push complex or simple discount campaigns. Finally, when a merchant voluntarily or passively chooses a multiple discount scheme, providing discounted prices can effectively attenuate the negative impact of multiple discounts [1].

Cai, Bagchi, and Gauri demonstrated that, in certain circumstances, when purchases are unnecessary, and purchase volume is limited, offering a low (vs. no) price reduction can diminish the inclination to acquire low-priced goods. The study contends that a low-price reduction for unnecessary purchases reduces perceived transaction value, diminishing customers' inclination to make purchases. This is based on the notion of buy value. However, the boomerang effect is reversed when there is a higher volume of purchases or when the purchase is necessary [2].

Balachander, Ghosh, and Stock studied how bundle discounts can boost revenue by fostering endogenous loyalty and lessening the intensity of promotional competition in a highly competitive market. Additionally, they discover that bundle reductions work well as a defensive marketing strategy to keep customers from switching to a rival brand [3].

Biswas, Bhowmick, and Guha showed how consumer judgments depend on where the sale price is shown, with evaluations constrained by the discount's depth. First, according to the authors' "subtraction principle," it is simpler to begin the subtraction assignment when the lower number is presented to the right instead of the left. Second, positioning sale prices to the right (as opposed to the left) of the original price makes it easier to calculate the depth of the discount, which raises evaluations for moderate discounts but not for low discounts because assessing sale prices naturally entails subtraction work. Both extremely low prices and excessive discounts may have the opposite impact. The research presented here provides fresh and counterintuitive insights into the relationship between discount depth and sale price display locations [4].

The results by DelVecchio, Krishnan, and Smith show that high-depth percentage-off promotions, as opposed to cents-off promotions, result in greater post-promotion pricing expectations. Similarly, the post-promotion choice is higher when high-depth promotions are expressed in percentage-off rather than cents-off terms [5].

1.3 Research framework

While the above literature studied related topics from a diverse set of perspectives, it can be noticed that most scholars and articles have focused on studying one promoting method at a time. On the contrary, very few have compared different discounting strategies cross-sectionally and how well they stack up together. The main reason behind this situation is the difficulty of obtaining related data, where datasets containing detailed information containing original prices and unit discount amounts in each kind are a tough find. This paper eliminates such a challenge by inherently possessing true sales data from JD.com

This paper aims to achieve the following goals. First, to validate that discounting stimulates consumption. Second, to compare which.

2. Methods

2.1 OLS Regression

Ordinary least-squares regression, also known as linear regression, is a common mathematical optimization method. The core idea of least squares is to estimate by minimizing the sum of squares of residuals. It is assumed that there is a linear relationship between the data samples x and y , i.e., a univariate linear regression model ($y=ax+b$) is expected to determine the specific functional relationship between X and Y . The aim is to determine the functional relationship between x and y by determining the parameters a , b , and hence the function between x and y . However, the problem is obvious, since the system of equations becomes overdetermined due to one more sample of data, the system of equations cannot be solved directly. Since it is impossible to find a straight line to satisfy all the sample points of the given data, it is a worthy attempt to find a line that minimizes the sum of residuals with each sample point. Although this line is not guaranteed to pass through all sample points, it can generally describe the relationship between x and y very well. Since the problem of positive and negative residuals requires the addition of absolute values, the absolute values are not well handled in the actual calculation, so simply square the residuals directly to ensure non-negativity. This is the idea of least squares, an estimation by minimizing the sum of squares of residuals, given by $S = \sum_{i=1}^n (\hat{y}_i - y_i)^2$. Then, when S is smallest, the parameters a and b are the values desired, i.e.

$$\arg \min_{a, b} \sum_{i=1}^n (\hat{y}_i - y_i)^2 = \arg \min_{a, b} \sum_{i=1}^n (ax_i + b - y_i)^2 \quad (1)$$

In this paper, the OLS regression is used to determine the effect of discount methods on sales. With a p -value less than 0.05, the corresponding variable can be stated as statistically significant, impacting the quantity sold.

2.2 Difference-in-difference

The differences-in-difference (DID) method is also known as the “double difference method”. As a major tool in policy effect assessment, it is becoming increasingly popular for economic and statistical research for the following reasons: (1) It can largely avoid the problem of endogeneity: policies are generally exogenous to microeconomic agents, so there is no reverse causality problem. Moreover, the use of fixed effects estimation alleviates the omitted variable bias problem to a certain extent. (2) In contrast to the traditional method, which assesses policy effects by setting a dummy variable for the occurrence or non-occurrence of policies and then running a regression, the model setting of the double difference method is more scientific and can estimate the policy effects more accurately. (3) The principle and model setting of the double difference method is simple, easy to understand and apply, and not as daunting as spatial measures and other methods.

