Volume 2, Issue 1, 2026, Pages 031–039 *Journal of Digital Business and International Marketing*
| Regular Article | Open Access

Location Based Targeting and Discount Depth in Mobile Promotions: Evidence from a Large Scale Experiment

Surender Rangaraju
Faculty of Business Administration, Van Lang University, Quan 1, Thành pho Ho Chí Minh 700000, Vietnam.
surendher23@outlook.com

Article Info
Journal of Digital Business and International Marketing
https://www.ansispublications.com/journals/jdbim/jdbim.html

https://doi.org/10.64026/JDBIM/2026004

Received 26 May 2025.
Revised form 25 September 2025.
Accepted 10 October 2025
Available online 05 January 2026.
Published by Ansis Publications.

Corresponding author(s):
Surender Rangaraju
Faculty of Business Administration, Van Lang University, Quan 1, Thành pho Ho Chí Minh 700000, Vietnam.
Email: surendher23@outlook.com

Abstract – This paper investigates the preference between real-time locational targeting and discount depth and how these factors influence consumer purchasing behavior in mobile marketing. We experiment with the context of the location (focal, competitive, benchmark), the timing (real -time vs. delayed) and the discounting depth (low, medium, high) using a 3 x 2 x 3 factorial field experiment with 36,000 observations. Causal effects are identified using random assignment, difference-in-differences estimation and triple differences regression. Results show significant locational targeting effects especially in competitive locations when combined with deeper discounts. Discount response curves vary significantly across locations, showing diminishing returns to focal locations as well as threshold effects in competitive situations. The findings provide useful information for mobile pricing strategies at the location level.

Keywords – Mobile Marketing, Locational Targeting, Discount Depth, Factorial Experiment, Difference-In-Differences, Price Elasticity.

I. INTRODUCTION

The rising application of smartphones and the development of mobile accessibility to the web contribute to the growth of context-aware technologies, such as location-based services (LBS). When location data is used, LBS provide data on the surroundings (e.g., restaurants, retailers, and shops) of mobile internet consumers. Thus, these context-aware technologies are a vital instrument for researches and companies alike.

In [1], scholars focus on mobile promotions, which is a dual-way/multi-way marketing and communication between the firm and its clients, using mobile technology, devices, or medium. Since it integrates dual-way/multi-way communications, mobile promotions are majorly engaging in nature, and can include mobile advertising, customer support, as well as related relationship-growing operations. These operations are becoming increasingly significant in the transformative organizational landscape. Literature on mobile business has addresses the significance of technology in enhancing the rise of mobile device transactions [2]. However, literature concerning mobile promotions is still in its infancy stage.

Mobile promotion campaign often targets potential customers by using their physical locations, real-time weather, and time of data to enhance the efficiency of their campaigns. These quantifiable insights are a significant advancement compared to offline (traditional) marketing approaches. Evaluating the novel features of mobile internet consumption, such as when and where users respond to location-based marketing, assists businesses and research to answer managerial questions related to context-aware marketing campaigns, enhancement of mobile promotion, and selection of offline redemption points [3].

Local-based promotions on mobile phones have a significant history connecting to the advent and development of location-monitoring devices and technologies. Mobile devices are highly customized and significant personal communication instruments, and many users keep them closely and within reach. These devices have allowed users to ubiquitously access digital data, anywhere and anytime, which shows that mobile devices allow advertisers to reach consumers directly and continuously.

Due to the fact that consumers used these devices to conduct many activities, beyond just texting or talking, marketers also have novel opportunities that target their engagements. Many users access the internet using mobile devices, and access mobile apps, most of which have mobile promotion content. Currently, social media platforms, such as YouTube, Twitter, and Facebook attract many consumers who access platforms using their mobile devices, these sites provide significant insights for marketers, due to their tremendous analytics capacity [4].

Considered as part of the contextual promotion market, LBMA (location-based mobile advertisement) services were worth more that USD 40 billion in 2020, and that amount is expected to double by 2030 [5]. These services provide significant insights to promoters, which are vital for i) addressing customers directly, ii) reaching users in a particular geographical area identified as target audience, iii) delivering real-time advertisement content, iv) personalizing advertisement, and v) replacing or changing message whenever needed.

This paper aims at establishing the interaction between real-time mobile targeting and physical location and depth of discount to influence purchase decisions. Through a combination of experimental design and elasticity analysis, the research can be strong enough to make location-specific promotional optimization in a mobile retail setting. The remainder of this research has been organized in the following manner: Section II provides a background analysis of mobile market research as well as LBMA literature. In Section III, we describe our experimental design, which integrate treatment manipulation, purchase measurement, and analytical model. Section IV discusses our findings, which begins with reviewing the assumptions related to the availability of instantaneous targeting impacts. Lastly, Section V concludes our findings and highlights the strategic significance of real-time locational targeting for mobile promotions.

