# Nudging Mobile Customers with Real-Time Social Dynamics


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## Abstract

The proliferation of mobile and sensor technologies has contributed to the rise of location-based mobile targeting. Beyond the location, time and spatial context of individuals, the social context wherein they are embedded can reveal rich information about individual behavior. In this study, we automatically detected the real-time social contexts of customers based on their detailed GPS trajectories using machine-learning methods. To evaluate the effectiveness of mobile targeting under different social contexts, we designed a randomized field experiment in a large shopping mall. Our analyses indicated significant heterogeneity in consumer behavior under different social contexts. We found a customer in a group with others is on average 1.5 times more responsive to mobile promotions than is a solo shopper, and this impact increases with increased group size (from dyad to triad). We also found significant heterogeneous interactions between mobile promotion design and social contexts. Overall, our study demonstrates the potential of inferring individuals' social contexts from their movement trajectories and the value of leveraging such real-time social dynamics for improved mobile-targeting effectiveness.


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## 1. Introduction

Smartphone usage is expected to exceed 6.1 billion users worldwide by 2020 (Ericsson 2014). The proliferation of mobile and sensor technologies has contributed to the rise of mobile location-based advertising. Such advertising can enable businesses to deliver to mobile users, in real time, information on offers in geographical proximity to them. Recent studies using randomized field experiments have causally shown: that mobile advertisements based on static location and time information can significantly increase consumers' likelihood of redeeming a geo-targeted mobile coupon (Molitor et al. 2014, Luo et al. 2014, Fong et al. 2015); that mobile ads have a synergistic relationship with PC ads; that mobile coupons' expiration length influences their redemption rates (Danaher et al. 2015), and that understanding consumers' contexts and movement patterns is integral to marketers' improved mobile marketing effectiveness (Andrew et al. 2016, Ghose et al. 2016).

Beyond a real-time snapshot of the static geographical location and the consumer contextual information, the overall mobile trajectory of each individual consumer can provide even richer information about consumer preferences. In particular, "trajectory" hereby refers to the physical-behavioral trace of an individual's offline movement. For example, it can include information on the locations the individual has been to in the past, at what time and for how long, as well as the associated contexts. Considering the significant search costs for consumers in the offline world, such a physical behavioral trace can be highly informative in revealing individual-consumer preferences for real-time decision making. This information is analogous to the search-click stream data that we have been studying in the online environment. Mobile and sensor technologies allow us to digitize such individual-behavioral trajectory in the offline environment.

Moreover, the social context wherein an individual is embedded can reveal rich information about behavior (e.g., the interactions of individuals in physical-world groups of couples, friends or families). Such real-time social dynamics can help mobile advertisers to more fully understand consumer contextual preferences and, on that basis, provide better digital experiences. Recent studies have shown that social dynamics have significant impacts on individual decision making (Aral and Walker 2011). Meanwhile, it has been well recognized from social psychology literature that individuals, due to increased arousal, behave differently when others are around than when alone (Zajonc 1965). Human-Computer Interaction (HCI) researchers studying individual responses to interruptions in different social contexts have found that when people are physically together in groups, they are more likely to pay attention to unexpected interruptions or notifications (Fisher and Simmons 2011). Furthermore, earlier psychology literature has found that group size also matters, and that small groups (i.e., dyads) are likely to show qualitative behavioral differences from larger groups (e.g., groups with three people or more) (Mills 1958).

Considering the importance of potential deviations in individual behavior in different social contexts, it is critical for mobile advertisers to design new advertising strategies that can leverage the social dynamics of individuals in real time. However, obtaining individuals' real-time social contexts can be challenging, especially when the number of individuals is large. Surveys might not work so well, because information needs to be collected frequently in real time and in a scalable manner. In this paper, we propose the application of state-of-the-art machine-learning tools for automatic real-time detection of different consumer social contexts (e.g., alone, in a group of two, in a group of three, etc.) by analysis of large-scale and fine-grained longitudinal digital behavioral traces of individuals, extraction of multidimensional trajectory features and provision of annotations on group interactions (Liu et al. 2013).

Based on trajectory analysis for social context detection, we aimed to understand consumers' decisions by leveraging not only full information on their offline moving trajectories from different mobility dimensions, but also their offline social dynamics. To evaluate the effects of different social contexts on consumer responses to mobile interventions, we conducted a large-scale randomized field experiment in one of the largest shopping malls in Asia in April 2015. Our experimental results were validated based on 52,500 unique user responses for a 21-day period. Our follow-up statistical analyses for both the group and individual-user levels demonstrated high consistency in our final results.

