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Do personalized product recommendations influence consumer purchasing decisions more effectively than price discounts in e-commerce?

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Abstract:
In this study, the authors examine the feasibility of discounts and product recommendations as marketing strategies that can be applicable in the context of consumer behavior within the e-commerce setting. The analysis was done based on a dataset and that was used to approximate the real-life purchasing behavior focusing on the comparison of the results of the conversion, the value of the order, and the heterogeneous effects within the treatment groups. The results show that the volume of discounts has a tremendous impact in increasing the conversion rates that confirm that it is an effective driving force behind making the purchase. The implication that they have on the order value is not important with the implication of a trade off in revenue in case they are overutilized on discounts. Product recommendations, on the contrary, possess lower conversion influences but higher order value among the customers thus portray their effectiveness in cross-selling and upselling. Customer attribute, previous history of purchase and price sensitivity is also highlighted in the research regarding the effectiveness of treatment. On managerial analysis, the report shows that it is preferable to use discounts to accomplish the short-term targets of the business in terms of traffic and sales volume and the long-term goals of recommendations in terms of value creation in the long run in terms of increased revenue per transaction. The best option, which can provide the highest possibility of maximizing the sales and profitability, is a balanced approach combining both strategies using discounts selectively and through personalized recommendations. The study highlights the importance of using data to make decisions in the development of promotional plans that are aligned to the business objectives and customer characteristics.

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1. Introduction

Monetary incentives such as price cuts and personalization through product suggestions are the two most common strategies that e-commerce platforms employ to drive sales. The two strategies have different operations (Purnomo, 2023). Discounts also reduce the cost of an immediate purchase and help to maximize consumer benefit and making the purchase easier for the customers. Being simple to implement and customers to understand, they have been a popular short-term option to clear out stock or to generate demand. Discounts, however, also have obvious disadvantages. These decrease the profit margins, are capable of making customers price sensitive, and can damage brand value when overused. Personalization alters the appearance of useful available products by emphasizing relevant products at the appropriate time (Riegger et al., 2022). Strong recommendation systems, whether collaborative, content, or a combination of both, can display the products that fit the customer, propose products of higher value or that are complementary, and provide a better connection between the browsing and purchase experience.

Given that recommendations can enhance the likelihood of making a purchase and overall order size, they can be used to increase revenue without negatively affecting margins. Moreover, customization would help to establish better long-term customer relationships as the customers would be more satisfied and relevant with the platform (Rane et al., 2023). The most important question to managers and marketers is not whether either of the strategies works, as numerous studies and vendor assertions indicate that both are effective, but which one has larger and more lucrative outcomes with the constraints of reality. Such factors as budget, development resources, inventory, and strategic focus are all significant. One of the biggest retailers must choose whether to spend scarce marketing resources on the short-term, easy-to-quantify benefits of discounts versus the initial cost of engineering and data science of high-quality personalization (Dawidson & Arkel, 2023). The long-term effects are also something they should take into account. The constant discounts may encourage customers to wait until the promotion is done before they make purchases, and low personalization may cause irrelevant recommendations that irritate customers and occupy too much space. This paper deals directly with that trade-off by making comparisons between personalized recommendations and price discounts in a randomized experimental format.

The most effective way of determining cause and effect in real-world conditions is through randomized controlled trials, as they isolate the effect of a treatment against changing preferences and trends of customers over time. With differentiating between the visitors or sessions randomly between a control group, a recommendation group, or a discount group, we can evaluate the impact of each strategy on conversion rates and financial outcomes, that is, the frequency of transactions and the value of orders. In addition to the average impact, managers must also be aware of dissimilarities among users: what groups can be more responsive to recommendations than to discounts, and how the impact varies with prior purchasing behaviour, price sensitivity, and product category? Our investigation into this area is aimed at contributing to the creation of specific strategies. As an example, price-sensitive low-value customers can be given discounts, whereas higher-value segments can be approached using recommendations. The insights will aid in making certain decisions regarding promotion, allocation of resources to engineering and marketing, and the need to focus on short-term revenue generation and long-term customer experience investment.

2. Literature review

Monetary promotions (price discounts, coupons, time-limited offers) and information-based personalization (product recommendations and offers) are two categories of tactical leverage that e-commerce companies use to drive short-term and long-term sales. Literature on price promotion and personalization has evolved more or less in parallel with complementary but sometimes opposing implications on revenue, margins, and customer behavior. The review summarizes empirical studies and theory on (1) the long-run and immediate impacts of price promotions, (2) the processes and quantified effects of product recommendation systems, (3) the studies that view both levers simultaneously (and hybrid methods), and (4) the methodological lessons and open questions which encourage a randomized, comparative study.

