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Abstract

Building on psychological reactance and uncertainty reduction theory, this research addresses how area familiarity, store knowledge, and promotional incentives impact the success of mobile targeting ads. To test our predictions, we conduct randomized field experiments in Japan. In Study 1, customers with different levels of area familiarity and store knowledge receive mobile ads with coupons. In Study 2, we replicate the same experiment in which consumers receive mobile ads without any coupons. The results indicate that whereas lower area familiarity contribute to geo-targeting ads effectiveness only when coupons are affixed, ads of higher store knowledge tend to increase the number of visitors regardless of the coupon attachment. We discuss our mixing results based on the dual-system theory, leading to some managerial implications.

Keyword: area familiarity, context-based marketing, mobile targeting, psychological reactance, promotional incentives, store knowledge, uncertainty reduction

1. Introduction

Geo-targeting mobile ads are growing at a rapid pace. Geo-targeting refers to the personalization of ad content based on target users' geographical location (Lian et al. 2019). In the US, their sales are expected to rise from $18.2 billion in 2019 to $38.7 billion in 2022 (eMarketer 2018). However, a recent survey of nearly 500 million digital impressions across the UK and the US found a surprising fact—almost 29% of these ads are being wasted due to mis-targeted location (Location Sciences 2019).

One of the limitations in geo-targeting is a lack of accurate location data based on target consumers' behavioral patterns; without it, markers are unable to predict and influence future actions. At the same time, geo-targeting seems beyond the scope of traditional segmentation-targeting-positioning models as the mobile market is a constantly moving target. Not surprisingly, a significant stream of empirical research has wrestled with this issue in terms of temporal and geographical targeting (Luo et al. 2014), competitive locational targeting (Fong et al. 2015), hyper-contextual targeting with physical crowdedness (Andrews et al. 2016), dynamic segmentation based on past marketing responses and location histories (Subcsek et al. 2017), trajectory-based targeting (Ghose et al. 2019), and personalized targeting against low-engagement consumers (Zhang et al. 2020), among others.

However, while these predecessors significantly advanced our knowledge on mobile ads, there appears to have left two prominent contextual effects unexplored: consumers' store knowledge and area familiarity. Both factors can impact consumers' response to mobile coupons, thus introducing a new perspective to temporal-behavioral targeting. Specifically, the goal of this research is to identify the effects of geo-targeting mobile ads in terms of the traffic generation in the implementation of promotional coupons. Based on an integrated view of the psychological reactance theory and the uncertainty reduction theory, we attempt to test our predictions as to whether the store traffic can increase when mobile ads consider area familiarity, and store knowledge in combination.

This article reports two randomized field experiments in the greater Tokyo and Osaka area, Japan, in collaboration with a large interactive marketing agency. We obtain our data from real-life promotional settings, which significantly increase the generalizability of our findings. We estimate shoppers' area familiarity in a given geographical area and store knowledge based on behavioral data. Unlike Luo et al. (2014) and Fong et al. (2015), who investigated the relationship between geographical distance and the mobile coupon, we used location data covering smartphone user's 24 hours information. Therefore, we can calculate area familiarity, store knowledge, and distance to the store from their home, which have not been considered in the context of the geo-targeting ads.

The intended contributions of the present study are two-fold. Our first focal construct is consumers' area familiarity. Unlike Fong et al. (2015), who investigated the importance of the location in relation to the competing stores, we focus on the areas consumers are both familiar and unfamiliar with, conceptualizing the level of area familiarity as the buffer of uncertainty reduction. In so doing, we try to seek reasons why most of geo-targeting mobile ads are mis-targeted, and therefore wasted, positing that mobile marketers and advertisers may not have taken into account the level of information appreciation by the targeted consumers.

Our second focal construct is consumers' store knowledge. Consumers are likely to assess the coupon offering from the mobile ad against their preferred choice. If the level of conflict between the preferred choice and the offering is high, psychological reactance is likely to happen. However, this is not the case when the coupon offering is an only available choice or when the consumers do not possess any prior store knowledge before receiving the offering.

We systematically examine the intertwined relationship between store knowledge and area familiarity in terms of the uncertainty and preference-offering conflict. Our dependent variable is the maximization of the store traffic in the areas mobile ads are targeting. The traffic generation has been studied previously mainly in terms of pricing and promotional discount (e.g., Gauri et al. 2017; Fox et al. 2009), In a recent exploration, Wang et al. (2019) examined the effect of geofencing mobile ads in the retail storefront traffic conversion because "mobile advertising has become a popular and powerful tool for retailers to convert traffic into sales" (p. 84). Yet, research focusing on the relationship between store traffic and geo-targeting mobile ads has been almost nonexistent.

In what follows, we first provide an overview of the related literature and build a theoretical framework, based on which we posit a series of predictions that are to be tested by a field experiment. Next, after providing an explanation of the method, we describe the results in detail. On this basis, we draw theoretical and managerial implications while recognizing limitations and suggesting future research directions.

2. Related Literature, Theoretical Framework and Hypothesis

2.1 Literature on geo-targeting ad response

The literature on mobile targeting ads seems mainly built on two streams of research. First, prior research addressed temporal and spatial boundary conditions that may influence consumers' mobile coupon redemption or conversion. For example, Luo et al. (2014) investigated the combined effect of promotion lead-time (i.e. time between the mobile coupon's delivery and expiration) and geographical location (i.e. distance between the user location and the promoted store location) on consumer purchase, finding that, when targeting proximal mobile users, the shorter lead time increased the likelihood of consumer purchases as a result of the mobile promotions. Similarly, Danaher et al. (2015) reported that the coupon redemption rates increased as face value increases, expiration length is shorter, and the distance to the store offering the coupons is shorter. While confirming the aforementioned findings, Fong et al. (2015) additionally revealed that competitive locational targeting or *geo-conquesting* increased purchasing response. In a recent exploration, Molitor et al. (2020) addressed the type of interface design in geo-targeting ad, demonstrating the effectiveness of distance-based ranking interface. Taking one step further in the quest for the spatial constraints, Andrews et al. (2016) found that consumers in physically crowded transit environments better responded to mobile promotion.

Second, the literature has taken into account the effectiveness of incorporating past marketing responses and location histories in targeting. For example, Subcsek et al. (2017) found that the prediction accuracy of the mobile coupon conversion rates has been improved by the inclusion of consumers' location information. In the same token, Ghose et al. (2019) found that mobile geo-targeting based on consumers' trajectory—the physical and behavioral trace of an individual's offline movement—leads to higher redemption probability, faster redemption behavior, and higher transaction amounts in a large shopping mall. Using the forward-looking hidden Markov model (FHMM), Zhang et al. (2020) studied personalized targeting against low-engagement consumers based on individual mobile users' continuous reading records on a mobile reading app. They found that personalized optimal dynamic engagement-based targeting based on the FHMM can generate more revenue for both price promotion and free-content promotion on a mobile e-book reading app. Matsui and Moriwaki (2021) study the effect of advertising on users' revisit behavior. They found that the ad-induced visitors are more likely to revisit the advertised stores than organic visitors.

The related literature is summarized in Table 1.

[Table 1]

2.2 Key Variables

In this subsection, we firstly introduce two key contextual variables that have not been investigated and hence our main focus; area familiarity and store knowledge.