The DID model for the benchmark is set as follows:

$$Y_{it} = \alpha_0 + \alpha_1 du + \alpha_2 dt + \alpha_3 dudu + \varepsilon_{it} \quad (2)$$

Where du is a grouping dummy variable, if individual i is affected by policy implementation, individual i belongs to the treatment group, and the corresponding du takes the value of 1. If individual i is not affected by policy implementation. Individual i belongs to the control group, and the corresponding du takes the value of 0. dt is a policy implementation dummy variable, dt takes the value of 0 before policy implementation, and dt takes the value of 1 after policy implementation. $dudu$ is a grouping dummy variable the interaction term with the policy implementation dummy variable, whose coefficient α_3 reflects the net effect of policy implementation.

This paper uses the DID method to examine the effect of sales by separating customers into four groups, as shown in the table below.

Table 1. Difference-in-difference demonstration in discount settings

	Before Discount	After Discount	Difference
Treatment Group	$\alpha_0 + \alpha_1$	$\alpha_0 + \alpha_1 + \alpha_2 + \alpha_3$	$\alpha_2 + \alpha_3$
Control Group	α_0	$\alpha_0 + \alpha_2$	α_2
Difference	α_1	$\alpha_1 + \alpha_3$	α_3

3. Results

First, it is essential to analyze the data used in this paper to get a general sense of the sample. The age of the JD.com user sample is distributed as in figure 1 below. The 26-35 age population is the group of interest in this paper because people in this age range tend to shop online more evenly than other age groups. For example, the 16-25 age group's purchasing power may be limited by personal allowances or student loans, and the 46-55 age group's online purchase activity may be correlated with how up-to-date they are with the latest technology compared to others. Therefore, the 26-35 group is the best option, which accounts for approximately 40% of the total sample.

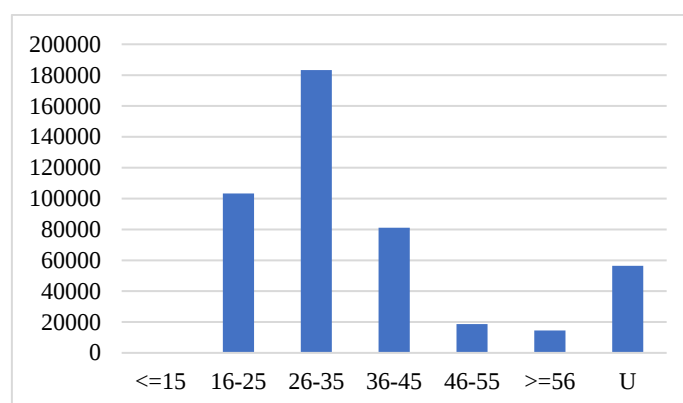


Fig. 1 User age distribution

Another important variable, Sku_ID, is the unique identification code of a product, whose distribution is shown below. With sku_ID, the different kinds of goods being sold in the dataset can be sorted into countable groups.

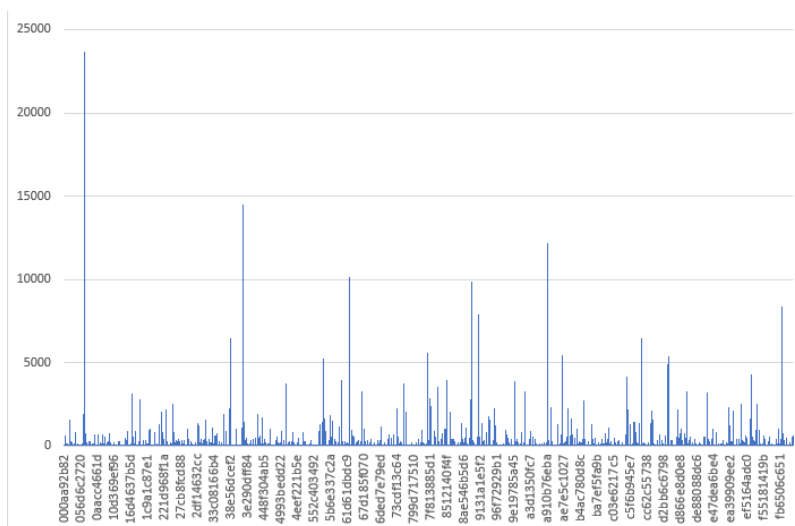


Fig. 2 Sku_ID distribution

There are 9,159 unique sku_ID, the most popular of which is 068f4481b3, which corresponds to 23,655 separate orders, and we use this product as the good being studied in the following analysis. After nailing down the sku_ID, proceed by finding the relationship between quantity sold and its pricing, namely the demand curve.