II. BACKGROUND ANALYSIS

Mobile marketing research shows that the context in which users are exposed to mobile advertisement significantly affects their behaviors. As shown in **Table 1**, most literature in this area focusses on the wider contextual spectrum, which impacts all users available in a particular location within a specific timeframe. For instance, Park, Shenoy, and Salvendy [6] highlight that mobile advertisement received on a sunny day is generally more effective than those received during the rainy season. Matsumoto and Hidaka [7] also found out that consumers traveling in a crowdy subway trains are significantly more probable to respond to mobile advertisement offers compared to those travelling in less crowded trains.

Table 1. Summary of Chosen LBMA Literature

Ref.	Approach	Location	Setting	Promotion Type	Behavioral approaches measured	Behavioral targeting	Summary
Kendrick [8]	Field experiment	Out-store	Movie theaters	Price promotion	-	-	Competitive location-based promotion is effective, whereas focal location-based one produced poor results, highlighting saturation effects ad income cannibalization.
	Field surveys & experiment	Out-store	Movie theaters	Price promotion	✓	-	
Qi, Yao, and Fan [9]	Field experiment	Out-store	Movie theaters	Price promotion	-	-	Rivalry enhances the profitability level of behavioral content targeting, while organizations face symmetric pricing motivations that eases competition.
Khajehzadeh, Oppewal, and Tojib [10]	Longitudinal field study	Out-store	Movie theaters	Price promotion	-	-	In case a mobile coupon is produced in the most convenient area (near the store providing it), within a shorter expiry period and large discount, it is more likely to be used; a collective offer results to higher rate of redemption compared to pricing formats (amount or percentage discounts).

Shamdasani, Stanaland, and Tan [11]	Experiment	In-store	Wine	Price & non-price promotion	✓	-	Location (in which advertisements are received near the product) is the most significant value measure and enhances customers purchasing intentions whereas personalization (advertisements targeting the user) is the second more significant, and pricing promotion (no discount vs. 30% discount) is least significant.

LBS describe services that are improved with and rely on data related to the location of mobile devices. This type of data is irrelevant if it is presented verbatim. It should be correlated with some form of services. LBS focus on supplying users with necessary services with customized data according to their location.

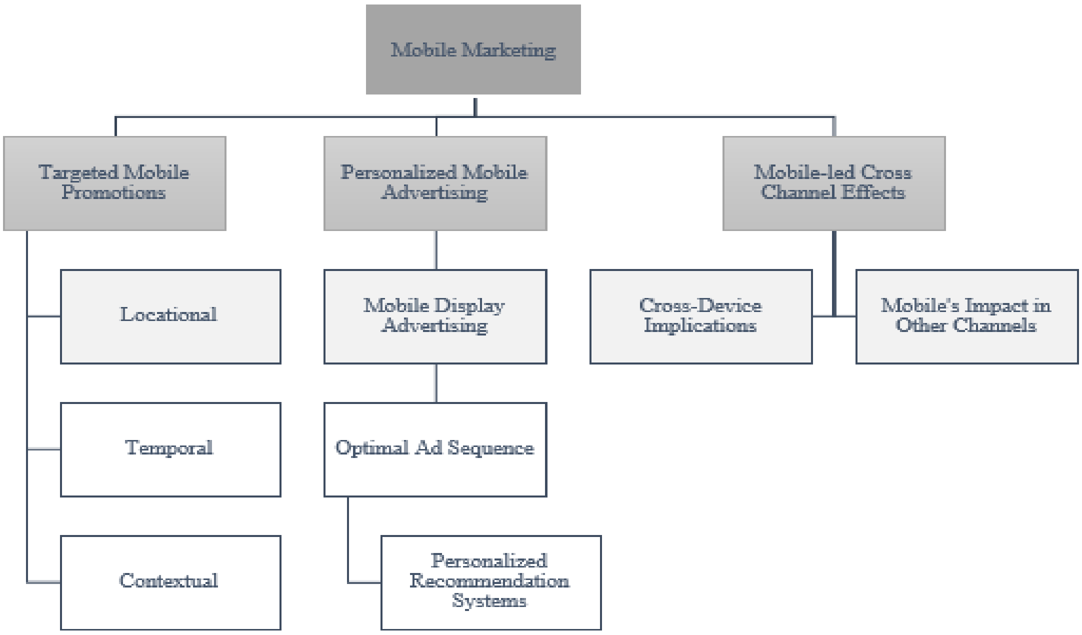

Fig 1. Recent Mobile Marketing Advancements.