Our main findings are the following. *First*, we uncovered significant heterogeneity in consumers' response to mobile promotion messages in different offline social contexts. In particular, consumers respond differently when shopping alone than when shopping with others. On average, a consumer who was in a group with others was 1.49 times more responsive to mobile promotions in focal store spending than was a solo consumer. Moreover, the size of the group also mattered. On average, a consumer in a triad was 1.57 times more responsive to mobile promotions in focal store spending than was a consumer in a dyad. *Second*, interestingly, we also found significant social-dynamic heterogeneity by group. Groups of couples are least responsive to mobile promotion messages on average, whereas groups of friends and groups with children are more responsive. This finding seems to indicate that with respect to mobile interventions, couples often have attention deficit, whereas the other group types seem to have more time to pay attention to mobile interventions. Meanwhile, we also found that high-income customers are more likely to respond to mobile promotions when shopping alone than when shopping with others in social groups. This finding indicates that high-income customers are sensitive to the real-time social contexts when receiving mobile interventions. Interestingly, high-income customers, unlike other demographic groups, demonstrate a potential "anti-social" character when exposed to mobile promotions. Shopping in groups might actually decrease their likelihood of responding to such promotions. *Third*, we found significant heterogeneity in the effect of interaction between mobile promotion design and real-time social contexts. It is particularly important for mobile advertisers to carefully design mobile messages to fit the relevant real-time social dynamics. For example, a social discount coupon (e.g., "buy one get one free") works more effectively than an individual price discount (e.g., "50% price off") on average. Moreover, a social discount coupon is especially effective for groups that contain couples. However, its effectiveness diminishes for groups with children or for solo shoppers. *Fourth and finally*, we found that on average, a mobile trajectory-based targeting strategy can lead to the highest mobile coupon redemption rates compared to the existing benchmark approaches such as current-location-based mobile targeting. Interestingly, mobile trajectory-based targeting becomes even more effective for larger social groups in real time. Overall, our findings suggest that businesses and marketers need to be mindful of the real-time social contexts when designing mobile targeting strategies.

Our major contributions can be summarized as follows. First, we demonstrate the value of mining large-scale, fine-grained offline mobile trajectory information to any understanding of individual decisions under different social contexts, as well as the importance of leveraging such information to improve the effectiveness of mobile marketing. Second, we establish a link between individuals' offline behavioral trajectories, offline social dynamics and digital behaviors. We aim to bridge the understanding of individual behavioral paths, social dynamics and decision making between the physical and digital worlds. Third, our analyses, as based on a combination of field experiments and surveys, allow us to quantify the economic impact of mobile targeting under different social contexts from a *causal* perspective. Advertisers can learn from our results in order to improve the design and effectiveness of their mobile targeting strategies. Finally, our interdisciplinary approach incorporates methodologies from statistical and machine learning, hierarchical Bayesian models, and field experiments. It provides a novel application opportunity to combine theory- and data-driven decision-making processes. It also paves a path on which future studies can travel in analyzing the problems that lie at the intersection of marketing and technology.

## 2. Related Literature

Our study builds on the following three streams of research: mobile advertising and location-based targeting; social dynamics, and behavioral targeting and recommendations, as treated in the three following sub-sections respectively.

### 2.1 Mobile Advertising and Location-based Targeting

Our paper is highly related to mobile and location-based advertising. Recent studies have shown that mobile ads have a synergistic relationship with PC ads, and that geographical proximity matters more for mobile ads than for PC ads. Using randomized field experiments, researchers have causally shown that mobile ads based on static location and time information can significantly increase users' likelihood of redeeming a geo-targeted mobile coupon (Molitor et al 2014, Luo et al. 2014, Fong et al. 2015). Molitor et al. (2014) demonstrated that the higher the discount from mobile coupons and the closer the consumers are to the physical store offering the coupons, the more likely they are to download them. Luo et al. (2014) discovered that temporal targeting and geographical targeting individually increase sales, but that the sales effects of employing these two strategies simultaneously are not straightforward, which suggests that advertisers need to carefully consider both temporal and spatial dimensions when designing mobile strategies. Furthermore, Fong et al. (2015), focusing on the effectiveness of competitive locational targeting, found that such targeting can produce increasing returns to promotional discount depth. More recently, studies have shown that understanding consumers' hyper-contexts, such as the crowdedness of their immediate environment, is critical to marketers' measurement of mobile marketing effectiveness (Andrew et al. 2016). In particular, the present authors have found that the more crowded the customer's current location environment, the more likely the customer will respond to a mobile ad. Danaher et al. (2015) showed that besides location and time of delivery, how long m-coupons are valid (expiry length) can influence redemption rates, as redemption times for m-coupons are much shorter than for traditional coupons. Ghose et al. (2016) conducted a large field experiment that showed that mobile advertisers' incorporation of individuals' mobile trajectory information can significantly improve the effectiveness of their ads. Our paper distinguishes itself from the extant literature by having leveraging not only the full historical information on consumers' digitized offline trajectories from different mobility dimensions but also their offline social contexts, in order to infer preferences and improve mobile advertising.

Previous studies also have examined consumer perceptions and attitudes toward mobile location-based ads. Gu (2012) investigated both the short- and long-term sales effects of location-based advertising. Bart et al. (2014) studied mobile advertising campaigns and found that they are effective in increasing favorable attitudes and purchase intentions for higher-

(versus lower-) involvement products as well as for products that are seen as more utilitarian (vs. more hedonic).