2.2.1. Area Familiarity

Previous studies considered many factors affecting redemption of geo-targeting ads such as distance and time. However, more individual-specific elements, *i.e.* consumers context, have received scant attention. Familiarity is thought to be an important context because it may moderate the effect of existing non-contextual factors (Han and Yamana 2016). The concept of familiarity has been examined in consumer research on product category (Jeng 2017), and information acquisition (Otterbring et al. 2017), reactions to advertising (Rhee et al. 2019), online communication (Pauwels et al. 2017; Bonnnin 2020), among others.

In the marketing literature, familiarity is thought to be one element of consumer knowledge construct (Cordell, 1997), and the product category is the main research field on familiarity (Carneiro and Crompton. 2010). Consumers do not search for the information about experienced goods (Moore and Lehmann 1980; Putrevu and Lord (2001). Wood and Neal (2009) indicated that past usage of a product lead to habit cuing, leading to make it less attractive to search about competing products.

This relation is also found in the research area on consumer's travel. Assael (2004) demonstrated that consumers who once visited a place tend not to rely on external information source but their experience. This study is related to our research since they considered the case of consumer's information search along with a trip. The relation is also supported in the studies on other research areas. Information-processing theory of a consumer proposed by Bettman (1979), whose scheme theorized knowledge and experience is negatively related to search cost, is consistent with the results obtained from marketing literature. To sum up, these works indicate that if consumers are more experienced and has sufficient information-processing capability, they will not change their mind.

The familiarity of a geographical area, however, has rarely been examined so far. Among the few, Han and Yamana (2016) suggest that people tend to visit unfamiliar area after work on weekdays to enjoy arts and entertainment. In such a case, they are more likely to engage unplanned behavior. The mobile coupon can be perceived as useful or beneficial since they can reduce their search cost due to a lack of information. On the other hand, when people are familiar with a specific location, they have sufficient information-processing capability and may not change their state of mind, even though they are exposed to the mobile coupons.

2.2.2. Store knowledge

Prior research examined the effect of the distance between the current consumer’s location and the focal store on the mobile coupon redemption (Spiekermann et al. 2011; Luo et al 2014). However, consumers' knowledge of the focal store seems unexplored in mobile targeting ad research.

People in unfamiliar areas do not have strong preferences about the store since the primary goal to visit unfamiliar areas is very different from the venues distributing mobile coupons (Han and Yamada 2016). Instead, they would like to spend their time and resources on the primary objective (e.g. arts or entertainment). If they are exposed to mobile coupons from the store to which they have higher familiarity, they can avoid the risks of visiting unfamiliar stores and hence follow the coupon recommendation.

2.3. Theoretical framework and hypothesis

Prior research suggests that people are less likely to accept a persuasive message due to the psychological reactance (Brehm and Brehm 1981). Psychological reactance is "a motivational state directed toward reattaining the restricted freedom" (Fitzsimons and Lehmann 2004, p. 83). When people's freedom is restricted, they may experience psychological reactance by ignoring or refuting product recommendations that contradict initial impressions of choice options. When shoppers receive unsolicited geo-targeting mobile ads, they first assess the fit between their 'ideal' selection and the offering from the ads. Psychological reactance is likely to occur when there is a conflict between the customers' preferred choice and the recommended product (Fitzsimons and Lehmann 2004). The level of preference-offering conflict is high when the offering is recommended against their preferred choice or when other alternative choices are eliminated from consideration. The level of preference-offering conflict is low when the offering is perceived as a clearly unattractive option or when there is no dominant option before receiving the coupon.

On the other hand, albeit unsolicited, geo-targeting mobile ads can be viewed as a form of intelligent recommendation tool that can reduce the uncertainty surrounding a decision as well as the effort required in making a choice. In our study context, such uncertainty includes area familiarity and store knowledge. For example, consumers with higher uncertainty (e.g., low in both area and store knowledge) tend to feel less confident in their ability to make a wise purchase choice, thus relying on choice heuristics, such as product bundles (Harris and Blair 2006). In close analogy, geo-targeting mobile ads can be received by consumers high in uncertainty.

The level of uncertainty may vary according to the combined effects of area familiarity and store knowledge. Whilst area familiarity affects the uncertainty at a more general level, store knowledge is individual-specific, as it acts as a base for the preference formation based on past usage experience.

Our theoretical framework is summarized in Figure 1. Whereas people in higher uncertainty (low in area or store knowledge) will “follow” or “ignore” the targeted advertisings, people in lower uncertainty (high in area or store knowledge) will “consider” or “reject” them. Simultaneously, whereas they will “follow” or “consider” the ads when the conflict by the offering against their preference is low (high in store knowledge), they will “ignore” or “reject” them when the conflict is high (low in store knowledge).

[Figure 1]

Given the discussions above, we constitute following hypotheses. A consumer at unfamiliar has higher uncertainty for the surrounding decision and absorb higher search cost, and geo-targeting ads relieve these burdens. Such consumer would tend to accept them. Therefore, lower area familiarity will contribute to the increase of the store traffic due to the geo-targeting ads exposure.

HYPOTHESIS 1 (H1). *An exposure to geo-targeting ads to mobile users located at lower area familiarity will have higher effect on the store traffic than those who located at higher area familiarity.*

When a customer has higher knowledge on the featured store, he may have less preference offering conflicts and do not feel psychological reactance. Such consumer would tend to accept the offer. On the other hand, he is exposed to the store ads that he has less experienced, the psychological reactance tends to occur. Therefore, higher store knowledge will contribute to the increase of the store traffic due to the geo-targeting ads exposure.

HYPOTHESIS 2 (H2). *An exposure to geo-targeting ads of higher store knowledge to mobile users will have higher effect on the store traffic than those of lower store knowledge.*

3. Study 1

3.1. Method

To explore the effectiveness of geo-targeting strategies of mobile ads, a large interactive marketing agency, CyberAgent, collaborated in this research. CyberAgent transmits mobile ads and coupons to mobile users in Japan. A food chain company which has 7 stores in a focal area issued mobile coupons with the expiration date for one month.

The mobile coupons are sent to customers based on the CyberAgent's systems. They conducted a randomized field experiment where the treated group subjects are exposed to mobile coupons during the campaign period. Corresponding control group are selected in order that "distance to the store from their home" and "frequency to visit the store before campaign (for a month)" are balanced. In detail, they stratified whole subjects into 4 groups based on the value of these two covariates, and divided them into treated and control group so that about 5 % of each subgroup being the control sample. As a result, 982,754 subjects are assigned to the treated, whereas 41,885 subjects are assigned to the control. Out of 982,754 subjects, 34,085 users recorded positive impressions on the mobile ads.

They capture the number of visitors to the store using location data from mobile phones, hence enabling us to observe its conversion. We calculate the number of people visiting the focal store and let it be the outcome of our interest. All the location data is collected with mobile user's consent and completely anonymized.