2.1 Price Promotions: Short-term Lift vs. Long-term Risk

The history of marketing and retail economics research abounds with the fact that price promotion is certain to increase the short-term demand by decreasing the effective price and increasing the consumer surplus (Dou et al., 2024). Promotion of prices has been found to increase probability of conversion and purchase incidence in a range of situations whether they are in the grocery and durable goods business or over the internet; cross section and panel studies all indicate that there is high level of heterogeneity based on the type of product being advertised, the extent of the discounted price and the format of the advertisement of the product. The empirical research on the trend of retail promotion highlights the fact that the trend of promotions is extensive and is being applied in assortments strategically to both balance the inventory and generate demand.

The frequent discounting will eventually lead to a decline in profitability in the long term, either by lowering margins or lowering the time of purchase in order to keep up with the promotions, or when the reference prices vary. Classic pricing research asserts that every day-low-pricing (EDLP) and high-low promotion systems have tradeoffs between volume and profit, and a high level of aggressive discounting can lower perceived brand value (Zafran, 2022). Consumer strategic action is also subject to promotions- consumers will hold off until they receive a discount, and this will reduce the full price sales and increase their dependence on promotions, or other longitudinal and platform studies refer to this as attenuation or even negative carryover effects of repeated promotions.

The studies on promotion exposures show that the continuous promotion activity may make prices sensitive and alter the moment to buy, since it becomes hard to define the impact of promotion as naive and short-term oriented (Brown et al., 2022). The importance of the structure and accuracy of discounts has been shown in recent practitioner studies, which have consequently narrowed this view. Small target groups, which receive narrow, short, or time-based discounts, are likely to be highly effective in profit efficiency compared to blanket, deep discounts. As an example, the managerial research recommends reduced and more precise discounts to increase sales without further reduction in margin.

2.2 Product Recommendations: Mechanisms and Measured Gains

The nature of the recommendation systems is that the compatibility between the preferences of the consumers and the items offered is improved. The academic literature puts recommendations into perspective relative to the addition of perceived utility to assortments offered, through personalization algorithms, that enable cross-selling, upselling, and discovery of pertinent products, and subsequently transform and enhance average order value (AOV) (Potla & Pottla, 2024). It is three-fold: (a) browse to buy: present good products to the consumer in browsers; (b) augment order value: build on recommendations of complementary and higher value products, and (c) reinforce loyalty: strengthen future interaction.

It has been noted by the empirical literature and reviews on platforms that a successful personalization may result in a large boost in the rate of click-through, conversion, and the AOV, but the degree of the effect varies with the quality of the algorithm and the amount of data. Methodologically, recommendation research is associated with algorithmic performance, causal analysis of downstream business outcomes. In some articles, it has been mentioned that the value of personalization is not just predictive quality, but how recommendations affect the decision sets and choices of the customer under certain settings (Adomavicius et al., 2022). This difference is significant to experimental design: experimental advantages may be a result of more relevance, the choice architecture (positioning and framing), or prompting complementary purchases. It is also implied in the literature to compare the recommendations regarding business KPIs (conversion, AOV, retention) with the proxy ones.

2.3 Joint and Comparative Considerations

Discounts and recommendations are less frequently studied in a randomized or quasi-experimental cross-sectional study comparing the variables directly. The theoretical and practical research on integrated measures, however, shows considerable interaction. Individualized promotions that consider willingness-to-pay estimates can give better allocation of discounts, price-sensitive users would not purchase at full price, and promotions can be left to price-sensitive users to boost AOV to the higher-latent-value-users. Research on the design of customized promotion suggests the joint optimization where both recommendation and price cues are modified to maximize incremental profit rather than conversion. According to platform and marketplace research, heterogeneous effects are also present: promotions have effects on seller behavior, platform dynamics, and personalization accuracy; competitive effects in recommendation slots are also changed by the effect of personalization accuracy. As an illustration, platform-based analysis of coupon schemes has shown that the effects of promotion depend on the seller‘s properties and can be externally spilled over the market. The above findings emphasize the role of the fact that the comparative usefulness of discounts and recommendations may vary according to the situation, i.e., the margins of the products, the level of competition, and the complexity of the personalization systems.