Personalized advertisements are related to offers and coupons send to potential consumers on their mobile devices based on various forms of targeting. These integrate the employment of display ads and mobile banners, as well as ad personalization displayed in every user. Lastly, mobile-led-channel impacts relate to the effect of mobile device and app usage displayed to every user. In addition, mobile-led cross-channel impacts relate to effects of mobile device and app usage on both offline and online channels. In **Fig. 1**, we illustrate the broad dimension of these three critical development areas of mobile promotion research.

In case a consumer is sensitive to uncertainties about a brands' qualities, consumers will be more concerned with quality uncertainties. In that regard, uncertainties may decrease price sensitivity, which defines price-searching behaviors. Nonetheless, in case consumers are insensitive to uncertainties about a brands' qualities, uncertainty may potentially increase price sensitivity (price-repugnance behaviors). This notion can be extended to all forms of brand qualities and positioning data, such as horizontally-segregated product qualities. Therefore, whenever there are uncertainties about a specific product quality, these uncertainties may impact consumer price sensitivities [12].

In addition, the impact of uncertainties on pricing sensitivity may be controlled by consumers' sensitivity to uncertainties. Therefore, product cluster-based factors that impact uncertainty levels, for instance whether a product is experience or search good, as well as factors, which impact sensitivity level of these uncertainties, such as engagement, are projected to impact brand credibility influence on consumer price sensitivity.

III. EXPERIMENTAL DESIGN

This study examines the impact of locational targeting and discount depth provided in real-time environment for mobile marketing and its effect on consumer purchasing behavior. Participants were recruited from active users of the retailer's mobile application who provided consent to be tracked by the application in terms of their location. The experiment used a $3 * 2 * 3$ factorial design where three location types were used (focal, competitive, benchmark), two targeting conditions (targeted vs. nontargeted), and three levels of discount (low, medium, high) (see **Table 2**). Use of a random assignment ensured balanced allocation of cells, and the elimination of selection bias in order to allow for causal inference.

Table 2. Results of the Factorial Design and Sample Distribution

Location Type	Targeting Condition	Discount Depth	Observations per Cell
Focal	Targeted	Low	2,000
		Medium	2,000
		High	2,000
	Nontargeted	Low	2,000
		Medium	2,000
		High	2,000
Competitive	Targeted	Low	2,000
		Medium	2,000
		High	2,000
	Nontargeted	Low	2,000
		Medium	2,000
		High	2,000
Benchmark	Targeted	Low	2,000
		Medium	2,000
		High	2,000
	Nontargeted	Low	2,000
		Medium	2,000
		High	2,000

The total observed data comprised 36,000 observations, which was high enough to ensure that we had enough power to detect small-to-moderate effect sizes. The entire experiment procedure is described in **Fig. 1**, where the procedure has been illustrated by describing the process of recruiting the individuals, randomly allocate the individuals to the experiment, manipulating the treatment and analyzing the results.

Purchase Measurement and Treatment Manipulation

The participants in the targeted condition received mobile promotional stimuli in real time when near their specific destinations and those in the non-targeted condition were offered the same offers with time lag.

The purchase outcome variable, which is referred to as $Y_{i,j,k}$, is formally defined in Eq. (1).

$$Y_{i,j,k} = \begin{cases} 1 & \text{if participant i purchases at location j under discount k,} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

The difference-in-differences model that was used to measure the locational targeting effect (LTE) was calculated using Eq. (2).

$$\mathrm{LTE_{j,k}} = \left(\bar{\mathrm{Y}}^{\mathrm{T}}_{\mathrm{j,k}} - \bar{\mathrm{Y}}^{\mathrm{NT}}_{\mathrm{j,k}}\right) - \left(\bar{\mathrm{Y}}^{\mathrm{T}}_{\mathrm{BM,k}} - \bar{\mathrm{Y}}^{\mathrm{NT}}_{\mathrm{BM,k}}\right) \tag{2}$$

In which T and NT are used to represent the targeted and nontargeted population, and BM is used to represent the benchmark location. In order to expand this framework to several discount levels, we introduce a weighted locational targeting effect given in the form of the Eq. (3).