## 2.2 Social Dynamics

Our work is also related to research on social dynamics and human decision making. Social dynamics, recent studies (e.g., Aral and Walker 2011) have shown, have significant impacts on individual decision making. Meanwhile, the social psychology literature has long shown that individuals, due to increased arousal, behave differently when others are around than when alone (Zajonc 1965). Researchers in HCI, having studied individual responses to interruptions under different social contexts, found that when people are physically together in groups, they are more likely to pay attention to unexpected interruptions or notifications (Fisher and Simmons 2011). Previous psychology studies, furthermore, have found that group size also matters, and that small groups (i.e., dyads) are likely to show qualitative differences in behavior from larger groups (e.g., groups with three people or more) (Mills 1958). Our work is related to these prior studies in its focus on examining individual behavior and response to mobile interventions in various social-group contexts. It builds on the social psychology theories, but differentiates itself from the existing work in its aims to (1) automatically detect individuals' social contexts on a large scale and in real time using a machine-learning method and (2) measure and quantify the causal impacts of different mobile interventions on individuals in different social contexts using randomized field experimentation.

## 2.3 Behavioral Targeting and Recommendations

Our work also is related to the literature stream on recommendation systems, especially behavior-based recommendation. Link, content, and location can be viewed as the results of users' different behaviors, though the work that has built trajectory community models to provide online recommendations is scanty. In recommender systems, behavior models are proposed for different purposes, such as the determination of the effects of behavior monitoring and perceived system benefits (Nowak and Nass 2012), navigational patterns for modeling of relationships between users (Esslimani et al 2009), context-aware recommendations on customer purchasing behavior and trust (Adomavicius et al 2011, Gorgoglione et al 2011), and utility query recommendation by mining of users' search behaviors (Bhargava et al. 2015). Compared with the previous studies, one unique feature in this present one is its modeling of individual behavior and decisions based on large-scale and granular information extracted from individuals' heterogeneous offline behavior using physical movement trajectories and offline social contexts.

### 2.4 Spatial-Temporal Mining and Trajectory Clustering

Finally, our study builds on the machine-learning literature's spatial-temporal mining and trajectory-clustering. Researchers have studied trajectory using a variety of measures ranging from the activity-monitoring mining of frequent trajectory patterns (Liu et al 2012), the probability function of time (Gaffney and Smyth 1999), behavior correlation representation (Xiang and Gong 2006), the density-based distance function (Nanni and Pedreschi 2006) and uncertainty measurement of trajectories (Pelekis et al. 2011). Different similarity measures (e.g., time and location distances) and clustering methodologies have strengths and weaknesses. In contrast to most prior work, our method can handle multiple information sources (not just movement trajectories, but also the semantics of the underlying space) and apply a general metric-based learning framework to the clustering problem. Studies have used trajectory-based clustering for a variety of broad objectives, such as the discovery of common sub-trajectories (Lee et al 2007) and the identification of spatial structures (Ng and Han 2002). However, such work is based purely on spatial locations, which renders problematic its extension for incorporation of semantic, velocity, or other information possibly containing distinctive markers of real community interaction. It is also related to the community-detection literature from machine learning and computer science. Communities in networks/graphs are groups of vertices within which connections are dense, but between which connections are sparser. There are four principal community-detection methods: hierarchical clustering (Huang et al. 2010), similarity in edge-betweenness scores (Leskovec et al. 2010), counts of short loops (Newman 2004), and voltage differences in resistor networks (Shi et al. 2011). However, these existing methods focus on detection given a network structure and social-link distance between nodes, which are difficult to capture from physical mobile trajectories. Instead, in our study, we focused on the detection of communities of similar users based purely on their movement-trajectory patterns.

## 3. Detecting Real-Time Social Contexts Using Mobile Trajectories

In this paper, we propose the application of a state-of-the-art machine-learning approach for automatic detection of different real-time social contexts (e.g., alone, in a group of two, in a group of three, etc.) of consumers by analysis of large-scale, fine-grained, longitudinal digital traces of their physical movements, extraction of multidimensional trajectory features and provision of annotations on group interactions. Our method is based on recent computer science research in spatio-temporal trajectory mining (Liu et al. 2013). Our machine-learning approach enables us to detect the social contexts (groups) of individuals based on the multidimensional mobile trajectory information of customers in shopping malls. Its advantage is that it can identify groups of customers based on their behavior-driven mobility features as they move together in shopping malls. It enables us to learn customer behavior via not only static spatial or contextual proximity information but also dynamic movement similarity obtained from the underlying mutual interaction or shared relationship.

The machine-learning approach entails three major steps: (1) Extraction of important features from individuals' mobile trajectories; (2) Computation of similarity score between each two-individual pair based on the multi-dimensional features extracted in step 1; (3) Clustering of individuals into groups based on the pairwise similarity scores computed in step 2.

In the first step, we extract important mobility features from multiple dimensions that can better capture individuals' movement patterns in the physical environment. Building on the literature, we extract the mobility features from the following dimensions: (1) Temporal information such as time of day, day of week, weekend or holiday indicators, etc.; (2) Spatial information such as pairwise distance between two customers over time, crowdedness (density of customers) of a location over time, altitude (floor level), movement directions (compass degree from north), etc.; (3) Semantic information such as customers' visit probabilities to different locations, transition probabilities from one location to another, etc.; (4) Velocity information such as speed of movement over time, acceleration, etc.

