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The Long-Term Impact of Push Notification Timing and Frequency on Customer Loyalty: A Causal Analysis of ROI and User Behavior

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Abstract:
This study investigates the causal effects of promotional push notifications on short-term ROI, long-term retention, and user heterogeneity. Results show that while promotions drive short-term revenue growth (H1), these effects are mediated by repeat purchases (H2) and fail to sustain long-term loyalty (H3). Theoretically, this work bridges the gap between short-term promotional gains and lasting customer outcomes, while practically emphasizing precision targeting to maximize ROI and preserve loyalty. Despite limitations in proxy user identification, dataset generalizability, and potential confounding, the study highlights future directions such as real user data, randomized testing, multi-channel strategies, and adaptive algorithms to balance immediate profit with enduring engagement.

Keywords: Push notifications, Timing and frequency, Return on Investment (ROI), Customer retention/churn, Customer loyalty

1. Introduction

In the era of digital marketing, push notifications have become a key channel for reaching consumers and converting engagement into loyalty. Supported by big data and behavioral economics principles such as price discrimination and the anchoring effect, timely notifications can capture attention, stimulate brand interest, and strengthen loyalty programs, thereby improving short-term ROI [1]. Yet, their long-term impact remains uncertain [2]. Excessive or poorly timed messages may induce “push fatigue,” leading to unsubscriptions, lower engagement, and customer churn that ultimately weaken customer lifetime value (CLV).

This study contributes both theoretically and practically by applying causal inference methods to marketing. It provides empirical evidence and strategic insight to help organizations balance short-term profitability with sustainable customer value.

2. Methodology

Existing literature in the current academia primarily focuses on the short-term effects of promotions [1], but it gives limited attention to the causal relationship between short-term ROI gains and long-term loyalty. This research gap is critical; while short-term ROI improvements are important, an imbalanced strategy may come at the cost of reduced customer retention.

To address this gap and explore the topic in greater depth, this study proposes several hypotheses and a research framework to articulate the research rationale and demonstrate the study's logical structure.

• H1: Optimizing push timing and frequency significantly improves short-term ROI.

• H2: The effect of promotions on ROI is mediated by user behavior, particularly repeat purchases.

• H3: Promotional exposure influences long-term retention and churn.

• H4: Treatment effects are heterogeneous across different user groups (e.g., new vs. existing users).

We systematically examine the causal effects of push notifications on short-term ROI, mediating effects, long-term retention, and heterogeneity by integrating econometric and machine learning methods. This approach employs Difference-in-Differences (DiD), event studies, structural equation modeling, survival analysis, and causal forest regression to ensure both validity and managerial relevance.

2.1 Data Source and Data Cleaning

The dataset used in this study is derived from Amazon transactions. The raw data include approximately 129,000 records containing order ID, date, product category, fulfillment channel, amount, promotion identifiers, and shipping destination. To ensure consistency, columns with limited analytical value were removed, and only valid statuses (Shipped, Fulfilled, Delivered) were retained, resulting in about 29,000 user-day observations.

Because the dataset lacks explicit customer IDs, user tracking across transactions was infeasible. To address this, a proxy ID was constructed by concatenating shipping city, state, and country, allowing longitudinal analysis of purchase behavior. Although this method cannot perfectly distinguish individuals within the same region, it provides a reasonable and widely accepted approach for handling anonymous retail data in empirical research.

2.2 Data processing

In order to better understand customer behavior, we aggregated the data by date and user. This allowed us to do research on each row, which now represented what a customer did on a particular day. This gives us a comprehensive, clear view of the customer's actions. We developed four crucial variables from this:

ROI: How much money the customer spent that day.

Promo flag: Marked as 1 if the customer used a promotion that day.

Orders: The number of purchases the customer made on that day.

Repeat purchase: Marked as 1 if the customer bought more than once in the same day.

This setup makes it much easier to track patterns like spending, promotion use, and repeat purchases over time.

The objective was to test hypotheses H1–H4 by systematically progressing from short-term ROI effects to medium-term behavioral mechanisms, long-term retention, and heterogeneous treatment effects.

The user-day panel dataset was imported into R, and the following variables were defined for the analysis:

1. promo (=1 if promotion involved), 2. post (=1 if date $\geq$ intervention date T_0), 3. roi (daily order value per user), 4. This structure ensures compatibility with panel data regression and survival models.