$$\mathrm{LTE^{W}_{j}} = \textstyle\sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{w_k} \cdot \mathrm{LTE_{j,k}}, \mathrm{w_k} = \frac{\mathrm{N_{j,k}}}{\sum_{\mathrm{k=1}}^{\mathrm{K}} \mathrm{N_{j,k}}} \tag{3}$$

where w_k represents the representation of the observations at discount k, this makes it possible to aggregate by discount segments. The discount elasticity demonstrates as an arc elasticity based on Eq. (4).

$$\mathrm{E^{j,k_1,k_2}_{arc}} = \frac{\Delta \mathrm{Q_{j,k_1,k_2}}/\bar{\mathrm{Q}}_{\mathrm{j,k_1,k_2}}}{\Delta \mathrm{P_{k_1,k_2}}/\bar{\mathrm{P}}_{\mathrm{k_1,k_2}}} = \frac{\mathrm{Q_{j,k_2}} - \mathrm{Q_{j,k_1}}}{0.5(\mathrm{Q_{j,k_1}} + \mathrm{Q_{j,k_2}})} \Big/ \frac{\mathrm{P_{k_2}} - \mathrm{P_{k_1}}}{0.5(\mathrm{P_{k_1}} + \mathrm{P_{k_2}})} \tag{4}$$

where $Q_{j,k}$ is purchases at location j under discount k, and P_k being the corresponding price. Arc elasticity was expanded to interaction elasticity to measure locational differences using Eq. (5).

$$\mathrm{E}_{\mathrm{int}}^{\mathrm{j_1,j_2,k_1,k_2}} = \mathrm{E}_{\mathrm{arc}}^{\mathrm{j_1,k_1,k_2}} - \mathrm{E}_{\mathrm{arc}}^{\mathrm{j_2,k_1,k_2}} \tag{5}$$

which is a measure of the relative responsiveness between two locations for a given length of discount.

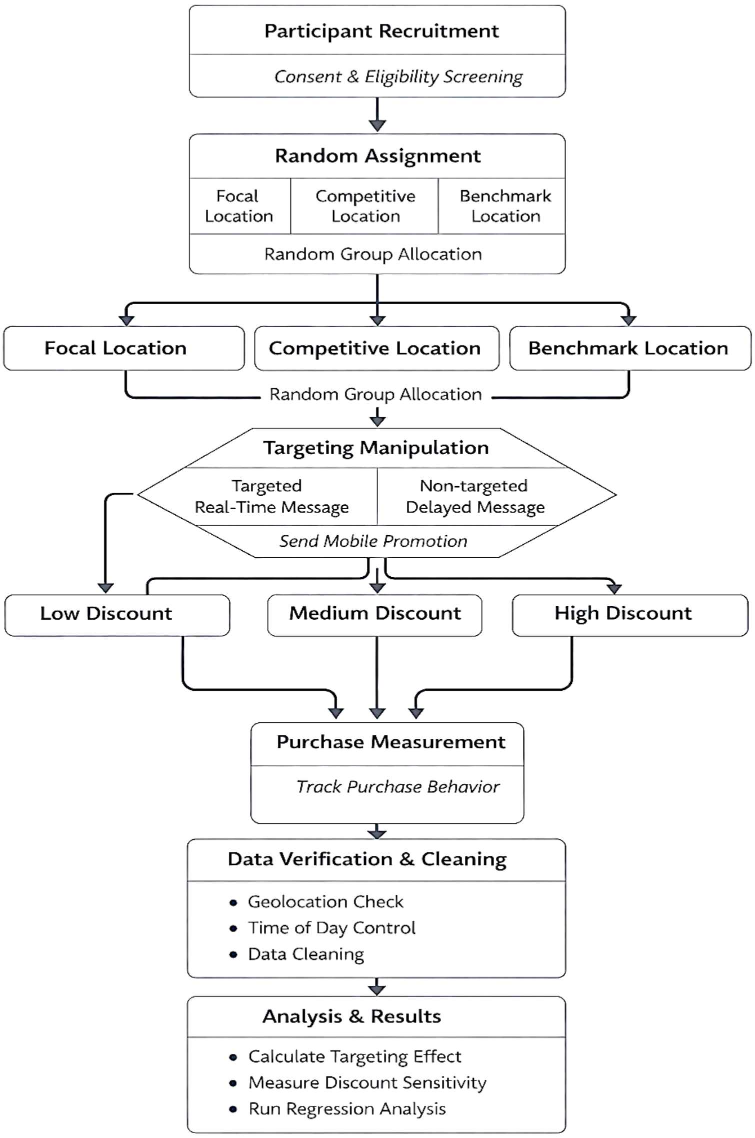

Fig 2. Breakdown of the Experimental Procedure.