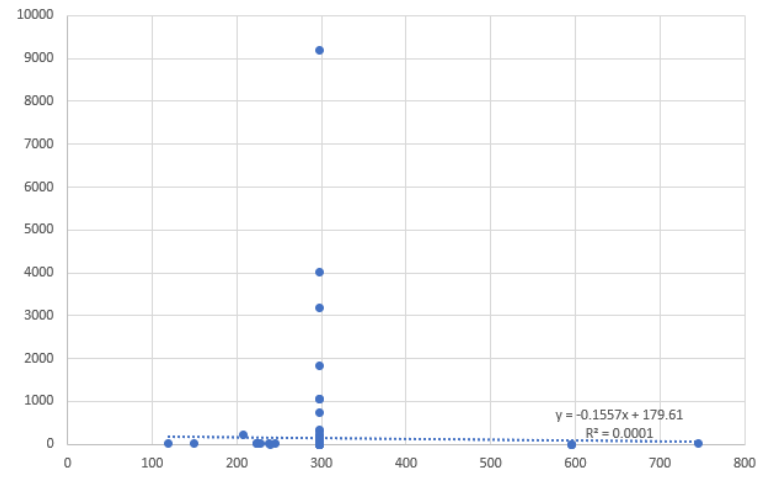


Fig. 3 Demand curve with the original price

As shown above, the quantity sold displays a negative relationship against its original price, which is consistent with the demand theory. However, the final price shows a contradicting demand curve, as the quantity demanded shows a positive relationship with its final price.

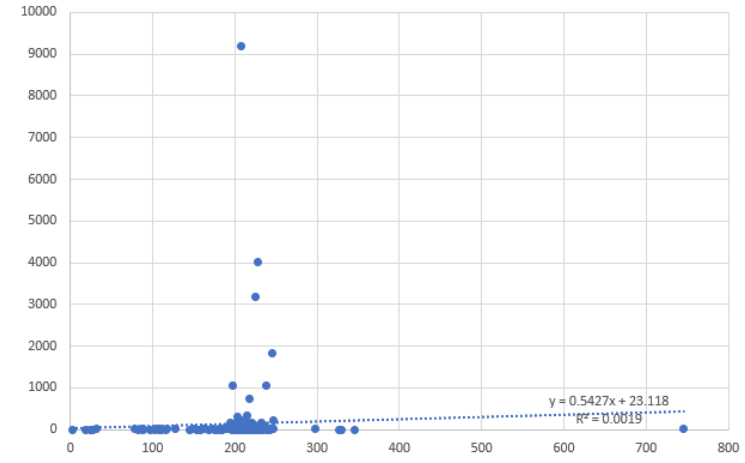


Fig. 4 Demand curve with the final price

This means that something more powerful dictates users' buying decisions, which can be speculatively assumed to be the discount.

$$\text{Define discount simply as } \left(1 - \frac{\text{final_unit_price}}{\text{original_unit_price}}\right) * 100\%$$

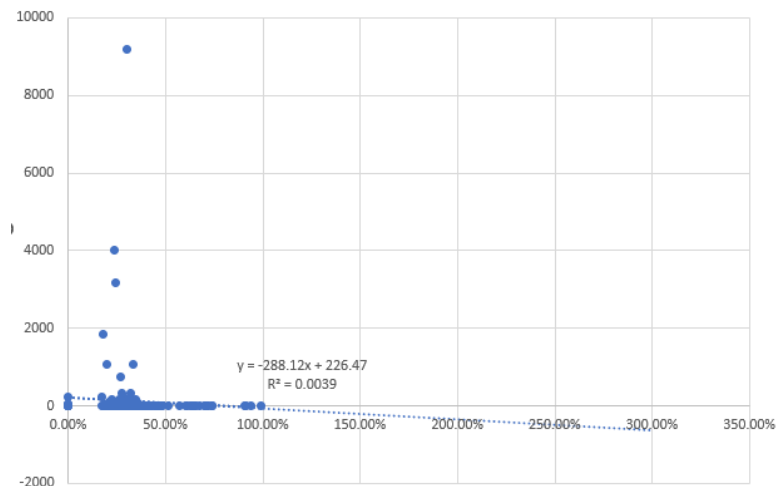


Fig. 5 Demand curve with the discount rate

Unfortunately, the above result cannot support the desired relationship between the discount rate and the quantity sold. The most likely reason for the above outcome is that few people get the chance to purchase the item when on sale. Thus, most people eventually purchase at the original price or at a very low discount.