In the second step, we compute the pairwise similarity score between each two-individual pair based on the multi-dimensional mobility features extracted in step 1. We first compute the pairwise similarity score under each of the four mobility dimensions described above. Such similarity scores can be calculated using various similarity functions such as cosine distance, histogram intersection or chi-square kernel (Liu e.g., 2013). Then, we combine the similarity scores from all the four dimensions using a weighted sum to compute the overall pairwise similarity score between two customers. We provide more details of this calculation in Appendix A.

In the third step, we use a graph-based clustering method to detect social groups of customers based on the similarity in their real-time movement patterns. The fundamental assumption of our approach is that customers who are in the same social group are highly likely to demonstrate similar movement patterns over time. Based on the pairwise similarity of consumers derived in the previous step, we can cluster similar individuals in real time. The main goal of this step is to identify clusters of consumers where the consumers within a cluster are similar to each other with regard to their real-time movement patterns but dissimilar to consumers not in the cluster. Overall, the intuition of our group detection approach is to identify groups of similar consumers based on the mobility features of individuals as they move together in a shopping mall.

For more technical details, we provide, in Appendix A, explanations of how we apply spatial-temporal data mining and machine-learning methods to extract individual mobility features, compute the pairwise similarity scores, and cluster groups of individuals using a graph-based clustering method.

### 3.1 Mobile Targeting Based on Offline Behavioral Trajectories and Real-Time Social Contexts

In this study, we examined the impact of mobile targeting on individual customers' behaviors under different real-time social contexts. We achieved this in two steps, which are outlined in the following two respective paragraphs.

First, we considered a variety of mobile targeting strategies including the industry's state-of-the-art approach with current-location-based targeting or random targeting. In fact, the literature suggests that mobile targeting based on customers' movement-trajectory patterns is more effective than the existing industry benchmark approaches (Ghose et al. 2016). Hence, we considered a similar approach using mobile trajectory-based targeting. The basic idea is to offer mobile recommendations to a customer from stores that are most frequently visited by customers with similar movement-trajectory patterns. This approach is similar to the collaborative filtering approach widely used in traditional recommender systems. We provide more details on how to generate the mobile trajectory-based targeting in Appendix B.

Second, and most importantly, we necessarily evaluated the effectiveness of those mobile targeting approaches by taking into consideration the consumer's algorithm-detected real-time social context. We particularly wanted to evaluate the impacts of different mobile targeting strategies based on different social contexts (e.g., solo shoppers vs. consumers who shop with friends or family). Our final goal was to design and measure the effectiveness of the mobile targeting strategy for individual consumers that accounts for not only consumers' own preferences but also their real-time social contexts.

In the following sections, we will discuss in more detail the implementation of our mobile targeting strategy, how we evaluate its effectiveness, and how we quantify, through randomized field experimentation, its causal impact on consumer purchasing behavior and store revenues.

## 4. A Randomized Field Experiment

To examine the effectiveness of the mobile trajectory-based targeting strategy, we designed and executed, in April 2015, a large-scale randomized field experiment in collaboration with one of the largest shopping malls in Asia.

### 4.1 Experimental Setting

The shopping mall contains over 300 stores spanning 1.3 million square feet. On average, it attracts over 100,000 visitors daily. At the entrance to the mall, if a consumer wanted to enjoy free WiFi, she was required to complete a Form A with information on age, gender, income range, credit card type (gold, platinum, gift card, others), and phone type (iPhone, Android, others). Then, at each store, when the consumer purchased a product, she was required to complete a Form B, which collected similar socio-demographic information as well as the amount spent and whether the purchase was related to a mobile coupon. We cross-validated Form A with Form B to confirm the accuracy of the individual-level information.

Once the consumer was connected to the WiFi, we were able to track the detailed mobile trajectory information during her visit to the shopping mall with precise time and location stamps. Finally, when the consumer left the mall, we conducted a short follow-up survey via mobile phone, asking whether or not she followed the mobile recommendations, whether she wanted to follow such recommendations in the future, her overall satisfaction with the shopping experience, and additional personal information (first-time visitor or not, WiFi user or not, shop alone or with others, money spent in the focal advertising store, total money spent in the mall).[2]

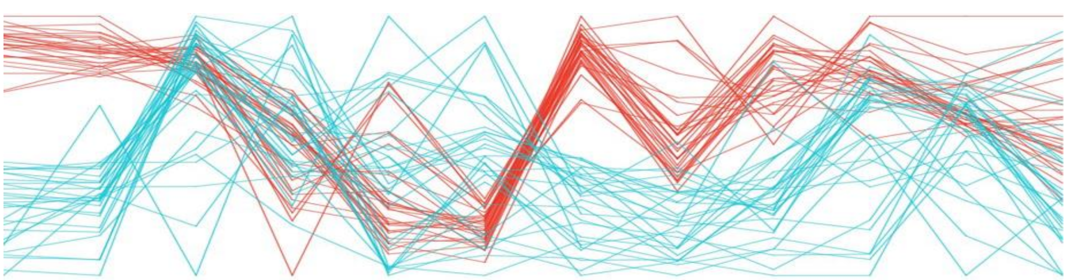

**Figure 1. Sample Mobile Trajectories of Consumers in Large Shopping Mall**

[2] Note that in the follow-up survey, the control group was not asked the two mobile-related questions (i.e., whether the mobile recommendations were followed, and whether such recommendations would be followed in the future). We used users' self-reported mobile redemption behavior from the survey as a source for verification of the redemption data we collected from the store sales. Furthermore, survey-based metrics such as "satisfaction rate" and "future-willingness-to redeem" are useful snippets of data in that they can indicate long-term effects of mobile advertising, which is an important topic of discussion amongst practitioners.