Analytical Model

We model the impact of targeting, location and depth of discount using a triple-difference regression in Eq. (6).

$$\begin{aligned}\mathrm{Y_{i,j,k}} &= \beta_0 + \beta_1 \mathrm{T_i} + \beta_2 \mathrm{L_j} + \beta_3 \mathrm{D_k} + \beta_4(\mathrm{T_i}\cdot \mathrm{L_j}) + \beta_5(\mathrm{T_i}\cdot \mathrm{D_k}) + \beta_6(\mathrm{L_j}\cdot \mathrm{D_k}) \\ &\quad + \beta_7(\mathrm{T_i}\cdot \mathrm{L_j}\cdot \mathrm{D_k}) + \epsilon_i\end{aligned} \tag{6}$$

where T_i is the targeted exposure, L_j represents the location, D_k is the discount depth and ϵ_i is error term. The triple-interaction coefficient betal measures the marginal effect of targeting at a particular location under particular discount that offers the option of optimisation of pricing strategy depending on location.

To include cumulative discount effects, we form the definition for the discount adjusted predicted purchase probability in Eq. (7).

$$\hat{Y}^{adj}_{i,j,k} = \frac{\exp(\eta_{i,j,k})}{1+\sum_{k'}\exp(\eta_{i,j,k'})}, \eta_{i,j,k} = \beta_0 + \beta_1 T_i + \beta_2 L_j + \beta_3 D_k + \beta_7(T_i \cdot L_j \cdot D_k) \quad (7)$$

This SoftMax specification is significant so as to make sure that the projections of the various levels of discounts are normalized and hence, adding to 1 per location in order to reflect the substitution effects. **Fig. 2** presents a distinct and well-organized sequence of steps which have already been fulfilled to date, such as participant recruitment, random assignment, targeting manipulation, discount allocation, purchase measurement, data check and analysis. The flowchart uses separate branches in ways of differentiate targeted and nontargeted conditions and varying levels of discount, and the use of directional arrows trace progression from treatment assignment to outcome measurement and analytical evaluation.

IV. RESULTS

In this study, we start with examining the assumptions related to presence of instantaneous targeting impacts. This is achieved by assessing purchasing rate of both targeted and untargeted clusters at every discount depth and location. The purchasing rate of each experimental cell is shown in **Fig. 3**. The contrast between bars that have been labeled as targeted and untargeted shows the effect of targeting in terms of discount depth and location.

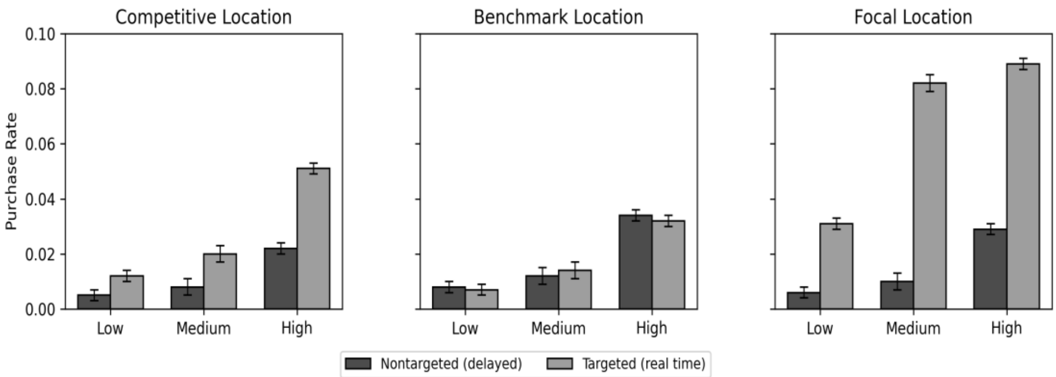

Fig 3. Targeting With Respect to Discount Depth and Location.

We assess such variations through manipulation with time, which is expected to affect consumers beyond the targeted location. The competitive cluster showed that location-based targeting significantly affected high and medium level of discounts. These variations support the assumption of the study, which posit that location-based targeting of consumers near the company's competitor can amount to increased marketing feedback.

Earlier research on mobile promotion has highlighted proximity to retailers' location [13, 14, 15]. In this study, we begin by providing rigorously managed evidence, which other possible target proximities represent instantaneous demand hotspots. The trend of feedback also indicate that competitive locational targeting should be integrated with increased discounts, which we evaluate further in our analyses across discount depths and locations. It is important to note that the location-based targeting is positively influencing the focal cluster at all levels of discounting. This observation is consistent with the previous literature and has implications on the study of mobile marketing channel efficacy in real-time in view of the location-based targeting.