2.4 Methodological lessons from prior experiments and observational work

The cause must be determined because a biased compar-

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ison may be realized due to the heterogeneity of customers, and time-related confounders (seasonality, marketing calendar). The gold standard of ITT quantification of treatment effects is still regarded as randomized controlled trials (A/B tests). The literature emphasizes the care to be observed in documenting the exposure, intent-to-treat or treatment-on-treated estimates, clustering, and power analysis that are susceptible to low baseline conversion. Research also indicates that there is a need to compare profit indicators (incremental margin) and more long-term outcomes (repeat purchase and retention) as opposed to immediate conversion lift.

2.5 Gaps and motivation for the present study

Although both of these levers have been separately discovered to be beneficial, causal, head-to-head proof regarding which lever provides more and more lucrative lifts in actual e-commerce situations is comparatively meager; much of the literature either considers promotions and individualization individually or discusses issues of hybrid optimization in theory. In recommendation studies, improvement in engagement measures or click rates is observed in most of the studies, which do not correlate with profit measures that are profitable to the margin. There is scant information on long-run and heterogeneous responses in relation to different classes of customers to discounts and recommendations in randomized comparisons. These loopholes invite a randomized trial that directly compares a recommended treatment to a discount treatment of conversion, AOV, and profitability, as well as a heterogeneity test using proxies of previous purchase behavior and willingness-to-pay.

3. Methodology and Analysis

3.1 Research Question and Hypotheses

RQ: Does social recommendation of products play a greater role than price discounts in online shopping?

In order to answer this question, four hypotheses are developed:

· H1 (Conversion Recommendation): Individualized recommendations are more effective in conversion compared to control.

· H2 (Conversion Discount): Price discounts increase conversion rates relative to control.

· H3 (Comparative): Personalized recommendations increase conversion more than price discounts.

· H4 (Order Value): When compared with price discounts, personalized recommendations boost average order value with purchasers.

3.2 Experimental Design and Identification Strategy

3.2.1 Treatment Arms

The study is proposed to be conducted in the form of an experimental study, the design of which is three-arm and indicates three variations of intervention strategies. The initial one is known as the control, which undergoes the regular website interface with no extra capability, like a recommendation, two-pane, or discounts. The second category is the recommended treatment, where the users are shown a customized recommendation pane on the product page or during the cart phase. The recommendation system underlines the top three items that can be considered the most relevant to a particular user based on the historical affinity, past browsing, or buying trends. Notably, there are no changes in prices in this treatment, and any effect observed can only be linked to personalization.

The third category, known as the discount treatment, shows an apparent decrease in price on the target product or products. A discount of 10 percent can be offered on the product being advertised. As opposed to the recommended treatment, there is no individualization in this case. The availability of the discount will be there to challenge the strength of the purchase behavior persuasive power of monetary stimulus. These three treatment arms offer a grounded context for making a straightforward comparison of the relative impact of personalization and price-based incentives on consumer decision-making. These are control, recommendation, and discount arms that determine the baseline, the effect of personalization, and the effect of monetary reduction, respectively.

3.2.2 Randomization and Unit of Assignment

The method of randomization is applied on a user or browsing session basis in order to guarantee that every participant is randomly allocated to any of the three treatment arms. The experiment also makes sure that no skewness of the results may occur through the distributing the users in the groups in approximately equal ratios in the form of 1:1:1. Internal validity of the study is enhanced by such a strategy because it reduces the risk of selection bias, and both observable and non-observable characteristics are distributed well across the treatments.

In this design, the Stable Unit Treatment Value Assumption (SUTVA) is the basis of credibility of causal inference. This assumption implies that a user of a specific treatment does not affect the results of another user. It further assumes that every condition of treatment is always reproduced and measured throughout the sample. The study design with strict randomization will contribute to the fact that different outcomes may be ascribed to interventions themselves, recommendations, or discounts, and not to confounding variables.

3.3 Statistical Models and Estimation

3.3.1 Logistic Model for Conversion

Let Y_i be the binary purchase outcome for unit i, the model specification is:

$$Pr(Y_i = 1) = logit^{-1}(\alpha + \beta_R R_i + \beta_D D_i + \gamma_1 \text{age}_i + \gamma_2 \text{gender}_i + \gamma_3 \text{prior}_i)$$

where R_i and D_i are dummies for recommendation and discount, respectively, with control as the reference group.