Figure 1 provides a sample of individual customers' movement trajectories upstairs and downstairs in the shopping mall. More specifically, the customer trajectories contain information such as what kinds of stores they visited, how long they stayed in each store, the transition probability between two stores, how fast they were walking, and so on. We were then able to generate mobile recommendations based on the four dimensions of mobility features extracted from the trajectory information (as described in the previous section).

### 4.2 Randomized Field Experiment Design

We designed our randomized experiment to contain the following four treatment groups:

- T1 (Single): Send mobile promotion to consumers who are shopping alone;
- T2 (Dyad): Send mobile promotion to consumers who are in a group of two;
- T3 (Triad): Send mobile promotion to consumers who are in a group of three;
- T4 (Co-Location): Send mobile promotion to consumers who are currently co-located with others, but not really in a social group.

We applied the group detection method to detect real-time social groups (see Section 3 above). We then counted the number of individuals in each group to identify singles, dyads, triads and co-locations. In this study, we focused only on groups with 1-3 people. [3]

Note that consumers who choose to shop under different social contexts above might have different inherent preferences for products. If so, then the selection of social contexts might be endogenous, and the direct difference in the consumer purchase outcome across the above four treatment groups may not be a proper measurement for the mobile treatment effect. To account for the potential selection bias for different shopping social contexts, we

[3] We found that the majority (over 90%) of customers traveled in groups of a size equal to or smaller than 3.

designed our experiment to further contain four control groups. In particular, we applied the group detection method to detect real-time social groups for all mall customers in real time. This allowed us to detect the social contexts for the non-treated baseline customers as well. This setting enabled us to use the non-treated customers' purchasing behavior in the various social contexts as a baseline to control for the potential inherent variation in consumer preferences among those social contexts. We will discuss in more details how we used a difference-in-differences method to identify the group-level treatment effect in Section 5.1. Our four control groups are the following:

- C1 (Control Single): Control group of consumers who are shopping alone;
- C2 (Control Dyad): Control group of consumers who are in a group of two;
- C3 (Control Triad): Control group of consumers who are in a group of three;
- C4 (Control Co- Location): Control group of consumers who are currently co-located with others, but not really in a social group.

Note that it is possible that our group detection algorithm might capture "false positive" groups. For example, two individuals might happen to move closely together in real time, but they do not really know each other and should not be identified as a social group. To account for such potential issues, we followed two approaches. First, we compared individuals' trajectory features in real time and calculated the pairwise similarity scores at granular time points (i.e., the frequency of comparison is dependent on the WiFi tracking system configuration; in our case, it was every 50 seconds). If the two individuals were always similar at each time point of their trajectories, they likely belonged to a true social group. Second, to further validate these algorithm-detected groups, we also conduct a survey for each customer (i.e., at the customer's registration for free WiFi) to ask their shopping social context (i.e., "how many people are you shopping with today," and "what is the relationship with you"). Based on this survey, we were able to determine with certainty whether a customer was indeed shopping in a social group, and if so, whether he/she was shopping with friend(s), child(ren) or significant other. By comparing the results from the two approaches, we are able to validate our results from the social-group detection process.

Each day, we randomly assigned 2500 unique users visiting the shopping mall to one of the above four treatment groups. In particular, we randomly selected 1000 single users to T1; for T2 and T3, we randomly selected 500 dyads and 500 triads based on the real-time group detection, and then selected a random user from each group to receive the treatment (i.e., mobile coupon); for T4, the co-location treatment group, we randomly selected 500 sets of co-located users in real time, and then selected a random user from each set to receive the treatment. Note that T4 was used mainly to control for the potential alternative explanation that individuals might behave differently because of the crowdedness of the environment (Andrews et al. 2016) rather than the group social dynamics. For control groups, we has done similar group assignment except these users were not treated with mobile promotions later. In particular, we randomly selected 2500 non-treated customers who were identified as single, dyad, triad, and co-location from all the mall shoppers. Similarly to the treatment groups, from the non-treated users we randomly selected 1000 singles to C1; we randomly selected 500 dyads, 500 triads and 500 co-locations to C2, C3, and C4.