Table 3. Location-Based Purchase Variations

Discount Level	***Comparison***	***Competitive–Benchmark***	***Focal–Benchmark***	***Focal–Competitive***
High	Targeted (A)	.019*** (.009)	.057*** (.011)	.038*** (.011)
	Difference-in-differences (A − B)	.031*** (.012)	.062*** (.013)	.031*** (.013)
	Nontargeted (B)	−.012** (.007)	−.005 (.008)	.007 (.007)
Medium	Targeted (A)	.010 (.007)	.065*** (.009)	.062*** (.010)
	Difference-in-differences (A − B)	.017*** (.007)	.070*** (.011)	.060*** (.011)
	Nontargeted (B)	−.007 (.004)	−.005 (.004)	.002 (.004)
Low	Targeted (A)	.005 (.004)	.024*** (.006)	.019*** (.006)
	Difference-in-differences (A − B)	.003 (.006)	.026*** (.007)	.018*** (.007)
	Nontargeted (B)	.003 (.004)	−.002 (.004)	.001 (.003)

**p< .05, ***p< .01.

Conversely, we did not find any difference in purchase rates of users in the benchmarking cluster because they were at the same distance to all the theatre locations. This discussion provides a large degree of falsification scrutiny, that is, we expect practically no variability, or at the most a weak one-time impact, in this cluster. The null impact could be recorded from travel expenses; nonetheless, note that consumers within a competitive proximity face slightly increased travel expense. We analyze the deficiency of a targeting impact for the standard location as indicating that where a customer decides to visit that day (for instance, a shopping mall with 1 or 2 competitor movie theatres) is fundamental for location-based responses.

We also carried out a comparison of the level of impacts across different target proximities. According to our findings, purchase rates are high in focal sites, then in competitive sites and finally in benchmarking sites. These results support the hypothesis that the retailer will find an increase of demand within the competitive and proprietary locations; the expenses of locational repositioning reduce the feedback effects in competitive locations.

In **Table 3**, we present the variations in buying rates based on location. Single variations represent the finding of two-sample t-tests, in which the interaction (variation-in-variation analyses) are evaluated using linear regression. Every t-test analyses the average feedback of two investigational cells (i.e., 2000 records). Every regression approximates the interactions using 4 cells (i.e., 4000 records). We identify that the focal location amounts in increased buying rates compared to the two other proximities, at all discounting levels. Despite the fact that the standardized location is near, its competitive proximity produces increased buying rate, but only at an increased discount level. This finding is consistent with anticipations that even though consumers in competitive and focal locations might have increased demands for retail goods, there are higher switching expenses for consumers within competitive proximities.

Arrangement of impact sizes integrates both the overall buying rate within the targeted clusters (identified as “Targeted”) and the buying portion characterized as location-based promotion using manipulation of time (identified as Var-in-Var). Therefore, we characterize the variations in feedback to location-based targeting. Our finding is consistent with the perspective that instantaneous mobile targeting enhances location-based switching expenses and provides more illustrations that competitive location-based targeting needs to be compared with deep discounts. On the other hand, discrepancies between purchase rates of delayed, untargeted clusters were created to be insignificant between dissimilar geographical regions, regardless of the level of the discount (a rise in purchases was forecasted with high discount rates). This result supports the fact that location-based targeting did not impose any selection biases which could jeopardize cross-regional tests in the present study [16].

Later on, the interaction between location specific targeting volumes and response rates to different levels of discounts is examined, and especially, we look at the higher discounts bands where structural differences could create pricing incentives. In **Fig. 3**, we have provided some highlights of consumer sensitivity regarding discount levels. Particularly, we observe a stronger visual proof of diminished returns to discount level within focal proximities. In addition, we tested the modulation of every curve by analyzing the variation in buying rate between medium and low discounts based on the variations in buying rates between high and medium discounts, in every location. Positive approximation shows a high variation with a convex response (discount depth). In **Table 4**, regression testing results have been presented to highlight the impacts of differentiating the discount levels.

In regards to the consumers in focal proximity, the buying rate increases significantly between medium and low discount levels, identified as M1. The buying rate does not indicate the same increase when analyzed from medium to high discount level (M2), and the Var-in-Var analyses show concave feedback to elevated discounts (M3). On the other hand, for consumers within competitive proximity, the buy rate increases when shifting from medium to higher discount levels (M5), compared to low levels of responsiveness when shifting from low to medium discount levels (M4). Var-in-Var analyses highlight convex feedback to elevated discounts (M6). These high returns will normally result in high optimal discount levels since it is more likely that enhancing discount levels will potentially enhance the speed of sold-out quantity to quickly offset abridged margins.