· Coefficients β_R and β_D capture treatment effects.

· Odds ratios, computed as e^{β}, provide interpretable effect sizes.

3.3.2 OLS Model for Transaction Amount (Purchasers Only)

For users who made purchases, the continuous transaction value A_i is modeled as:

$$A_i = \delta + \theta_R R_i + \theta_D D_i + \varphi_1 \text{age}_i + \varphi_2 \text{gender}_i + \varphi_3 \text{prior}_i + u_i,$$

where θ_R and θ_D measure average changes in order value associated with recommendations and discounts, respectively.

3.3.3 Hypothesis Tests (Simple Comparisons)

Simple statistical tests are used to give clear and easy-to-understand comparisons between the treatment groups to complement the regression-based analyses. Two-proportion z-tests are performed in case of the main result of conversion. These tests compare the percentage of users who purchased the recommendation group as compared to the control group and the discount group as compared to the control group. The z-tests will be suitable in this case as the data are proportions based on large sample sizes, and therefore, the normal approximation can be used with confidence. Considerable differences in these tests would give some early evidence that recommendations or discounts would lead to higher purchasing than the base.

On the secondary outcome of transaction value, the 2-sample t-tests are applied to evaluate the mean values of the order of purchasers with the various treatment arms. The test that Welch uses is preferred to the conventional Student t-test, as it does not assume that the variances between groups are the same, which in the context of e-commerce data represents a fair point that can be spent in very different ways. The test is used in pairs to determine whether users who are exposed to recommendations or discounts spend much more than the control group. The z-tests that would be used in the conversion rate and the t-tests that would be used in the number of transactions would allow examining the two aspects of consumer behavior that these responses would focus on: whether treatments lead to purchases and whether those purchases are going to be of a monetary nature.

3.3.4 Inference Strategy

The study inference plan is grounded on the conventional demands of applied econometrics, experimental researches. The level of testing all hypothesis tests is determined at the 5% level and two sided alternative is taken to depict negative and positive deviations against control group. Both treatments are further reported with 95 percent intervals of confidence besides the point estimates to indicate the level of accuracy, besides demonstrating a possibility to interpret the level of statistical and substantial significance.

Cluster-robust standard errors are proposed to ensure that when applied in practice (where a single user can make various sessions), there is robustness. The adjustment considers potential within-user correlations, otherwise it would create biases in estimations of variance and significance tests. The most important estimand of interest is the intention-to-treat (ITT) effect, which measures the impact of assignment of the treatment regardless of the full adherence of the users to the intervention. Where data on exposure can be utilized in order to decide whether a user accessed or utilized a suggestion or a discount or not, per-protocol or treatment-on-the-treated analyses are also executed as additional estimations. These complementary practices combined provide a comprehensive approach to derive true convincing rigorous evaluations of the test results.

3.4 Results Analysis

3.4.1 Descriptive Statistics

The descriptive statistics of treatment groups must make a point of reference of having an idea of the data prior to formal modeling. According to Table 1, the descriptive statistics of the three treatment groups including the control, recommendation and discount are provided. The control group reported a 4.8% conversion rate, and the recommendation and the discount group found 6.0% and 8.1% respectively. This itself shows that a lot of alterations are observed in the purchasing behavior between treatments. The average number of items bought in the control group was very low (0.08), which means that most of the sessions were not converted as compared to the recommendation group (0.11) and discount group (0.14).

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Table 1: Summary Statistics

treatment	conversion_rate	avg_item	avg_order_value	n
control	0.04818195	0.07601377	7.279366	6683
recommendation	0.05998515	0.10883445	11.019370	6735
discount	0.08143421	0.14129444	13.024559	6582

The same case was with average order values, where, in the control group, the average was the lowest with an average value of 7.28, recommendations were the highest with an average value of 11.02, and discounts were the highest with an average value of 13.02. These values are not high due to the inclusion of non-purchasing sessions in the averages, but they provide the first impression of the existence of a correlation between treatments, increased engagement, and expenditures. These descriptive tendencies give the foundation for the more formal regression trends in subsequent sections.