We implemented the mobile coupons by sending short message service (SMS) texts. Note that to control for the potential bias related to the popularity or quality of the stores or products, we randomized the participation among 252 stores in the shopping mall for various categories including fashion, dining, supermarket, and others. To control for the potential bias introduced by the format and price discount level of the coupon, we considered different coupon designs with regard to both format and price discount, and randomized them among the four experimental groups. For example, for the same store, we randomized the level of price discount (e.g., 25% off, 33% off, or 50% off). For the same level of price discount, we also randomized the coupon format (e.g., “price 50% off” vs. “buy one get one free”) to minimize the potential bias the coupon format might introduce. Finally, to control for the potential bias due to the effectiveness of the mobile targeting algorithm, and meanwhile, to examine the performance of the different mobile targeting methods in various real-time social contexts, for each experimental group we randomized the algorithm design for mobile targeting among different approaches. In particular, we considered three types of algorithms for generation of the mobile recommendations: trajectory-based, current-location-based, and random-based. The latter two, widely used in industry today, were used as baselines in our experiment. [4]

Note that to implement current-location-based mobile targeting, we used a similar approach to that used in previous studies (e.g., Spiekermann et al. 2011, Luo et al. 2014). In particular, we defined “distance to a store” as the mobile user’s physical distance from the center of the store. We sent the real-time location-based mobile promotion to a consumer based on the store that had the shortest distance to her at the time the coupon was sent.

Moreover, to control for the potential bias introduced by the timing of the coupon, we randomized the timing of its sending. Note that for the efficiency and effectiveness of the mobile recommendation, we conducted trajectory mining based on a large pool of historic individual-consumer trajectories collected by the shopping mall in the previous year. This process allowed us to quickly identify trajectory similarity when a new customer walked into the shopping mall.

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[4] It is also important to note that these m-coupons are tied to a specific mobile phone number and cannot be exchanged between individuals. This alleviates concerns about any potential interference from possible exchanges.

Moreover, to avoid a "cold start," we waited for a random time period *t* (*t* >=10 mins) after the customer walked into the mall before sending any kinds of mobile coupons. Hence, for each customer in the treatment groups, we implemented the corresponding intervention after this random waiting period *t* and then recorded this "Critical Intervention Moment (CIM)" with a time stamp.

**Table 1a. Definitions and Summary Statistics of Variables in Treatment Groups**

| Variable | Definition | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| $T_1$ | Treatment Group 1, Single | .4000 | .4899 | 0 | 1 |
| $T_2$ | Treatment Group 2, Dyad | .2000 | .4000 | 0 | 1 |
| $T_3$ | Treatment Group 3, Triad | .2000 | .4000 | 0 | 1 |
| $T_4$ | Treatment Group 4, Co-Location | .2000 | .4000 | 0 | 1 |
| *Couple* | Shopping group that contains couple | .0997 | .2796 | 0 | 1 |
| *Friend* | Shopping group that contains friends | .1102 | .3012 | 0 | 1 |
| *Child* | Shopping group that contains child(ren) | .1005 | .3006 | 0 | 1 |
| *Other* | Shopping group of other types of composition | .1996 | .2995 | 0 | 1 |
| *Sunday* | Whether the visit was on Sunday | .1429 | .3499 | 0 | 1 |
| *Monday* | Whether the visit was on Monday | .1429 | .3499 | 0 | 1 |
| *Tuesday* | Whether the visit was on Tuesday | .1429 | .3499 | 0 | 1 |
| *Wednesday* | Whether the visit was on Wednesday | .1429 | .3499 | 0 | 1 |
| *Thursday* | Whether the visit was on Thursday | .1429 | .3499 | 0 | 1 |
| *Friday* | Whether the visit was on Friday | .1429 | .3499 | 0 | 1 |
| *Saturday* | Whether the visit was on Saturday | .1429 | .3499 | 0 | 1 |
| *Morning* | Whether the visit was in the morning | .3337 | .4704 | 0 | 1 |
| *Afternoon* | Whether the visit was in the afternoon | .3336 | .4710 | 0 | 1 |
| *Evening* | Whether the visit was in the evening | .3327 | .4712 | 0 | 1 |
| *Male* | Whether the customer is male customer | .3985 | .4262 | 0 | 1 |
| *Age* | Age of the customer | 42.473 | 16.2316 | 15 | 70 |
| *Income* | Monthly Income (1000 RMB) | 10.272 | 5.6168 | .5 | 20 |
| *First Time* | Whether the customer is first-time visitor | .2120 | .1789 | 0 | 1 |
| *Redemption* | Whether the customer redeemed the coupon | .2132 | .4038 | 0 | 1 |
| **Total # Observations: 52,500** | **Time Period: 4/1/2015-4/21/2015 (21 days)** | | | | |

To account for potential daily variation in a week, we conducted the same experiment for 21 consecutive days over three weeks from April 1, 2015 to April 21, 2015. Overall, we obtained

21,000 unique user responses from T1, and 10,500 unique user responses from each of the treatment groups T2−T4, which yielded us a total of 52,500 unique user responses from the four treatment groups. In the meantime, we also obtained 52,500 user responses from the four control groups C1-C4 correspondingly. For better understanding of our data, we present definitions and summary statistics for all of the variables in treatment groups in Table 1a. For randomization check, we also provide the corresponding variable statistics in control groups in Table 1b.