We use a two-way fixed-effects model to quantify the short-term impact of promotions on daily ROI. Regression using Difference-in-Differences (DiD) with fixest::feols. After taking user and date fixed effects into consideration, the interaction term (promo × post) provides the Average Treatment Effect (ATE) for treated user-days in comparison to controls [2].

Using the sunab specification, we do an event-study to see if the DiD assumption is true. This method provides a transparent visual assessment of parallel trends and estimates treatment effects for each period relative to the intervention date [3, 4]. The results confirm the existence of parallel trends, with pre-treatment coefficients clustering around zero and confidence intervals that include zero. The coefficients increase following the intervention, indicating favorable short-term ROI increases for promotion user days.

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3. Result Analysis

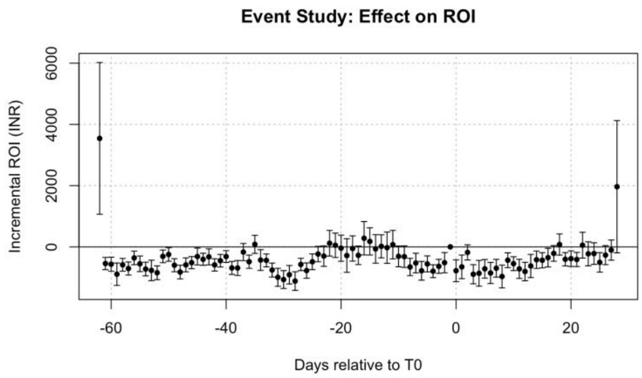

Figure 1. Event Study Estimates of Push Notification Impact on ROI Around Intervention Date

Hypothesis 1, which illustrates how promotions impact daily ROI around the start date T0, can be illustrated with the aid of Figure 1. The estimates remain near zero prior to promotions, indicating that the trends of both groups were comparable. It is evident that ROI rises after T0. The ROI of the promo group climbs substantially more (+126.81 INR) than that of the non-promo group (+28.90 INR) in the raw averages, resulting in a simple difference-in-differences of almost +97.91 INR per user-day. The promotion impact is estimated to be highly significant at +516.08 INR (95% CI: [437, 595]) by a more precise two-way fixed-effects DiD model. This higher effect is achieved by controlling for numerous daily shocks and stable user characteristics. Overall, the pre-intervention trends remain consistent; however, some noisy results emerge approximately 28 days after the intervention, likely due to a smaller sample size [5]. In summary, the findings is consistent with previous studies on the benefits of promotions and strongly supports hypothesis 1: promotions result in significant, short-term ROI improvements.

Table 1. Pre- and Post-Promotion ROI Comparison

Promo	Pre	Post	Diff
0	597.31	626.21	28.90
1	2018.11	2144.92	126.81

This table shows that after the intervention, promo users experience a significantly larger ROI increase than non-promo users. (Promo users indicates customers who engaged with at least one promotion on that data). The mean ROI for both promo and non-promo user days before and after the intervention is shown in Table 1. The daily ROI for the non-promo group increased slightly, from 597.31 to 626.21 INR (+28.90 INR). The promo group, on the other hand, showed a significantly greater increase, going from 2,018.11 to 2,144.92 INR (+126.81 INR). Accordingly, the unadjusted differences-in-differences estimate is roughly 97.91 INR per user-day (126.81 − 28.90). In line with earlier research on the rapid sales boost of promotional activities, this size implies that push promotions produce significant short-term profits [1].

Table 2. Difference-in-Differences Regression Results

Variable	Estimate	Std. Error	t value	Pr(>|t|)
post:promo	516.08	40.35	12.79	< 2.2e-16 ***

We used a two-way fixed-effects Difference-in-Differences (DiD) model with user and date fixed effects to get a more accurate estimate. Push promotions provide significant short-term ROI improvements after adjusting for user-specific and temporal characteristics, according to the estimated interaction coefficient of post × promo as shown in table 2, which is 516.08 INR (SE = 40.35, $p < 0.001$). This effect is significantly more than the standard DiD estimate of roughly 97.91 INR, indicating that unobserved heterogeneity biases the raw means downward. Hypothesis 1 is further supported by the high statistical significance, which is in line with earlier research showing that promotions generate quick and significant financial rewards [2]