Table 4. Regression Comparing Impacts of Varying Level of Discount

Group	**Triple-Diff (M6−3) (M9)**	**Var-in-Var (M6−2) (M8)**	**Var-in-Var (M6−5) (M7)**	**Competitive Location Low (M6)**	**Competitive Location Mid (5)**	**Var-in-Var (M2−1) (M4)**	**Focal Location High (M3)**	**Focal Location Low (M2)**	**Focal Location Mid (M1)**
Sample Size (N)	12,000	8,000	8,000	6,000	4,000	6,000	6,000	4,000	4,000
A − B	.043*** (F = 7.30)	.015 (.012)	−.032*** (.010)	.011 (F = .63)	.028*** (.005)	.000 (.007)	.029*** (F = 7.55)	−.012 (.014)	.011 (.010)
Targeted (A)	.067*** (F = 13.0)	.024** (.012)	−.043*** (.009)	.023** (F = 4.62)	.031*** (.005)	.008 (.006)	.044*** (F = 8.39)	.007 (.013)	.051*** (.010)
Nontargeted (B)	.024*** (F = 7.30)	.009 (.005)	−.011 (.004)	.014*** (F = 1.06)	.003 (.003)	.008 (.003)	.015 (F = 7.95)	.019** (.006)	.040 (.004)

*p< .10. **p< .05. ***p< .01.

Even though we observe the same trend in the benchmark location, the recorded convex response is not statistically significant. In that regard, within the standardized location, there is significantly less anticipation of high returns to higher discounts. Three more regressions compare the impacts of varying discount levels between competitive and focal locations. Competitive locations indicate feedback with positive inflection rate comparative to focal proximities' reduced returns (tripled-variation evaluated in M9 to compare inflection in focal proximity with competitive proximity).

This is partly initiated by increased rate of feedback with shifting from low to medium discount levels within focal proximity (M7). Nonetheless, an increased feedback rate when shifting from medium to high discount level within a competitive proximity also contributes significantly to inflection variation (M8) [17]. The analyses will be based on the variable feedback rates. Another measure of discount sensitivity is the elasticity of pricing that reflects proportional changes in consumer demand.

We also estimate arc elasticity on the basis of pricing (where 1 was the level of discount) and it does not change the trend of our results. Within the focal proximity, we recorded an elasticity of -3.2 shifting from low to medium levels of discount, and -2 recorded from medium to high levels. However, the elasticities that were experienced in the competitive proximities were -1.7 in transitions between low to medium segments and -2.2 in transitions between medium to high segments. An elasticity bootstrap test of the differences in the elasticities produced a similar result, that of Model 9 which showed the relationship between the low -to-medium -to-high elasticity in competitive vs. focal proximity had a 95 percent confidence interval. The discount feedback curves go hand in hand with the increased diminishing marginal returns of saturated effects or deep discounts that are evident in areas of focal proximities.

Contrarily, the high returns to high discounts at competitive proximities match the threshold impact, in which the discount level should be deeper enough to wholly compensate customers for their location-based switching expenses. This variation in feedback can establish an incentive for determining pricing [18]. A critical revenue analysis shows that short-range profit-increasing standards are meant to offer higher discount depths within a competitive proximity, and medium discounts within focal proximities.

V. CONCLUSION

We provide empirical evidence on strategic importance of real-time locational targeting for mobile marketing. By jointly modeling the context of location, better targeting time, and discount depth, we demonstrate that promotional effectiveness is strongly dependent on location. Focal locations show diminishing returns to deeper discounts, implying saturation effects whereas competitive locations show increasing returns consistent with threshold compensation for switching costs. The lack of targeting effects in benchmark locations is further evidence to validate the causal interpretation of the findings. Methodologically speaking, use of difference in difference, triple differences regression, and elasticity analysis provides a stronger inference and generalizability. Managerially, the results provide support for differentiated pricing policies that come in the form of moderate discounts close to locations with many focal locations and deeper discounts close to competitors.

CRediT Author Statement

The author reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests

The authors declare no conflict of interest.

Funding

No funding agency is associated with this research.

Competing Interests

There are no competing interests.