**Table 1b. Randomization Check for Variable Summary Statistics in Control Groups**

| **Variable** | **Definition** | **Mean** | **Std. Dev.** | **Min** | **Max** |
|---|---|---|---|---|---|
| $C_1$ | Control Group 1, Single | .4000 | .4899 | 0 | 1 |
| $C_2$ | Control Group 2, Dyad | .2000 | .4000 | 0 | 1 |
| $C_3$ | Control Group 3, Triad | .2000 | .4000 | 0 | 1 |
| $C_4$ | Control Group 4, Co-Location | .2000 | .4000 | 0 | 1 |
| *Couple* | Shopping group that contains couple | .0961 | .2862 | 0 | 1 |
| *Friend* | Shopping group that contains friends | .1114 | .3001 | 0 | 1 |
| *Child* | Shopping group that contains child(ren) | .1109 | .3025 | 0 | 1 |
| *Other* | Shopping group of other types of composition | .1980 | .2978 | 0 | 1 |
| *Sunday* | Whether the visit was on Sunday | .1429 | .3499 | 0 | 1 |
| *Monday* | Whether the visit was on Monday | .1429 | .3499 | 0 | 1 |
| *Tuesday* | Whether the visit was on Tuesday | .1429 | .3499 | 0 | 1 |
| *Wednesday* | Whether the visit was on Wednesday | .1429 | .3499 | 0 | 1 |
| *Thursday* | Whether the visit was on Thursday | .1429 | .3499 | 0 | 1 |
| *Friday* | Whether the visit was on Friday | .1429 | .3499 | 0 | 1 |
| *Saturday* | Whether the visit was on Saturday | .1429 | .3499 | 0 | 1 |
| *Morning* | Whether the visit was in the morning | .3336 | .4709 | 0 | 1 |
| *Afternoon* | Whether the visit was in the afternoon | .3336 | .4704 | 0 | 1 |
| *Evening* | Whether the visit was in the evening | .3328 | .4711 | 0 | 1 |
| *Male* | Whether the customer is male customer | .4012 | .4215 | 0 | 1 |
| *Age* | Age of the customer | 43.061 | 16.1190 | 14 | 69 |
| *Income* | Monthly Income (1000 RMB) | 10.210 | 5.6089 | .6 | 20 |
| *First Time* | Whether the customer is first-time visitor | .2138 | .1796 | 0 | 1 |
| *Redemption* | Whether the customer redeemed the coupon | -- | -- | -- | -- |
| **Total # Observations: 52,500** | | **Time Period: 4/1/2015-4/21/2015 (21 days)** | | | |

## 5. Main Results

In this section, we discuss our experimental results based on different levels of analysis. We first demonstrate our results from group-level analyses of the mean treatment effect. Then, we discuss our findings from individual-level analyses of the distribution of the treatment effect.

### 5.1 Group-level Diff-in-Diff Analysis

First, we were interested in the overall trend in customer behavior across different experimental groups. To obtain this, we conducted group-level mean analyses. We compared the daily group means (based on 21-day average) of consumer coupon-redemption rate, money and time spent in focal advertising store, total money and time spent in the shopping mall, and overall satisfaction rate. To examine the statistical significances of the differences in group means, we conducted a one-way ANOVA.

One potential issue that arose in the direct comparison of the group means is that a customer's decision on which social context to choose for this shopping trip might be endogenous. For example, if customers who are "shopaholic" tend to shop with friends in triads, then observing a higher amount of purchases associated with the triad groups might not indicate any impact related to the social context; rather, simply the inherent characteristics of customers might drive both their initial choice of social context and their purchasing decisions. To address this issue, we needed to better account for the baseline purchasing propensity of customers in different social contexts in the absence of any mobile intervention.

For this purpose, we conducted a group-level diff-in-diff analysis. Based on our experimental setting, we were able to obtain the individual trajectory data and purchase records from all of the mall customers, including the ones who had been randomly selected for our experiment as well as those who had not ("baseline customers"). Moreover, our group detection algorithm could be applied to all mall customers in real time, which allowed us to detect the social contexts for the non-experimental baseline customers as well. This setting thereby enabled us to use the non-experimental c1ustomers' purchasing behavior in the various social contexts as a baseline to control for the potential inherent variation among those contexts.

More specifically, we computed the first-level difference as the difference between customers in the same social context (single, dyad, triad, co-location) who had experienced the mobile intervention and who had not. We examined the average amount of money and time spent by each customer in the focal advertising store, and in the mall as well. Then, we could compute the second-level difference as the discrepancy in the first-level difference across the different social contexts. The results of the diff-in-diff comparison across different social contexts are summarized in Table 2.