3.4.2 Conversion Outcomes (ITT Analysis)

The first formal test of treatment effectiveness focuses on whether assignment to recommendations or discounts increased the probability of purchase. Table 2 presents the findings of the logistic regression model that estimated the intention-to-treat (ITT) effect of conversion. Both treatments also had high chances of conversion as compared to the control. The presence of the assignment to the recommendation group was linked to 26% increased probability of conversion (OR = 1.26, $p < 0.01$), and an even greater percentage of the odds of conversion under the discount treatment (OR = 1.75, $p < 0.001$). None of the significant predictors of conversion had a covariate of demographics or behavior (age, gender, previous purchases, or price sensitivity), and the purpose of this is to establish this as the primary treatment effect in the determination of the changes in the purchase intent.

Table 2: Logistic Regression Results for Conversion (ITT) with odds ratios and confidence intervals.

term	estimate	std. error	statistic	p.value	conf. low	conf. high
(Intercept)	-3.103646758	0.11965053	-25.9392653	2.403248e-148	-3.338157481	-2.869136035
assigned_rec	0.232497281	0.07631417	3.0465806	2.314605e-03	0.082924247	0.382070315
assigned_disc	0.562219036	0.07222825	7.7839215	7.031039e-15	0.420654265	0.703783806
age_user	0.001703703	0.00191156	0.8912629	3.727882e-01	-0.002042887	0.005450292
gender_userM	-0.070141733	0.05847433	-1.1995303	2.303218e-01	-0.184749315	0.044465850
gender_userOther	0.302948293	0.25881004	1.1705430	2.417825e-01	-0.204310067	0.810206652
prior_purchases	0.031222236	0.02117101	1.4747635	1.402762e-01	-0.010272187	0.072716658
price_sensitivity	0.085292617	0.16673104	0.5115581	6.089603e-01	-0.241494208	0.412079442

The rates of conversion by treatment group and these differences are well visualized as seen in Figure 1. Control conditions maintained conversion to less than 5% and recommendations promoted conversion to approximately 6 and discounts above 8. This confirms that the largest impact of discounts is the immediate boost in the conversion, which is the most immediate, but a slight, though statistically significant, effect is also produced by the recommendations.