Our main interest lies in whether area familiarity and store knowledge have significant effect on the number of customers visiting the store after an impression on mobile coupons. We employ zero-inflated Poisson regression model since some subjects have never visited the store during the campaign period even though they are exposed to the ads. The model is described as follows.

$$\Pr\left(N\_VISIT_i = j\right) = \begin{cases} p_i + \left(1-p_i\right)\exp\left(-\alpha_i\right) & \text{for } j = 0 \\ \left(1-p_i\right)\dfrac{\alpha_i \exp\left(-\alpha_i\right)}{N\_VISIT_i\,!} & \text{for } j > 0 \end{cases}$$

where

$$\alpha_i = \beta_0 + \beta_1 STORE\_KNWL_i + \beta_2 DIST\_HOME_i + \beta_3 DEST\_FAM_i + \boldsymbol{\beta}_4 PLACE\_FE_i\,, \quad (1)$$

and

$$\begin{aligned}\log\left(\frac{p_i}{1-p_i}\right) = {} & \gamma_0 + \gamma_1 AREA\_FAM_i + \gamma_2 STORE\_KNWL_i + \gamma_3 AREA\_FAM_i \times STORE\_KNWL_i \\ & + \gamma_4 DIST\_IMP_i + \gamma_5 DIST\_HOME_i + \gamma_6 DEST\_FAM_i + \gamma_7 PLACE\_FE_i \end{aligned}. \quad (2)$$

The definition of variables are provided in Table 2. Zero-inflated Poisson models can account for not only whether the customer just visited the store once but also whether they repeatedly visited there.

[Table 2]

The interested variables are *AREA_FAM* representing the degree of area familiarity of the area where they are exposed to the coupons, and *STORE_KNWL* as a proxy for the degree of knowledge on the focal store. *AREA_FAM* is only included in the logistic regression predicting whether or not they visit the store but not in Poisson model since they are measured at the moment of the first impression and it is natural to assume that these should work only for the very first visiting immediately after the impression. We also included the interaction term of *AREA_FAM* and *STORE_KNWL*.

To finely identify the effects of the area familiarity and the store knowledge on mobile ads effectiveness, we included several controlling variables in the model. Firstly, we consider the distance to the store from the location where they are exposed to the coupon (*DIST_IMP*). Consumers tend to accept promotional offers when they are close to the promoting store (Banerjee and Dholakia, 2008). Luo et al. (2014) and Danaher et al. (2015) show that near-distance mobile coupons are more likely to be redeemed. Therefore, it is expected that the larger value of the distance to the store from the location will decrease the number of people visiting the store. Due to the same reason with *AREA_FAM* we do not include *DIST_IMP* in the Poisson regression.

Second, to control for ease of visiting the store, distance between the store and their home is considered in the models. In our case, mobile coupons are not always redeemed immediately after exposition since it has an expiration period of about one month. Therefore, the distance from the place where they usually are, *DIST_HOME* is included. It is expected that they tend to visit the store more frequently if their home is close by.

Third, *DEST_FAM* is also considered in the model to account for the ease of reaching the store. If they have an image of the area a focal store locates (such as the route to the store), they have less reluctance to visit the area (Baloglu 2001). Hence, we posit that higher *DEST_FAM* results in more frequent store visiting.

One concern is that the effect of *AREA_FAM* and *STORE_KNWL* are only observed for the subsamples which have positive impression, hence the analysis based on these subsamples might result in biased, even though this study is designed to be a randomized field experiment. Therefore, we conduct propensity score analysis (Rosenbaum and Rubin 1983), especially the inverse probability weighting (IPW) procedure (Williamson et al. 2013) in order to correct this selection bias. IPW is frequently employed in many empirical fields where randomized controlled trial is infeasible. Robins et al. (1994) developed a class of IPW estimator for regression model, and we adopt this procedure. Firstly, we prepare a probit regression model which predicts each customer reacting to the mobile ad and records positive impressions. The outcome (equals to 1 if subject *i* has positive impression, and 0 otherwise) is explained by factors affecting the propensity to react to the ads, which is;

$$\begin{aligned} q_i &= \Pr\left(IMP < 0\right) \\ &= \Phi\left(\delta_0 + \delta_1 OS_i + \delta_2 STORE\_KNWL_i + \delta_3 DIST\_HOME_i + \delta_4 DEST\_FAM_i + \boldsymbol{\delta}_5 PLACE\_FE_i\right) \end{aligned} \tag{3}$$

where Φ is a cumulative distribution function of normal distribution. *OS* is believed to be a good predictor since the users of iOS are known to view mobile ads more than Android uses. In fact, revenues obtained from mobile app ads on iOS are about 2.5 times larger than that of Android, although Android gains a larger market share (Smaato 2020). Then, each treated observation is weighted by the inverse of the estimated propensity score q_i, and $1/q_i$ is treated as sampling weight when estimating zero-inflated Poisson regression model (equation 1).

3.2. Results

The descriptive statistics appear in Table 3. The table shows that covariates *STORE_KNWL*, *DIST_HOME*, and *DEST_FAM* are balanced well between treated group and non-treated group. The table also tells us that treated samples with positive impression and without impression differ in variables. In detail, the positive impression group has visited the store more nearly twice than the no-impression group, and the former group has more store knowledge, live in a closer area to the store than the latter group. As expected, iOS users tend to view mobile ads more than Android users. These differences require us to adjust the selection bias.

[Table 3]

Table 4 describes the Pearson's and Spearman's correlation matrix for covariates. As can be seen from the table, *STORE_KNWL* and *DEST_FAM*, and *DIST_HOME* and *DIST_IMP* has positive correlations. When a customer visited the store, it contributes the increase of both *STORE_KNWL* and *DEST_FAM*, then they are positively correlated. Also, some customers would view the ads when they are at home, hence *DIST_HOME* and *DIST_IMP* positively correlates each other. In any case, there seems to exist no multicollinearity.

[Table 4]

The main results are provided in Table 5. Before conducting regression analyses, all the variables in the empirical models are transformed to be standardized. This process makes it possible to easily compare the magnitudes of the effects on the coupon effectiveness for each variable, and to easily interpret the meanings of the obtained results of the interaction term coefficient.

[Table 5]

The upper block shows the estimated coefficients, standard errors, and p-values for the Poisson regression model defined in equation (1), and the lower block shows the results for logistic regression model defined in equation (2). For readability, the coefficients of logistic regression γ is shown in the form of $-\gamma$, meaning a positive coefficient indicates increase in the corresponding variable increases the probability of a customer visiting the store.

MODEL 1 column of the table describes the result without propensity score adjustment, and MODEL 2 column describes the result with propensity score adjustment. Here, before discussing the results of zero-inflated Poisson with and without the propensity score adjustment, we briefly confirm the results of probit regression in equation (3), which estimates the tendency of a customer viewing mobile targeting ads. Table 6 shows the results of equation (3), indicating customers tend to view mobile targeting ads when they use iOS (p<.0001), have higher store knowledge (p<.0001), and live in a closer area to the store (p<.0001). As expected, iOS users tend to be exposed to the ads. The customers with higher store knowledge are more likely to view the ads. If they live far from the store, they tend not to tap the ads because the information of the store with a larger travel and time cost might be less precious for them. Using the estimated coefficients, we calculated the propensity score for subject *i*.

[Table 6]

Next, we move on to the zero-inflated Poisson results. The estimated coefficient of *AREA_FAM* in MODEL 1 from logistic regression shows that if the customer is unfamiliar with the current area, coupon has a positive impact on visiting (p<.0001). Thus, H1 is supported. This is the case if the model is adjusted (MODEL 2).

As expected, the coefficients of *STORE_KNWL* are positive for the Poisson model and logistic model (p<.0001), both indicating that store knowledge promotes visiting and re-visiting the store when they are exposed to mobile ads (MODEL 1). This is the case if the model is adjusted (MODEL 2). Both results support H2.