The possibility that the above finding is susceptible to being an extraordinary case of its kind; this paper presents another example with sku_ID: *3c79df1d80*, the distribution of whose discount in percentage is displayed as follows:

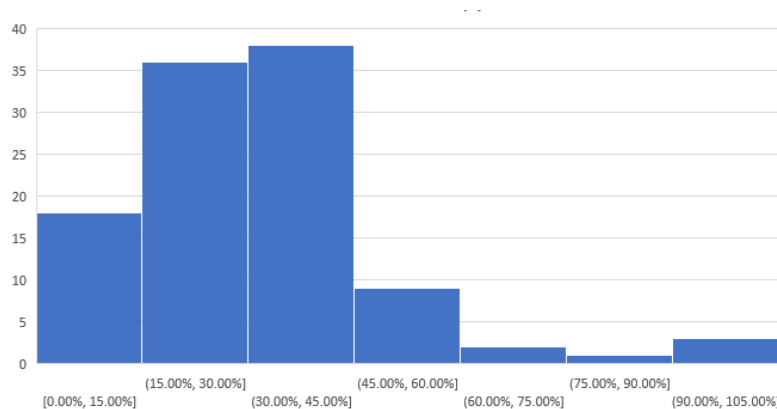


Fig. 6 Discount percentage distribution

Perform another regression, with extreme values removed, and it can be clearly seen that a positive relationship exists between discount and quantity sold, indicating that users are more willing to make the purchase when the discount is stronger.

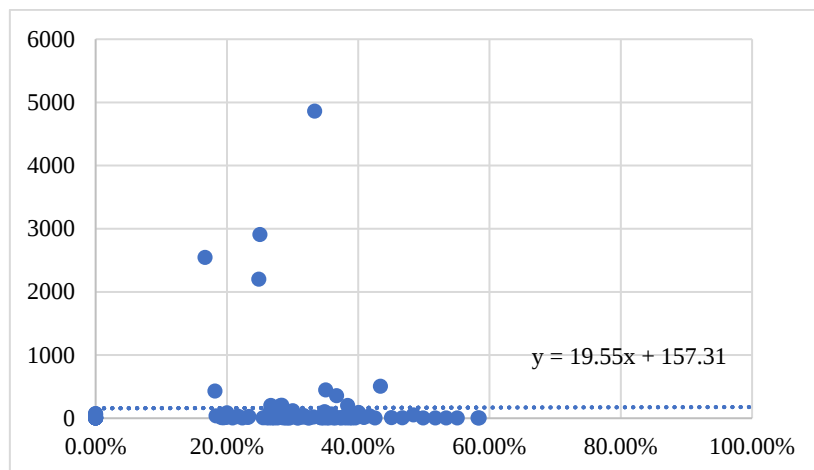


Fig. 7 Discount versus quantity sold

The research is continued by comparing which discount method is the most efficient, and the regression is given by:

$$quantity = \beta_0 + \beta_1 * direct\ discount + \beta_2 * quantity\ discount + \beta_3 * bundle\ discount + coupon\ discount + \varepsilon \quad (3)$$

Table 2. Regression report

	Coefficient	Standard Error	p-value
Intercept	1.177e+00	3.935e-03	2e-16***
Direct_discount	6.927e-05	8.179e-05	0.3971
Quantity_discount	4.783e-03	1.501e-04	2e-16***
Bundle_discount	7.792e-04	4.070e-04	0.0555
Coupon_discount	1.587e-03	2.268e-04	2.57e-12***

With the regression illustrated above, the conclusion may have arrived that among all discounting strategies, quantity discount and coupon discount are the two most effective ones and are statistically significant, with p-values both less than 0.05.

Last but not least, this paper solidifies the above finding with DID analysis and recalls the DID formula.

$$Y_{it} = \alpha_0 + \alpha_1 du + \alpha_2 dt + \alpha_3 dudu + \varepsilon_{it} \quad (4)$$

In this case, du is the grouping dummy variable with a value of 1 if the order is after the discount implementation date 20180315 and takes 0 otherwise, and dt is the implementation dummy variable with a value of 1 if the discount is nonzero and non-empty, otherwise, 0. dudu is the interaction term. The outcome is shown below. The coefficient for the interaction term du*dt is 0.067>0 and statistically significant, showing discount indeed boosts quantities sold.

Table 3. DID regression report

	Coefficient	Standard Error	p-value
Intercept	1.268198	0.008953	2e-16***
du	-0.116849	0.012574	2e-16***
dt	-0.024347	0.009772	0.0127*
du*dt	0.067506	0.013693	8.22e-07***

4. Discussion

In modern society, people can see stores, shopping malls, supermarkets, street vendors, and online shopping platforms. All know how to use promotions, discounts, rebates, and other means to attract consumers and improve their profits. No doubt, businesses know how to use people's consumer psychology to run their businesses so as not to lose money.