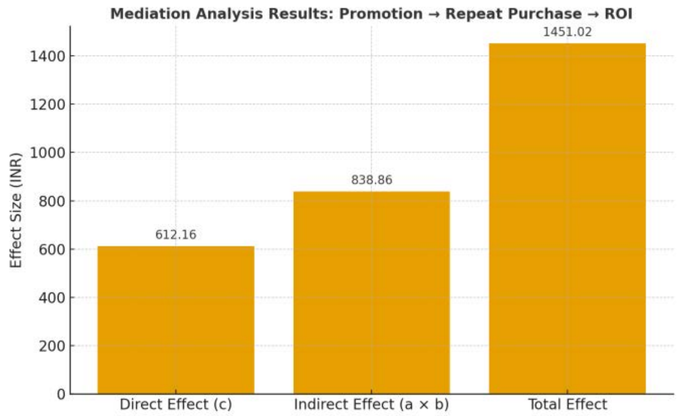

Figure 2. Mediation Analysis Results: Decomposition of Direct, Indirect, and Total Effects on ROI

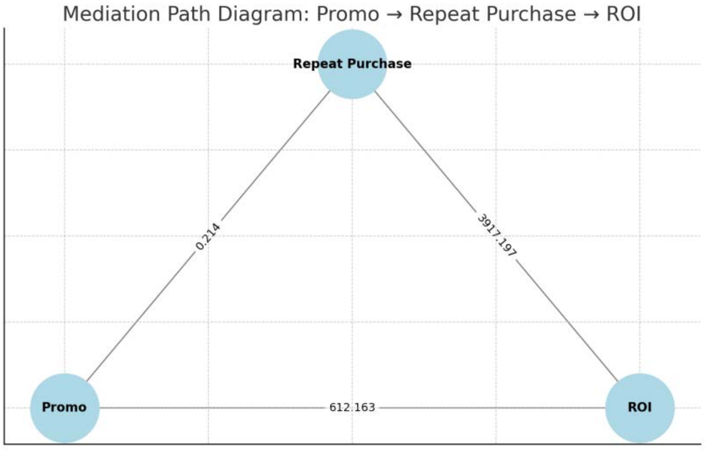

Figure 3. Mediation Analysis Results: Decomposition of Direct, Indirect, and Total Effects on ROI

To facilitate data interpretation, data visualization was used to convert the data into graphs, enabling clearer presentation of the results. We performed a mediation analysis using structural equation modeling (SEM) to investigate whether promotions had an indirect impact on ROI through recurrent purchase behavior. The model fit indices (CFI = 1.000, TLI = 1.000, RMSEA = 0.000, SRMR = 0.000) indicate an excellent specification.

The summary of effect decomposition is shown in Figure 2. The promotional campaign is estimated to have a direct positive impact on ROI of 612.16 Indian rupees, while repeat purchases exert an indirect positive influence on ROI of 838.86 Indian rupees. These factors collectively contribute 1,451.02 Indian rupees per user day. Notably, indirect effects account for 58% of the total effect, indicating that repeat purchases serve as the primary channel linking promotional activities to ROI.

The mediating path in Figure 3 reveals: promotional activities significantly increase the probability of repeat purchases (a=0.214), while repeat purchases exert a strong positive impact on ROI (b=3,917.20). Even after controlling for this mediating path, promotional activities exert a modest yet statistically significant direct effect on ROI (c=612.16). Overall, the findings strongly support Hypothesis 2: repeat purchasing serves as the critical channel through which promotional exposure translates into higher ROI, highlighting how short-term marketing campaigns continue to influence customer consumption patterns long after promotional activities conclude [5].