References

[1]. P. Grifoni, A. D'Ulizia, and F. Ferri, "Context-Awareness in location based services in the big data era," in Lecture notes on data engineering and communications technologies, 2017, pp. 85–127. doi: 10.1007/978-3-319-67925-9_5.
[2]. D. Asamoah, S. Takieddine, and M. Amedofu, "Examining the effect of mobile money transfer (MMT) capabilities on business growth and development impact," Information Technology for Development, vol. 26, no. 1, pp. 146–161, Apr. 2019, doi: 10.1080/02681102.2019.1599798.
[3]. O. Yurur, C. H. Liu, Z. Sheng, V. C. M. Leung, W. Moreno, and K. K. Leung, "Context-Awareness for Mobile Sensing: A survey and future directions," IEEE Communications Surveys & Tutorials, vol. 18, no. 1, pp. 68–93, Jan. 2015, doi: 10.1109/comst.2014.2381246.
[4]. C.-D. Ham, J. Lee, J. L. Hayes, and Y. H. Bae, "Exploring sharing behaviors across social media platforms," International Journal of Market Research, vol. 61, no. 2, pp. 157–177, Jun. 2018, doi: 10.1177/1470785318782790.
[5]. A. Ahmed and A. Palusa, "A Location-Based mobile advertising system for Small-to-Medium businesses," in EAI/Springer Innovations in Communication and Computing, 2022, pp. 1–14. doi: 10.1007/978-3-031-07670-1_1.
[6]. T. Park, R. Shenoy, and G. Salvendy, "Effective advertising on mobile phones: a literature review and presentation of results from 53 case studies," Behaviour and Information Technology, vol. 27, no. 5, pp. 355–373, May 2008, doi: 10.1080/01449290600958882.
[7]. T. Matsumoto and K. Hidaka, "Evaluation the effect of mobile information services for public transportation through the empirical research on commuter trains," Technology in Society, vol. 43, pp. 144–158, Oct. 2015, doi: 10.1016/j.techsoc.2015.08.001.
[8]. Kendrick, "Promotional products vs price promotion in fostering customer loyalty: a report of two controlled field experiments," Journal of Services Marketing, vol. 12, no. 4, pp. 312–326, Aug. 1998, doi: 10.1108/08876049810226982.

[9]. H. Qi, X. Yao, and W. Fan, "Competitive rivalry in the digital market: an action-configuration perspective," Management Decision, vol. 61, no. 1, pp. 144–175, Nov. 2022, doi: 10.1108/md-09-2021-1158.
[10]. S. Khajehzadeh, H. Oppewal, and D. Tojib, "Mobile coupons: what to offer, to whom, and where?," European Journal of Marketing, vol. 49, no. 5/6, pp. 851–873, May 2015, doi: 10.1108/ejm-04-2014-0252.
[11]. P. N. Shamdasani, A. J. S. Stanaland, and J. Tan, "Location, location, location: Insights for advertising placement on the web," Journal of Advertising Research, vol. 41, no. 4, pp. 7–21, Jul. 2001, doi: 10.2501/jar-41-4-7-21.
[12]. E. M. K. Shiu, G. Walsh, L. M. Hassan, and D. Shaw, "Consumer uncertainty, revisited," Psychology and Marketing, vol. 28, no. 6, pp. 584–607, May 2011, doi: 10.1002/mar.20402.
[13]. N. M. Fong, Z. Fang, and X. Luo, "Geo-Conquesting: competitive locational targeting of mobile promotions," Journal of Marketing Research, vol. 52, no. 5, pp. 726–735, Feb. 2015, doi: 10.1509/jmr.14.0229.
[14]. S. F. Bernritter, P. E. Ketelaar, and F. Sotgiu, "Behaviorally targeted location-based mobile marketing," Journal of the Academy of Marketing Science, vol. 49, no. 4, pp. 677–702, Jun. 2021, doi: 10.1007/s11747-021-00784-0.
[15]. Y.-M. Chen, T.-Y. Chen, and L.-C. Chen, "On a method for location and mobility analytics using location-based services: a case study of retail store recommendation," Online Information Review, vol. 45, no. 2, pp. 297–315, Jun. 2020, doi: 10.1108/oir-10-2017-0292.
[16]. J. Bacon, J. Bates, and D. Halls, "Location-oriented multimedia," IEEE Personal Communications, vol. 4, no. 5, pp. 48–57, Jan. 1997, doi: 10.1109/98.626983.
[17]. T. Zhu and V. Singh, "Spatial competition with endogenous location choices: An application to discount retailing," Quantitative Marketing and Economics, vol. 7, no. 1, pp. 1–35, Jan. 2009, doi: 10.1007/s11129-008-9048-6.
[18]. E. J. Salazar, M. Jurado, and M. E. Samper, "Reinforcement Learning-Based pricing and incentive strategy for demand response in smart grids," Energies, vol. 16, no. 3, p. 1466, Feb. 2023, doi: 10.3390/en16031466.

ISSN: 3104-4115