In the above DID analysis, the effect of discount has been verified by the statistically significant interaction term coefficient, showing that discount draws more interest in the product sold and boosts sales. It was a surprise at first that direct discount and bundle discount did not significantly impact the increasing quantity sold. What needs to be emphasized in the act of promotion is often not the strength of the promotion or the promotion method, but the key is how to make the consumer feel that they gain surplus from the sale. This could explain why these strategies were not so effective. Direct discounts felt too easy for consumers, while bundle sales made them feel like they were being forced to buy things that they did not need. Krishna supports the idea with her study on consumers' perception of promotional activity, where results from the survey indicate that many consumers are reasonably accurate about deal frequency and sale price [6]. Direct discount does not stimulate sales as predicted when a great number of consumers anticipated it to happen. A study by Berkowitz indicates that comparison cues produce positive results, whereas the effect of semantic cues depends on the particular stimulus [7].

On the other hand, quantity discounts and coupon discounts were statistically significant in boosting sales. This is not a surprise since these strategies are ubiquitous in the market nowadays, with widely used buy-one-get-one sales and all kinds of coupons from both online and in-person marketplaces [8]. The reason these strategies work so well could be the same as why the previous two did not work too well: a good promotion must make the consumers feel that they gain extra surplus from a deal. Using a game-theoretic model, Balachander and Ghosh showed that bundle discounts can help increase profits in a competitive market by creating endogenous loyalty, thereby reducing the intensity of promotional competition [9]. Quantity discount encourages consumers to buy more of what they like, so they can enjoy or share with people they care about at a lower average cost. Coupon discount makes consumers feel fulfilled that they have "unlocked" a special discount unavailable to everyone else. It also forces the consumers to return to the marketplace after the initial purchase from which the coupon was gained, during which they have a good chance of buying more items when browsings through the platform. Darke and Dahl examined the surprising value consumers attach to getting a bargain [10-11]. And past research has largely understood this phenomenon in terms of the impact discounts have on perceptions of fairness". A coupon discount adds more sense of getting a beginning to the deal. Both of these aspects make coupon discounts the more successful promotion strategy of the bunch. The friction of utilizing the coupons is also minimized as the age group being studied is between 26-35 because people whose ages are within this interval are most capable of catching up with the latest technology and collecting information from multiple venues.

5. Conclusion

5.1 Findings

With the increasingly fierce competition in the market, enterprises widely use promotional activities to develop the market. The promotion war of each e-commerce platform is intensifying, and the form of promotional activities is endless. Many businesses strive to stimulate consumers to buy through promotional activities. The research found that inappropriate promotional activities not only can not stimulate consumers to buy but also will cause a negative impact on the psychology of consumers, making it difficult to sell goods. This paper takes the JD.com marketplace as an example to compare and study the effects of the most commonly used promotions in the domestic market: direct discounts, quantity discounts, bundle discounts, and coupon discounts on consumers' purchase

intentions. Based on data analysis on the 26-35 age group, which accounts for about 40% of the sample size, a conclusion was drawn from the empirical evidence. Under the same promotional efforts, quantity discount brings the greatest perceived promotional benefits to consumers, and coupons come second, bundles bring the least perceived promotional benefits to sellers, and perceived promotional benefits positively affect consumers' purchase intentions. Based on the study results, the following conclusions were drawn: increasing the promotional efforts of gifts and coupons to different degrees. Hence, the promotional efforts of coupons are the largest, gifts and promotions such as buy-one-get-one are the second largest, and direct discounts are the smallest. Therefore, when formulating promotional strategies, enterprises should reasonably grasp the psychological needs of consumers, and different promotional methods bring different perceptions to consumers. In particular, coupons and quantity discounts should be placed at the top considerations when trying to market a new product to consumers aged between 26-35.

5.2 Limitations

The limitations of the data lie in the lack of knowledge of the specific type of products studied in the given dataset. The only variable to distinguish products in the data provided is sku_ID, which is encrypted and does not give additional information on the specific type of goods sold. If more insight on the types of goods had been given, a more insightful comparison could have been made. More studies could be conducted on how people of different ages react to promotional strategies. Even though direct discount did not appear statistically significant in the 16-35 group, it could be for the 36-45 age group. Last but not least, this paper lacks the use of primary data. In the future, gaining access to primary data through a survey, interview, etc., to obtain direct consumer feedback should be considered.

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