The results of other covariates can be interpreted straightforwardly as expected. The coefficient of *DIST_IMP* in the logistic regression is negatively significant (p<.0001), meaning that if the subject locates far from the store area when exposed to ads, they tend not to visit the store during the campaign. This is consistent with the findings from Luo et al. (2014) and Danaher et al. (2015). The results on *DIST_HOME* indicates the customers exposed to the ads who live in distant areas less frequently visit the store ($p<.0001$; for both Poisson and logistic regression) as expected. The coefficients of *DEST_FAM* imply that the customers with larger experience at store area visit the store more frequently if they view the coupons ($p<.0001$; for both Poisson and logistic regression).

As all the variables in the regression model are standardized, we can compare the magnitude of the variables' effect on the number of people visiting the store. MODEL1 and MODEL2 in Table 5 tell us that area familiarity, store knowledge, and distance to the store from home are more important triggers to visit the focal store after their coupon impression than destination familiarity and distance to the store. Luo et al. (2014) and Danaher et al. (2015) state the significance of the distance to the focal store, but in this study, the other contextual factors are more prominent in terms of the geo-targeting ads effectiveness.

3.3. Discussion

We discuss our results from the perspective of the marginal effect of geo-targeting ads on visiting the focal store via store knowledge and area familiarity. Because our model contains the interactions of area familiarity and store knowledge in logistic regression model and also these variables are transformed to be standardized, it is difficult to straightforwardly interpret the obtained results when considering the coupons effectiveness.

Thus, we discuss the obtained results using estimated marginal mean effects. Note that marginal mean effect considered in this section is calculated based on the propensity score adjusted results. Figure 2 describes the marginal mean effects of area familiarity and store knowledge on visiting the focal store at least once after the coupon issue, given other variables are fixed to be their sample mean. The effects are shown with the scale of percentile for each variable since the raw value of the area familiarity is not straightforwardly interpreterble. Since these variables are transformed and x-axis is described in percentile, the effect is not S-shaped unlike the logistic curve. We can see from Figure 2 that area familiarity and store knowledge interestingly have almost equivalent impact on coupon effectiveness.

[Figure 2]

On average, the customers with bottom 25th percentile of area familiarity (those who are less familiar with the area where they are exposed to the coupon) have 7.6% possibility of visiting the store, although those with top 25th percentile of area familiarity (those who are more familiar with the area where they are exposed to the coupon) only have 4.4% possibility. Similarly, the consumers with first quartile of store knowledge (those who had experienced the store better) visit the store with 7.6% after an exposure to the geo-targeting ad, whereas the consumers with third quartile of store knowledge (those who had less experienced the store) have only 4.3% chance of visiting the store after the exposure. These results indicate that when a manager issues geo-targeting ads, they should consider area familiarity and store knowledge of the target customers.

Our main focus is on customer targeting with a combination of area familiarity and store knowledge factors. Figure 3 shows the estimated marginal mean effects of the combination of area familiarity and store knowledge on visiting the store. In the figure, we divide area familiarity and store knowledge into three levels, bottom 25th percentile (low), 50th percentile (mid), and top 25th percentile (high), respectively, and consider 3x3 combinations of marginal effects. The figure shows that targeting the customers with high store knowledge and low area familiarity will produce 10.1% visiting rate through the coupon. On the other hand, if the manager mistakenly focuses on those who have low store knowledge and high area familiarity, the likelihood shrinks to only 3.3%. Thus, the results indicate that targeting customers with the first or the third quartile of area familiarity and store knowledge generates more than 3 times the difference of geo-targeting ads effectiveness.

[Figure 3]

4. Study 2

4.1. Method

Study 1 considered the case where a geo targeting ads contains coupons. However, in some cases, the ads do not offer any discounts but just appeal or remind their products or stores. In the second study, we deal with such cases.

A retail store offers a space where several restaurants are located on the same floor. The store issued mobile ads without coupons. The ads only explain the location of the restaurants, therefore the consumers do not enjoy the discounts nor any benefits from them. CyberAgent, likewise Study 1, is the advertising agency of the coupon. They conducted a randomized field experiment where the treated group subjects are exposed to mobile ads during the campaign period. Corresponding control group are selected in the same order as study 1. In this study, 515,738 subjects are assigned to the treated, whereas 9,989 subjects are assigned to the control. Out of 515,738 subjects, 9,853 users recorded positive impressions on the mobile ads.

Again, we record the number of visits to the store for each subject using location data from mobile phones. We calculate the number of people visiting the focal store and let it be the outcome of our interest. Note that because the GPS is used to count the visiting, we cannot identify whether the customers visited the retail store space, the restaurants space, or both of them. All the location data is collected with mobile user's consent and completely anonymized.

Our main interest lies in whether the area familiarity and the store knowledge have positive effects on the number of people visiting the store after an impression on mobile ads. We employ the same zero-inflated Poisson regression model described in equation (1). The definition of variables are provided in Table 2. Other control variables (*DEST_FAM*, *DIST_HOME*, *DIST_IMP*) are also included in the model like Study 1. We also conducted propensity score adjustment to remove the selection bias.

4.2. Results

The descriptive statistics in this study are described in Table 7. The table shows that covariates seem to be balanced between two groups. The table also tells us that the coupon impression increases the number of people visiting the store almost twice. The positive impression group has more store knowledge, lives in a more proximal area to the store than the no impression group, has higher familiarity on the area store located. iOS users tend to view mobile ads more than Android users. These tendencies are very similar to those of Study 1. Hence, we adjust selection bias using propensity score weighting.

[Table 7]

Table 8 describes the Pearson's and Spearman's correlation matrix for covariates. As can be seen from the table, *STORE_KNWL* and *DEST_FAM* have smaller correlation coefficient than that of Study 1. Since the focal store of this study is located in an urban area and there exist a lot of places to visit, store knowledge measured by number of past visits to the focal store and destination area familiarity measured by number of past visits to the focal area would be more weakly correlated than Study 1. That is, the visits to the focal area rarely imply the visits to the focal area. In any case, there seems to exist no multicollinearity.

[Table 8]

The results from zero-inflated Poisson regressions are provided in Table 9. Before the analyses, all the variables in the empirical models are transformed to be standardized. The upper block shows the estimated coefficients, standard errors, and p-values for the Poisson regression part defined in equation (1), and the lower block shows the results for the logistic regression part defined in equation (2).

[Table 9]

The probit regression result for estimating propensity score, which corresponds to the probability estimates the tendency of a customer to view mobile targeting ads, is shown in Table 10. The table indicates customers tend to view mobile targeting ads when they use iOS ($p<.0001$), have higher store knowledge ($p<.0001$), live in a proximal area to the store ($p<.0001$), and have higher familiarity to the area where the store locates. Using the estimated coefficients, we predict the propensity score for subject *i*.

[Table 10]

The zero-inflated Poisson results show that although the coefficients of *STORE_KNWL* in the logistic regression models are both positively significant in MODEL 1 and MODEL 2 ($p<.0001$), those of *AREA_FAM* are neither statistically significant. This is a different result to Study 1, where coefficient of *AREA_FAM* are negatively and statistically significant in the logistic regression part. Thus, H1 is not supported in Study 2.

The coefficients of *STORE_KNWL* are also positively and statistically significant in the Poisson regression part ($p<.0001$), indicating that, given the coupon impression and the positive number of visiting, customers who had experienced the store more tend to revisit the store more. Thus, H2 is again supported.

Therefore, in the setting of Study 2, customer's those who have a larger number of visiting the store before the coupon launch for a month tend to visit the focal store by its impression, but area familiarity of customers seems to have no effect on coupon efficiency. We will discuss this point in the next section.