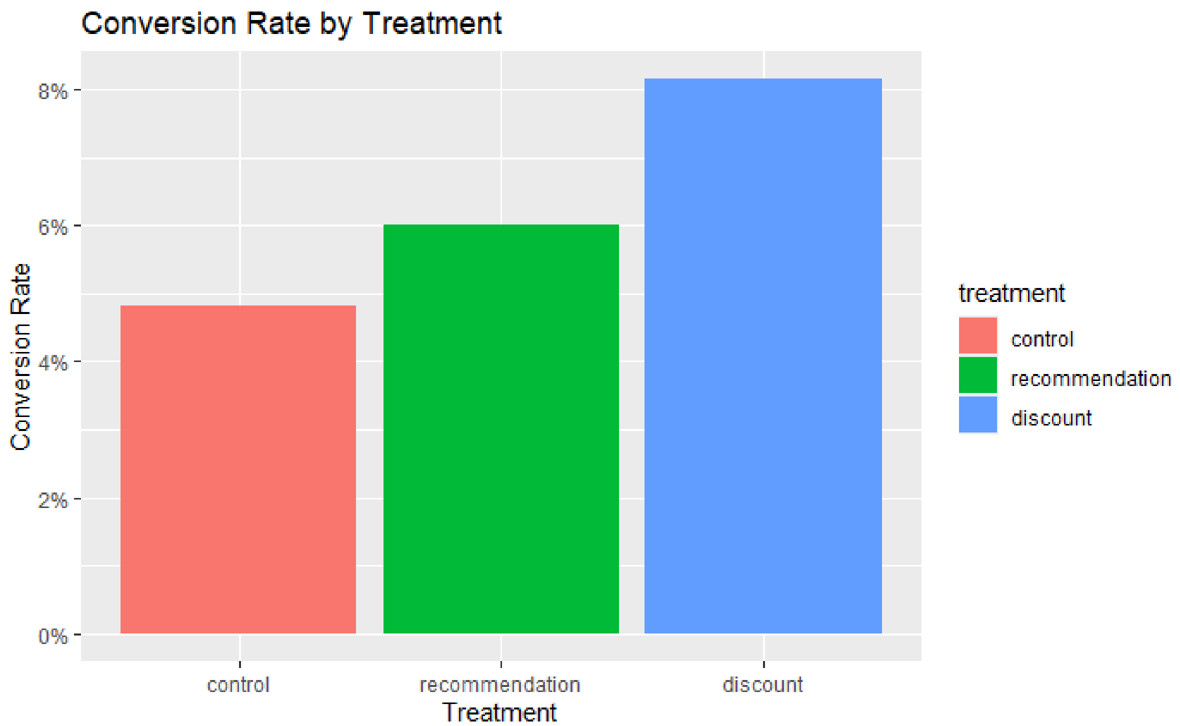

Figure 1: Conversion Rates by Treatment

3.4.3 Order Value Outcomes (Purchasers Only)

Besides conversion, there is also a need to test the extent to which the treatments influenced customer expenditure following a purchase. Table 3 consists of the outcomes of the OLS regression of order value in those who are purchasers only. The group assignment of recommendation had a significant influence on the mean order value of about 32 (p less than 0.01) since it was postulated that the cross-selling or upselling should be initiated by recommendation. It was, however, discovered that there was no statistically significant influence that the assignment to the discount group had on the order values ($b = 9.68$, $p = 0.33$).

Table 3: OLS Results for Order Value (Purchasers Only)

term	estimate	std. error	statistic	p.value	conf. low	conf. high
(Intercept)	133.571839	18.9852189	7.0355701	3.256095e-12	96.3255436	170.8181336
assigned_rec	32.201148	11.6137370	2.7726775	5.642041e-03	9.4166501	54.9856451
assigned_disc	9.675058	9.9963456	0.9678594	3.333012e-01	-9.9363485	29.2864635
age_user	0.114547	0.3083249	0.3715140	7.103175e-01	-0.4903425	0.7194365
gender_userM	-3.486879	9.0580151	-0.3849496	7.003401e-01	-21.2574142	14.2836563
gender_userOther	8.080244	32.0161983	0.2523799	8.007888e-01	-54.7309760	70.8914644
prior_purchases	6.280867	3.7630055	1.6691091	9.534537e-02	-1.1016140	13.6633473
price_sensitivity	10.750709	25.6956724	0.4183860	6.757366e-01	-39.6605400	61.1619576

The control variables, age, gender, previous purchase history, and price sensitivity did not turn out to be the significant predictors of the order value in this model, though previous purchases were near to be significant ($p = 0.095$), which means that they are weakly positively correlated with the order size. Figure 2 shows the order values distribution of purchases by the treatments alone, and the histogram shows that most of the purchases are not beyond 200, unlike the recommendation group, which has a wider distribution with more of the purchases centered around the upper value end of the distribution. This supports the regression proves that recommendations enhance the purchase incidence, not the expenditure, and basically, a consequence of a discount.

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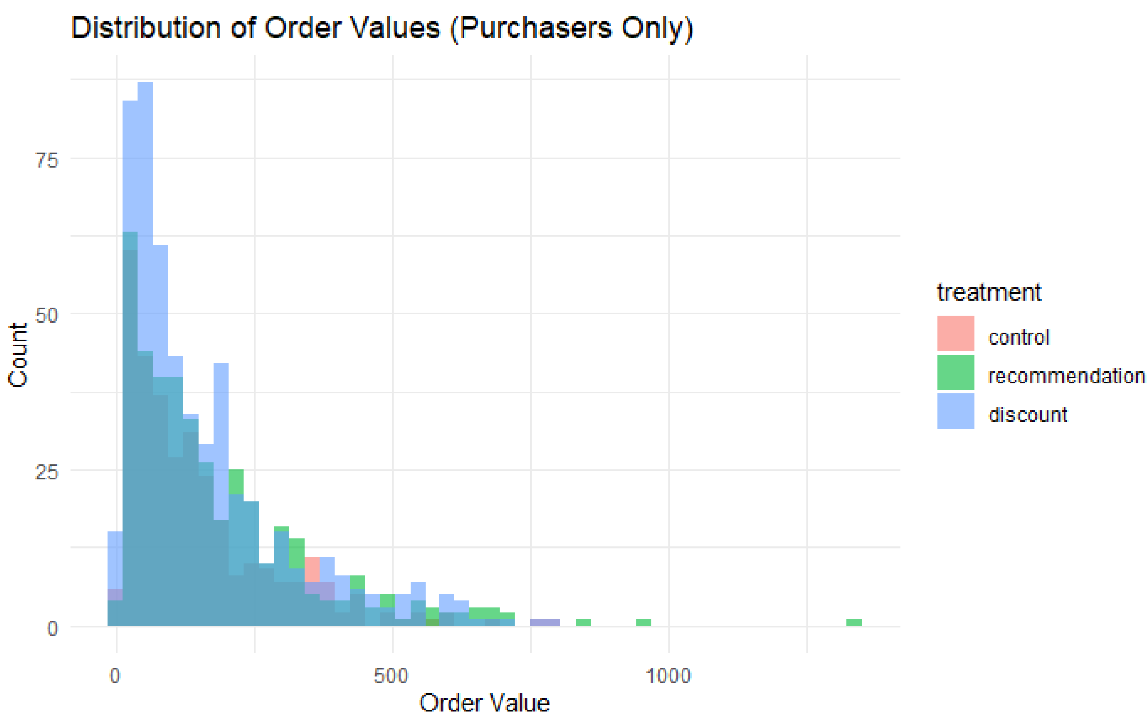