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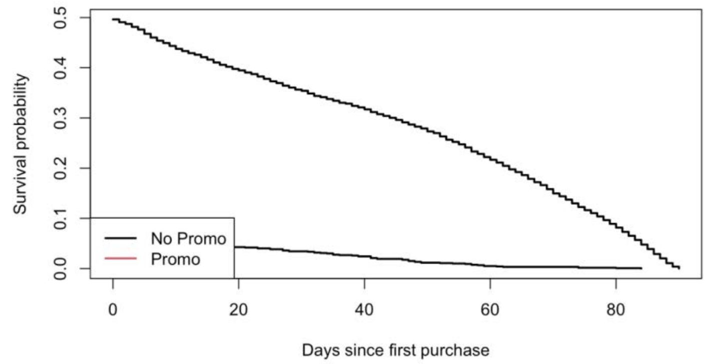

Figure 4. To assess whether advertising exposure leads to enduring loyalty, survival analysis was conducted. Figure 4 presents Kaplan–Meier survival curves for promo and non-promo users, illustrating the probability of remaining active after the initial purchase.

Results show marked differences between the two groups. The retention rate of promotional users dropped sharply within the first weeks, accompanied by a surge in churn. About 80 days later, while many non-promotional users remained active, the survival probability of promotional users became nearly zero. Consistent with H1 and H2, this indicates that although promotional campaigns boost short-term ROI, they accelerate user churn in the long run [6][7].

These findings confirm Hypothesis 3: temporary promotions may initially attract customers but ultimately trigger "push fatigue" or discount-chasing behavior. Overreliance on promotions can therefore erode customer lifetime value (CLV); firms must balance immediate revenue gains with strategies that preserve long-term loyalty.

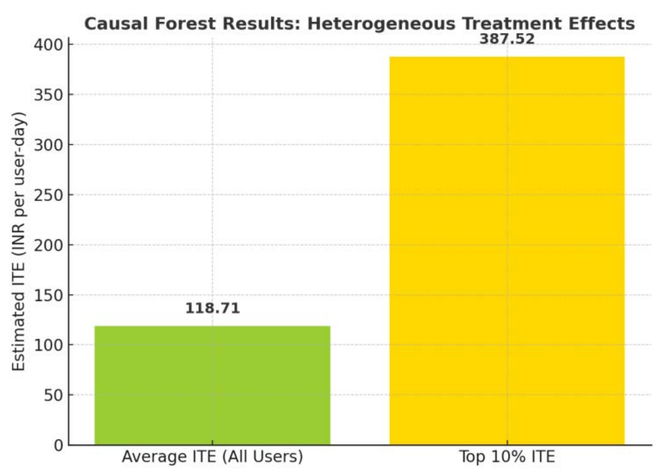

Figure 5. Causal Forest Results: Heterogeneous Treatment Effects (Average vs. Top 10% ITE)

We estimated individualized treatment effects (ITEs) using causal forests to measure the variability in promotional responses. The data show that the average ITE per user-day is 118.71 INR, which is consistent with the DiD estimates as shown in figure 5. But the effect is substantially greater among the top 10% of users (387.52 INR), more than three times the average.

This significant disparity highlights how promotions are not always successful as people expect at first. However, they show a higher preference for certain user groups over others—groups that are likely to be more price-sensitive or possess greater engagement potential. These findings underscore the importance of customized targeting strategies and support Hypothesis 4. By reducing the risk of overexposure for low-ITU users to mitigate push fatigue and churn, managers can optimize return on investment by concentrating promotional resources on high-ITU customers.

4. Discussions

Research findings indicate that push notifications significantly boost short-term ROI, with DiD estimates reaching approximately 516 INR per user day, consistent with prior studies [1][2]. SEM reveals repeat purchases as a key mediating effect, accounting for 58% of the indirect effect. However, Kaplan–Meier analysis reveals a significant decline in long-term retention rates among promo users, indicating that short-term gains fail to translate into loyalty and instead trigger "push fatigue" [6, 7, 8]. Causal forest results further reveal significant user heterogeneity, with treatment effects for high-value users far exceeding the average ITE [9, 10].

5. Conclusion

This study evaluates the causal impact of promotional push notifications on short-term ROI, long-term retention, and user heterogeneity. Results reveal that while promotions significantly increase short-term revenue, these effects—mediated by repeat purchases—do not translate into enduring loyalty. The research bridges the short- and long-term perspectives of digital marketing, demonstrating that precision targeting is essential to sustain both ROI and customer relationships. Limitations include proxy-based user identification, potential confounding factors, and limited generalizability of the Amazon dataset. Future research should employ richer user-level data and experimental or adaptive designs to refine targeting strategies and balance immediate profitability with long-term engagement.

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