The results on *DIST_HOME* indicates the customers exposed to the ads who live in distant area less frequently visit the store ($p<.0001$; for both Poisson and logistic regression) as expected. The coefficients of *DEST_FAM* imply that the customers with larger experience at store area visit the store more frequently if they view the coupons ($p<.0001$; for logistic regression).

4.3. Discussion

We also discuss Study 2 results from the perspective of the marginal effect of geo-targeting ads on visiting the focal store via store knowledge and area familiarity. Discussion here is based on the propensity score adjusted results (i.e., MODEL 2 results).

Figure 3 describes the marginal mean effects of area familiarity and store knowledge on visiting the focal store at least once after the coupon issue, given other variables are fixed to be their sample mean. Likewise Figure 1, the effects are shown with the scale of percentile for each variable. We can see from Figure 1 that area familiarity and store knowledge interestingly have almost equivalent impact on coupon effectiveness.

[Figure 3]

On average, the consumers with first quartile of store knowledge (those who had experienced the store better) visit the store with 7.0% after an exposure to the geo-targeting ad, whereas the consumers with third quartile of store knowledge (those who had less experienced the store) have only 4.1% chance of visiting the store after the exposure. These are similar results to Study 1's, indicating that when a manager issues geo-targeting ads, they should consider area familiarity and store knowledge of the target customers.

However, with respect to area familiarity, the marginal mean effect is very different. As can be seen from Figure 3, the visiting probability after an exposure to the geo-targeting ads is unchanged if a consumer is familiar or unfamiliar to the area.

Figure 4, describing the estimated marginal mean effects of the combination of area familiarity and store knowledge on visiting the store, tells us the similar. In the figure, we divide area familiarity and store knowledge into three levels, bottom 25th percentile (low), 50th percentile (mid), and top 25th percentile (high), respectively, and consider 3x3 combinations of marginal effects. The figure shows that although higher store knowledge results in higher visiting rate for every scenario (6.9% - 7.2%), area familiarity does not affect the probability.

[Figure 4]

5. General Discussion and Conclusion

In this section, we discuss our results obtained from two studies to obtain a better understanding of the behavioral mechanism. We firstly conduct some but simple additional analysis. We then introduce a theory called "dual-system theory", which seems to be consistent with our results from main and additional analysis. We also discuss some managerial implications lead by the results along with the theory. We also discuss some limitations of our research.

5.1. Implications from two study results inconsistency

To short, two studies consistently show that, irrelevant to the coupon attendant, those who have higher store knowledge tend to follow the geo-targeting recommendations. On the other hand, consumers with lower area familiarity tend to follow the geo-targeting recommendations when the coupons are attached, whereas the area familiarity do not affect visiting probability when recommendations without coupons (just advertising) are offered. We discuss the varying results about the area familiarity.

Then, we again conduct the zero-inflated Poisson regression analysis by dividing the samples into two parts; whose store knowledge are positive (who have visited the store at least once; *STORE_KNWL*>0) and zero (who have never visited the store; *STORE_KNWL*=0) for study 1 and study 2 datasets, respectively. Since we split the samples based on the store knowledge level, this analysis does not include *STORE_KNWL* as an explanatory variable. The results of this analysis, along with the main analysis are summarized in Table 11.

[Table 11]

In the case where the geo-targeting recommendations with the coupons attached (study 1 case), the negative effects of area familiarity on visiting are both observed, but the effects seem to be stronger if a customer has never visited the store. That is, the logistic regression coefficient of *AREA_FAM* for *STORE_KNWL*=0 group is -0.586 which is statistically significant at p<.0001 level, but that of *STORE_KNWL*>0 group is -0.138 with *p*=0.107. This heterogeneous result, namely *AREA_FAM* coefficient differs depending on *STORE_KNWL* level, is consistent with the main results that shows negatively and statistically significant cross-term (i.e., *AREA_FAM*STORE_KNWL*) coefficient in the logistic regression part.

In the case where the geo-targeting recommendations where the coupons are not attached (study 2 case), the negative effects of area familiarity on visiting are not observed in neither group (the logistic regression coefficient of *AREA_FAM* for *STORE_KNWL*=0 group is 0.037 with *p*=0.676, and that of *STORE_KNWL*>0 group is 0.174 with *p*=0.311).

5.2. Habitual system and goal-directed system

We introduce the theory on habitual versus goal-directed control (e.g., de Wit and Dickinson, 2009) to explain these heterogeneous results. Recent neuroscience and behavioral studies have found evidence that decision-making is based on dual systems, habitual system and goal-directed system, which rely on distinct neural networks (Clithero et al., 2021). In this theory, the habitual system begets behavior which is automatically caused by some stimuli via past learned stimulus-response associations, owing to some positive or negative reinforcements. The goal-directed system causes behavior which is driven by goal expectancy and desire, where decisions are mediated by the expected positive outcomes or the expected relief obtained from avoiding negative outcomes (Balleine and O'doherty, 2010).

Only when consequences are assumed to be desirable, or when the behavioral consequences constitute a “goal”, the goal-directed control works and activate actions toward the goal (de Wit and Dickinson, 2009). Under the goal-directed system, people involve careful consideration with higher cognitive resource cost for the expected outcome. On the contrary, when they are exposed to extensive and repeated reinforcements, the habitual control exerts dominant control on their decision-making process. Under the habitual system, people make more simplistic and repeated action based on the past experience and attain efficiency in terms of cognitive resources, but they lose behavioral flexibility independent of the outcome’s value.

We adopt this dual system theory to our settings. When geo-targeted offers without coupons nor discount are exposed to consumers, they only have a reminder effect they tend to stay in habitual systems and follow past learned behavior. Therefore, in the study 2 setting, people tend to visit stores with higher store knowledge.

On the contrary, when geo-targeting ads are equipped with coupon information, the customer considers desirable “goal” and shifts to the goal-directed system. Because people whose goal-directed control is dominant make careful consideration for the expected benefit, they will attentively consider cost of uncertainty and searching for their decision making. Then, because the area familiarity, which is related to be the search cost and uncertainty, is the key driver to visit the store, and the customers who are exposed to mobile coupon at unfamiliar area tend to follow the recommendations. Especially, those who have never visited the store tend not to be reinforced to visit the store under the habitual system, they are more likely to retain goal-directed system. Therefore, in the same vein, the area familiarity effect on the direct to the store is more prominent for the customers who have never visited there than for the customers who have experienced the store.

5.3. Practical implications

In light of these arguments supported by the theory of habitual and goal-directed system, we can suggest some managerial implications.

People may visit unfamiliar area to enjoy unusual events (e.g., at a venue of arts and entertainment) on a weekend or after work (Han and Yamada, 2016). In this time, people tend not to be in the habitual but the goal-directed control, and therefore area familiarity would have great impact on the geo-targeting ad redemption. In addition, geo-targeting ads with coupons can make people more goal-directed. Hence, managers should consider area familiarity and attach coupons when they distribute their ads on weekend or after work hours.

On the other hand, people in working time on weekdays would be in the habitual system. In this time, the value of the area familiarity is lower and it is not a key factor of the ads effectiveness. The store knowledge is more important. Then, managers should send geo-targeting ads which have higher store knowledge for every customer. But if they want to induce a customer to the store people are unfamiliar, the coupon should be attached with the ads because it may get him more goal-directed. Some customers may rationally consider search cost and coupon discount, then visit the focal store.