Figure 2: Distribution of Order Values by Treatment

3.4.4 Heterogeneity Analysis

The analysis focuses on the impact of finding out whether the impacts of treatment varied with the consumer characteristics, particularly the price sensitivity. The heterogeneity of effects on treatment is studied in Table 4 by including the price sensitivity interactions. Discounts and recommendations were also significant key effects, and odds ratios are 1.44 ($p < 0.01$) and 1.70 ($p < 0.001$), respectively. The conditions of interaction with the price sensitivity were, however, not significantly important. The sensitivity of recommendation x price (0.62) and insignificant ($p = 0.15$), but interaction between discount x price (0.14) and insignificant ($p = 0.74$). It suggests that user price sensitivity was not quantifiably dependent on the effectiveness of both treatments in this dataset in a systematic way. The lack of heterogeneity effects implies that the impact of the recommendation, along with the discounts, impacted the users, both sensitive and not, to the prices on the basis of the same amount.

Table 4: Logistic Regression Results with Interaction Terms (Price Sensitivity × Treatment)

term	estimate	std. error	statistic	p.value	conf. low	conf. high
(Intercept)	-3.136943857	0.13151472	-23.8524160	9.558390e-126	-3.394707975	-2.879179739
assigned_rec	0.364775227	0.12144623	3.0035945	2.668107e-03	0.126744990	0.602805464
price_sensitivity	0.225107662	0.31134936	0.7230067	4.696758e-01	-0.385125863	0.835341186
assigned_disc	0.531259057	0.11786054	4.5075226	6.558893e-06	0.300256641	0.762261472
age_user	0.001747654	0.00191261	0.9137536	3.608463e-01	-0.002000993	0.005496302
gender_userM	-0.071231970	0.05848777	-1.2178952	2.232638e-01	-0.185865885	0.043401945
gender_userOther	0.299320034	0.25845863	1.1580965	2.468247e-01	-0.207249575	0.805889644
prior_purchases	0.031695853	0.02119814	1.4952186	1.348574e-01	-0.009851739	0.073243445
assigned_rec:price_sensitivity	-0.623397939	0.43656125	-1.4279736	1.532995e-01	-1.479042273	0.232246394
price_sensitivity:assigned_disc	0.137085413	0.40901666	0.3351585	7.375055e-01	-0.664572516	0.938743342

3.4.5 Interpretation and Insights

The results were effective in proving that the two interventions, that is, discounts and product recommendations, influenced the customer behavior positively, though in different ways. Conversion was greatest with promotions and a great number of sessions that resulted in purchase. However, once turned into a customer, discounts did not influence the size of an order greatly, which indicated that the most significant impact of a discount is that it encourages customers to buy rather than to buy more. The recommendation had less influence on conversion, though, in a case where customers purchased, they had more chances of purchasing items at a higher cost or had more items, leading to high order values on mean. This contrast elicits two kinds of behavioral reactions, which consist of discount decreases the purchase barriers, and recommendations elicit broader buying or greater purchasing choices.

These results suggest that the strategic objectives are where the decision of using discounts or recommendations rests in terms of management. Discounts are the most appropriate in the case of maximizing the number of buyers who buy the product, but the managers must pay much attention to the long-term impact on the profit margins since frequent discount offers will cause a drop in revenues, and the customers will become accustomed to discount offers. Recommendations, on the other hand, offer a less assertive but worthy plan of promoting the increase in revenue on each transaction, particularly by instigating cross and upsell without the perceived value being affected. Therefore, selective implementation of discounts in terms of achieving conversions and customized recommendations can be considered a compromise policy in order to receive the greatest revenue per order and, ultimately, a volume and value increase.