5.4. Limitation, and Future Research Suggestions

First, we do not consider customers demographics. Likewise prior research investigating the geo-targeting ads, the customer information such as age, gender, or income is hard to obtain because these data are not recorded in the location information source (Luo et al. 2014). Therefore, we couldn’t consider the heterogenous effect of the area familiarity or the store knowledge to the coupon redemption. Future research could explore this issue.

Second, although we supported our result based on the theory of control and goal-directed systems, we do not have any evidence whether they are under the goal-directed or habitual control. In neuroscience, functional magnetic resonance imaging (fMRI) studies makes it possible to judge their dominant systems. However, since our research rely on field experiment, such studies are difficult to execute. With technological progress, such investigation could be possible in the future.

Lastly, we acknowledge that our findings are limited to specific stores and ads. Although our hypotheses and the explanation for the result do not heavily rely on the store and ads characteristics, and area familiarity and store knowledge are always conceptualizable in geo-targeting ads study and hence commercially implementable, future research should consider a variety of store and advertisement characteristics. *6.3 Conclusion*

In this paper, we suggest two customer contextual factors affecting geo-targeting ads response: area familiarity and store knowledge. We show that the targeting based on appropriate combination of the area familiarity and the store knowledge can improve coupon redemption rate. Moreover, we found that, in our randomized field experiment setting, the area familiarity has more prominent impact on coupon redemption than the geographical distance, which is often considered in geo-ad research. We hope future research will investigate the effect of area familiarity and store knowledge on mobile targeting advertising at various ads and store attributes.

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Table 1. Selected Studies on Geo-Targeting Mobile Ads

Authors (year)	Objectives	Theories	Study Method	Analytical Approach	Findings
Luo et al. (2014)	To investigate geo-targeting mobile advertising effectiveness with time and location	Contextual marketing theory and construal level theory	Field experiments with 12,256 SMS users	Logistic regression model where they regress purchase likelihood on distance, time , and these cross term with control variables	The closer in time and location for consumers, the more effective the mobile ads.
Danaher et al. (2015)	To examine whether the coupon redemption rates are affected by its expiry length and distance to the store		Field experiments in a shopping mall of 38 stores with 8,534 SMS users	Multivariate binomial probit regression model where they regress the coupon redemption on coupon characteristics	Mobile coupons are more likely to be redeemed if the expiry length is shorter and location received is closer to the store.
Fong et al. (2015)	To investigate the effect of competing store location		Field experiments with 18,000 SMS users	Two-sample t-test comparing mean purchasing rates	Consumers located near a competitor's store tend to follow geo targeting promotions.
Andrews et al. (2016)	To examine the effects of physical crowdedness on consumer responses to mobile ads.	Mobile immersion	Field data with 10,690 SMS users	Logistic regression model where they regress purchase likelihood on crowdedness with control variables	Consumers in crowded subway trains are respond more to a mobile ad offers than those in noncrowded subway trains
Zubcsek et al. (2017)	To improve the dynamic segmentation of consumers according to their past responses to marketing activities and their location histories	Dynamic location behavior and consumer preferences based on standard economic theory	Data based on a panel of 15,353 observations on 96 offers sent to 217 participants in a pacific country	Logistic regression model where they regress offer redemption likelihood on consumers network variables with control variables	Colocated consumers tend to respond to coupons in the same category, indicating that consumers' location patters provide information on their preferences
Grewal et al. (2018)	To examine whether mobile phone use in store increase	Limited attentional capacity theory	Eye-tracking technology in field	Two-sample t-test comparing mean purchasing amount	In-store mobile phone use increases the total time spend in the store, and

	the purchases		study and field experiment		also it increases the total purchases as a result
Ghose et al. (2019)	To investigate the effectiveness of "trajectory-based" targeting strategy for mobile recommendation	Spatial affinity (homophily), temporal duration, and movement velocity	Randomized field experiment in a major shopping mall in Asia based on 83,370 unique user responses for a 14-day period	Machine learning based clustering and recommendation system using features on temporal, spatial, semantic, and velocity information	"Trajectory-based" targeting for mobile promotion can increase the redemption rate of coupons
Qiu and Zhao (2019)	To evaluate how store clusters affect acquisition and redemption of mobile coupons	Symbiosis effect	Field data with 1,799 restaurants (11,222 mobile coupons)	Mixed-effect linear regression model for coupon acquisition and mixed effect logistic regression model for coupon redemption	When the shopping center density is higher, the coupon acquisition rate is also higher, but result in lower coupon redemption rate
Zhang et al. (2020)	To propose a new personalized-targeting approach to tackle the challenge of low engagement with mobile apps	User engagement and personalized targeting	Randomized field experiment on a Chinese mobile reading app with 9,255 active users in total.	New structural forward-looking hidden Markov model (FHMM)	By considering the time-varying factor of engagement and forward-looking behavior, FHMM can estimate their engagement stage which is not explicitly observed.
Molitor et al. (2020)	To study location-based coupon effectiveness with the provision of distance information and the distance-based ranking of coupons	Relevance-caused ranking	Field experiments with 10,690 users	Hierarchical Bayesian logit model with mixed effects where they regress coupon clicking likelihood on distance and display rank with control variables	Distance-based ranking of coupons is the most effective factors for location-based ads, and the provision of distance information is less important.
Present study	To explore the effectiveness of geo-targeting mobile ads in	Psychological reactance theory, regulatory focus theory	Field experiments with 982,754 users (Study 1) and 515,738 users	Zero-inflated Poisson regression model with the inverse of propensity score adjustment,	

	terms of area familiarity, store knowledge, and type of incentives.		(Study 2)	where we regress store traffic on area familiarity, store knowledge, and other controls	

Table 2. Definition of variables

Variable name	Definition
N_VISIT_i	The number of visiting the focal store during the campaign of subject *i*
$TREAT_i$	1 if subject *i* is assignt to treatment group (coupon exposure group), and 0 otherwise
$AREA\_FAM_i$	Approximated ratio of time staying in the 1km mesh where subject *i* is exposed to the ad before the campaign for a one month
$STORE\_KNWL_i$	The number of visiting the focal store before the campaign for one month of subject *i* (store familiarity)
$TIME12\_14_i$	1 if subject *i*'s first impression is from 0 p.m. to 2 p.m. and 0 otherwise
$TIME15\_17_i$	1 if subject *i*'s first impression is from 3 p.m. to 5 p.m. and 0 otherwise
$TIME18\_20_i$	1 if subject *i*'s first impression is from 6 p.m. to 8 p.m. and 0 otherwise
$DIST\_IMP_i$	The distance to the focal store from subject *i*'s location when exposed to the ad (km)
$DIST\_HOME_i$	The distance to the focal store from subject *i*'s home (km)
$DEST\_FAM_i$	Approximated ratio of subject i's time staying in the 1km mesh where the focal store locates before the campaign for a one month
OS_i	1 if subject *i*'s OS is iOS, and 0 if subject i's OS is Android.
$PLACE\_FE_i$	The 7 stores fixed effect

Table 3. Descriptive statistics (Study 1)

	Whole sample (N=1,024,639)				Treated sample (N=982,754)				Non-treated sample (N=41,885)			
Variable	p1	mean	p99	s.d.	p1	mean	p99	s.d.	p1	mean	p99	s.d.
N_VISIT_i	0.000	0.082	2.000	0.656	0.000	0.082	2.000	0.658	0.000	0.083	2.000	0.610
$TREAT_i$	0.000	0.958	1.000	0.201	1.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000
$STORE\_KNWL_i$	0.000	0.142	2.000	1.215	0.000	0.142	2.000	1.221	0.000	0.138	3.000	1.051
$DIST\_HOME_i$	0.877	6.489	10.00	2.476	0.878	6.491	10.00	2.476	0.835	6.452	10.00	2.491
$DEST\_FAM_i$	0.000	0.003	0.042	0.038	0.000	0.003	0.042	0.038	0.000	0.004	0.054	0.040

	Treated sample with impression (N=34,085)				Treated sample without impression (N=948,669)			
Variable	p1	mean	p99	s.d.	p1	mean	p99	s.d.
N_VISIT_i	0.000	0.156	3.000	1.176	0.000	0.080	2.000	0.631
$AREA\_FAM_i$	0.000	0.311	1.000	0.290	missing			
$STORE\_KNWL_i$	0.000	0.240	4.000	2.284	0.000	0.139	2.000	1.165
$DIST\_IMP_i$	0.766	27.46	396.7	254.7	missing			
$DIST\_HOME_i$	0.680	5.960	10.00	2.531	0.887	6.510	10.00	2.472
$DEST\_FAM_i$	0.000	0.004	0.081	0.038	0.000	0.003	0.040	0.038
OS_i	0.000	0.774	1.000	0.418	0.000	0.387	1.000	0.487

Table 4. Pearson's correlation (lower left) matrix and Spearman's correlation matrix (top right) (Study 1)

	TREAT$_i$	*AREA_FAM$_i$*	*STORE_KNWL$_i$*	*DIST_IMP$_i$*	*DIST_HOME$_i$*	*DEST_FAM$_i$*
TREAT$_i$	1	-	-0.001	-	0.003	-0.005
AREA_FAM$_i$	-	1	-0.068	-0.273	-0.023	-0.078
STORE_KNWL$_i$	0.001	-0.021	1	-0.019	0.120	0.481
DIST_IMP$_i$	-	-0.069	-0.004	1	0.651	-0.172
DIST_HOME$_i$	0.003	-0.022	-0.049	0.019	1	-0.098
DEST_FAM$_i$	-0.002	0.011	0.156	-0.007	-0.126	1

Table 5. Results of zero-inflated Poisson regression model (Study 1)

	MODEL 1 (no adjustment)				MODEL 2 (propensity score adjusted)			
Independent Variable	Estimate	S.E.	p-Value		Estimate	S.E.	p-Value	
Poisson regression predicting the number of visit								
Intercept	0.207	0.083	0.013	**	-0.074	0.087	0.398	
STORE_KNWL	0.047	0.001	<.0001	***	0.061	0.001	<.0001	***
DIST_HOME	-0.178	0.021	<.0001	***	-0.196	0.020	<.0001	***
DEST_FAM	0.023	0.004	<.0001	***	0.021	0.004	<.0001	***
PLACE_FE	Included				Included			
Logistic regression predicting the number of visit to be positive								
Intercept	-3.267	0.120	<.0001	***	-2.778	0.096	<.0001	***
AREA_FAM	-0.482	0.037	<.0001	***	-0.438	0.024	<.0001	***
STORE_KNWL	0.425	0.028	<.0001	***	0.441	0.026	<.0001	***
*AREA_FAM*STORE_KNWL*	-0.073	0.031	0.019	**	-0.069	0.036	0.055	*
DIST_IMP	-0.030	0.041	0.466		-0.042	0.040	0.294	
DIST_HOME	-0.624	0.035	<.0001	***	-0.449	0.027	<.0001	***
DEST_FAM	0.070	0.018	<.0001	***	0.052	0.013	<.0001	***
PLACE_FE	Included				Included			
N	34,085				33,132			

Table 6. Results of Probit regression model (Study 1)

Independent Variable	Estimate	S.E.	p-Value	
Probit regression predicting positive impression				
Intercept	-2.255	0.005	<.0001	***
OS	0.735	0.005	<.0001	***
STORE_KNWL	0.012	0.002	<.0001	***
DIST_HOME	-0.107	0.003	<.0001	***
DEST_FAM	-0.004	0.003	0.136	
PLACE_FE	Included			
c-stat.	0.726			
N	982,766			

Table 7. Descriptive Statistics (Study 2)

	Whole sample (N=525,727)				Treated sample (N=515,738)				Non-treated sample (N=9,989)			
Variable	p1	mean	p99	s.d.	p1	mean	p99	s.d.	p1	mean	p99	s.d.
N_VISIT i	0.000	0.057	1.000	0.679	0.000	0.057	1.000	0.680	0.000	0.049	1.000	0.649
TREAT i	0.000	0.981	1.000	0.137	1.000	1.000	1.000	0.000	0.000	0.000	0.000	0.000
STORE_KNWL i	0.000	0.010	1.000	0.245	0.000	0.010	0.000	0.118	0.000	0.010	0.000	0.114
DIST_HOME i	0.487	5.198	9.950	2.709	0.487	5.198	9.950	2.709	0.483	5.186	9.931	2.695
DEST_FAM i	0.000	0.008	0.194	0.049	0.000	0.008	0.193	0.049	0.000	0.009	0.232	0.055

	Treated sample with impression (N=9,853)				Treated sample without impression (N=505,885)			
Variable	p1	mean	p99	s.d.	p1	mean	p99	s.d.
N_VISIT i	0.000	0.102	3.000	0.924	0.000	0.057	1.000	0.674
AREA_FAM i	0.000	0.433	1.000	0.339	missing			
STORE_KNWL i	0.000	0.043	1.000	0.371	0.000	0.020	1.000	0.243
DIST_IMP i	0.599	25.66	405.8	101.8	missing			
DIST_HOME i	0.347	4.863	9.76	2.716	0.491	5.204	9.95	2.708
DEST_FAM i	0.000	0.013	0.295	0.061	0.000	0.008	0.190	0.048
OS i	0.000	0.569	1.000	0.495	0.000	0.378	1.000	0.485

Table 8. Pearson's correlation (lower left) matrix and Spearman's correlation matrix (top right) (Study 2)

	TREAT i	*AREA_FAM i*	*STORE_KNWL i*	*DIST_IMP i*	*DIST_HOME i*	*DEST_FAM i*
TREAT i	1	-	0.004	-	0.001	-0.003
AREA_FAM i	-	1	-0.019	-0.151	0.009	-0.101
STORE_KNWL i	0.004	-0.019	1	-0.008	0.010	0.150
DIST_IMP i	-	-0.151	-0.008	1	-0.014	-0.026
DIST_HOME i	0.001	0.009	0.010	-0.014	1	-0.101
DEST_FAM i	-0.003	-0.101	0.150	-0.026	-0.101	1

Table 9. Results of zero-inflated Poisson regression model (Study 2)

Independent Variable	MODEL A (no adjustment) Estimate	S.E.	p-Value		MODEL A' (propensity score adjusted) Estimate	S.E.	p-Value	
Poisson regression predicting the number of visit								
Intercept	2.196	0.027	<.0001	***	1.994	0.030	<.0001	***
STORE_KNWL	0.027	0.001	<.0001	***	0.090	0.001	<.0001	***
DIST_HOME	-0.165	0.022	<.0001	***	-0.266	0.024	<.0001	***
DEST_FAM	-0.011	0.008	0.175		0.013	0.010	0.192	
Logistic regression predicting the number of visit to be positive								
Intercept	-3.102	0.052	<.0001	***	-2.821	0.048	<.0001	***
AREA_FAM	0.002	0.049	0.976		0.016	0.048	0.736	
STORE_KNWL	0.379	0.044	<.0001	***	0.360	0.051	<.0001	***
*AREA_FAM*STORE_KNWL*	-0.085	0.047	0.071	*	-0.063	0.037	0.086	*
DIST_IMP	-0.026	0.059	0.662		0.003	0.052	0.950	
DIST_HOME	-0.261	0.050	<.0001	***	-0.164	0.048	0.001	***
DEST_FAM	0.083	0.025	0.001	***	0.108	0.037	0.003	***
N		9,752				9,752		