4. Discussion and Conclusion

4.1 Discussion

The findings of the study can be applicable in providing information on the extent to which different marketing instruments, such as discounts and product recommendations, can affect consumer behavior in e-commerce. The analysis shows that discounts affected conversion the best since it increased the probability of purchase by a wide margin compared to the control group. It can be explained by the fact that the past researches suggest that monetary stimulus is a powerful driving factor since it lowers the barrier the cost in the short-term and leads to impulse purchasing. These results further indicated that although transactions made when there are discounts are also high, discounts have no significant impact when it comes to increasing the value of orders among the buyers. It implies that promotion policies can be effective in relation to the effect they have on the sales volume but still they can be linked to the potential trade-offs or reduction in the profitability level per order in case the customers experience the habit of the reduced price level.

Product recommendations on the other hand were any more moderate in adding to conversion rates but more effective in increasing the average order value. The exposed customer who also experienced a recommendation purchased more or more highly, which denotes that the recommendation is effective in cross-selling and upselling. This is in line with the results of previous studies, where it is found that personalized strategies not only make the consumer more likely to purchase a product but also encourage the consumer to purchase more in their basket. Whereas recommendations may not result in such high levels of new conversion as discounts, it also results in the long-term growth of revenue by increasing the size and interactivity of the transactions. The price-sensitive users were more highly responsive to the discounts, and the influence of recommendations in the present case was more significant than the prior purchasing experience. Instead, interventions can be optimized to produce the best results by tailoring them to the profiles of customers.

Discounts may also be offered to customers when new or highly price-sensitive customers are considered, and rewarding repeat buyers may be motivated to make recommendations, since they may be more willing to take the recommendations of the products that are curated. These findings have implications to the management in that they involve ensuring that promotion activities are organizational goal oriented. The promotions are especially handy in achieving the short term goals to increase the traffic and the penetration rates of the market but it should be done in a targeted way not to damage the margins. Recommendation made the other way is a more feasible strategy of creating long-term profitability as it accelerates the revenue per order, although not the price integrity. Segmenting discounts when it comes to encouraging conversions and recommendations to facilitate more purchases is not without justification and, hence, it can be implied that the use of a moderated approach, where discounts are not arbitrary when it comes to influencing the aforementioned, can be the most appropriate mechanism of achieving customer acquisition and maximization of profits in the competitive e-commerce settings.

4.2 Conclusion

The findings indicated that discounts are very effective in increasing the conversion rates, therefore, it is a beneficial tool in encouraging buying. Their influence on order value was not high and so this begs the question of whether or not there is revenue trade-off in the case of over-utilization. The determinant of product recommendation is less but higher orders are more material since it can be specifically useful in the context of cross-selling and upsell. These results prove that the promotional actions have to be adjusted to relate to the certain business objectives. Discounts will be the most appropriate intervention in the

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event that it intends to cause the level of sales in the short-term period. When the priority is laid on maximization of revenue per transaction and creation of long-term customer value, the recommendation is more fruitful. The managers are then expected to apply the balanced approach that will include the discriminated use of the discount to spur sales, along with application using the use of customized suggestions to produce better profits and customer loyalty. The creation of customer-oriented and organization-centered planning strategies could help the business to realize optimum sales and financial outputs in the long run.

5. Evaluation

According to this work of writing, data simulation, analysis and the interpretation of the obtained results have not only been fascinating but have not been smooth sailing as well. A strong form of modeling the realistic trends of consumer dynamics as part of a controlled dataset also constituted a major strength of the work as it will then be feasible to measure the efficacy of various marketing tactics in an environment that closely mimics the processes in the real world. The practice also enabled me to know that the methodological decisions,e.g. a conversion with logistic regression, order values with OLS, etc. have a direct impact on the richness and validity of the insights. It was also an educational experience in the need to maintain technical stringency and clarity especially on how far the results in a table and graph form are to be presented to the remaining audience.

Besides that, although the requisite impacts of discounts and recommendations had been measured in the analysis, higher-order modeling, e.g., multi-level or causal inference can be adopted to reference the behavioral providers of the same. On a personal scale it has managed to enlighten me to greater heights in regard to how a set of statistical outcomes can be translated to significant management outcomes. It has also found the need to critically examine not only what is shown in the results, but also what it has told about the strategy and practice. The experience has developed the technical expertise of analyzing data and my ability to contemplate whether scholarly studies were practically useful or not.

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