Table 10. Results of Probit regression model (Study 2)

Independent Variable	Estimate	S.E.	p-Value	
Probit regression predicting positive impression				
Intercept	-2.168	0.006	<.0001	***
OS	0.275	0.009	<.0001	***
STORE_KNWL	0.010	0.002	<.0001	***
DIST_HOME	-0.026	0.004	<.0001	***
DEST_FAM	0.026	0.003	<.0001	***
PLACE_FE		Included		
c-stat.		0.60		
N		515,738		

Table 11. Heterogeneous effect of the area familiarity on geo-targeting ads

	Study 1	Study 2
	Geo-targeting ads with coupon	Geo-targeting ads without coupon
Area familiarity	Negative effect on visit	No effect on visit
Area familiarity of those who have no store knowledge	Strong negative effect on visit	No effect on visit
Area familiarity of those who have store knowledge	Weak negative effect on visit	No effect on visit

Figure 1. Theoretical framework

Uncertainty	*High*	*Follow*	*Ignore*
	Low	*Consider*	*Reject*
		Low	*High*
		Preference-offering conflicts	

Figure 2. Effect of mobile coupons via area familiarity and store knowledge (Study 1)

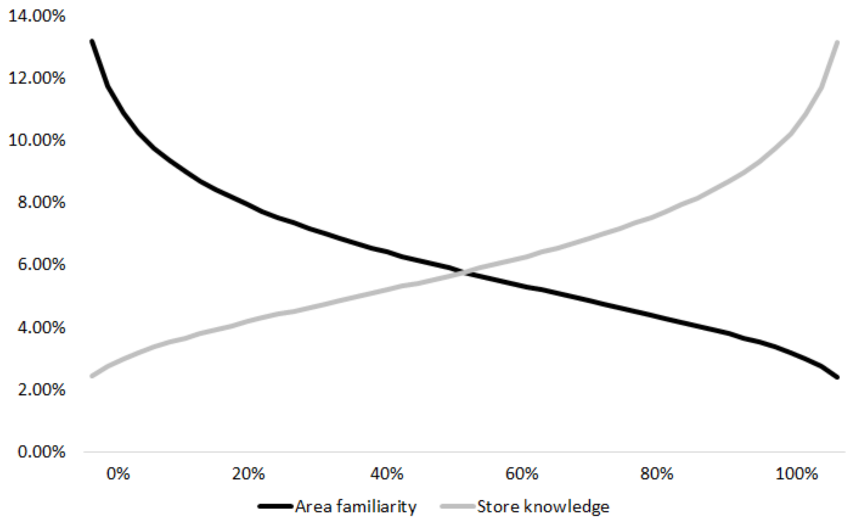

Figure 3. Effect of mobile coupons via combining area familiarity and store knowledge (Study 1)

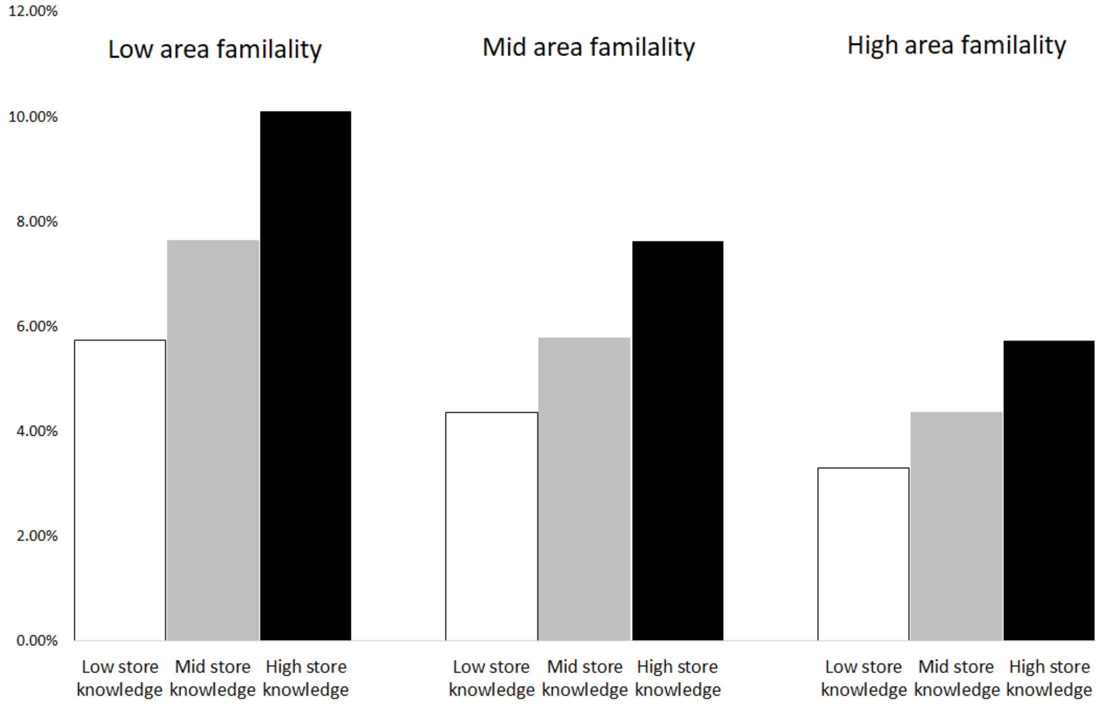

Figure 4. Effect of mobile coupons via area familiarity and store knowledge (Study 2)

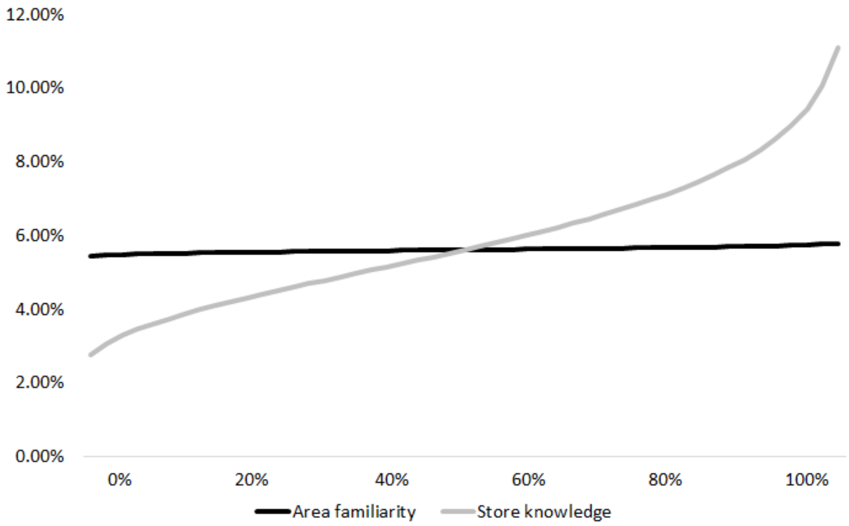

Figure 5. Effect of mobile coupons via combining area familiarity and store knowledge (Study 2)