**Table 2. Group-Level Diff-in-Diff Analysis (Daily Mean, 21-Day Period)**

| Group | Diff in Spending in Focal Store ($) | Diff in Spending in Mall ($) | Diff in Time in Store (min) | Diff in Time in Mall (min) |
|---|---|---|---|---|
| **$T_1$ (Single)** | 36.75 | 68.01 | 2.10 | 10.06 |
| **$T_2$ (Dyad)** | 42.62 | 95.16 | 4.08 | 16.24 |
| **$T_3$ (Triad)** | 66.71 | 128.31 | 6.16 | 22.12 |
| **$T_4$ (Co-Loc)** | 31.59 | 60.11 | 2.67 | 12.63 |

Note: The values in the table represent the first-level difference between customers in the same social context (single, dyad, triad, co-location) who had experienced the mobile intervention and who had not (i.e., with intervention – baseline without intervention)

We found that after accounting for the baseline purchasing propensity of customers in different social contexts (i.e., without mobile interventions), the differences in consumer behavior in the different social contexts were statistically significant. Consumers responded to mobile interventions differently when shopping alone compared with shopping with others. On average, a consumer who was in a group with others was 1.49 times more responsive to mobile promotions in focal store spending and 1.64 times more responsive in total spending in the mall than was a solo consumer. Moreover, the size of the group also mattered. On average, a consumer in a triad was 1.57 times more responsive to mobile promotions in focal store spending and 1.35 times more responsive in total spending in the mall than was a consumer in a dyad.

This group-level diff-in-diff analysis provided us with interesting evidence on the heterogeneity of customers' reactions to mobile interventions in different social contexts. In the next subsection, we will further examine this problem from an individual-customer level.

### 5.2 Individual-level Analyses

Beyond the group-level analyses, our unique data set acquired from the field experiment also allowed us to conduct individual-level analyses on the effect of mobile targeting on consumer coupon redemption and purchasing behavior. Specifically, we observed individual-level consumer characteristics (e.g., demographics), mobile promotion response, and purchasing behavior. Such data helped us examine the distribution of the treatment effect of mobile targeting as well as its interaction with consumer heterogeneity.

In our examination of the effect of mobile targeting on the likelihood of consumer response to mobile coupons in different real-time social contexts (i.e., single, dyad, triad, co-location), importantly, to control for the potential endogenous formation of social groups, we applied our proposed simultaneous equation model for both shopping social context and redemption probability at the individual-consumer level. As based on the literature (e.g., Ghose and Yang 2009), the model was implemented in a hierarchical Bayesian framework and estimated using Markov Chain Monte Carlo (MCMC) methods.

#### 5.2.1 Simultaneous Equation Model of Social Context and Redemption

We modeled the consumer's shopping context decision to shop alone or with a group (dyad or triad) as a function of consumer characteristics and control variables such as time of day and day of week. We then modeled the consumer coupon-redemption probability as a function of consumer characteristics, real-time social contexts (e.g., solo, couple, friend, child) and mobile targeting design (e.g., coupon type). To account for the potential heterogeneity in the mobile targeting effects, we include interaction effects among the consumer characteristics, social contexts and mobile-targeting strategies. Each model contained an unobserved error that was normally distributed with mean zero. To capture the unobserved co-variation between the shopping context and redemption decision, we assumed that the two error terms were correlated and followed the multivariate normal distribution with mean zero.

More specifically, we first modeled the probability of consumer *i* choosing shopping social context *k* as

$$p_{ik} = \frac{e^{U_{ik}^{Social}}}{1+\sum_{j=1}^{4} e^{U_{ij}^{Social}}}, \tag{3}$$

where $U_{ik}^{Social}$ is the utility for consumer *i* to shop under social context *k*. This could be modeled as

$$U_{ik}^{Social} = \overline{U_{ik}^{S}} + \varepsilon_{ik} = \beta_{0i} + \beta_{1i}\boldsymbol{T}_i + \beta_{2i}\boldsymbol{S}_k + \beta_{3i}\boldsymbol{T}_i \times \boldsymbol{S}_k + \varepsilon_{ik}, \tag{4}$$

where $\boldsymbol{T_i}$ is an individual-specific control vector containing the time and day indicators for consumer *i*'s shopping trip ($\boldsymbol{T_i}$ = [$Morning_i$, $Afternoon_i$, $Evening_i$, $Mon_i$, $Tue_i$, $Wed_i$, $Thu_i$, $Fri_i$, $Sat_i$, $Sun_i$]) and $\boldsymbol{S_k}$ is a vector containing characteristics and indicators related to the corresponding social context *k* consumer *i* has chosen ($\boldsymbol{S_k}$ = [$Frequency_k$, $Single_k$, $Dyad_k$, $Triad_k$, $CoLocation_k$, $Couple_k$, $Friend_k$, $Child_k$, $Other_k$]). We defined $Single_k$, $Dyad_k$, $Triad_k$, $CoLocation_k$, $Couple_k$, $Friend_k$, $Child_k$ and $Other_k$ as the binary indicators for a certain social context *k*. Note that in our model, we defined *k*=1…9, as indicative of all of the nine possible social contexts (single, dyad (couple), dyad (friend), dyad (child), dyad (others), triad (friend), triad (child), triad (others), co-location). Also, to control for the popularity of a certain social context among shoppers, we included an additional feature, *Frequency*$_k$, as the observed frequency of a social context *k*. We acquired this value from our historical data.

To capture the unobserved individual heterogeneity, we modeled all coefficients $\boldsymbol{\beta_i}$ as individual-specific random coefficients with subscript *i*. We assumed each random coefficient to vary along its population mean and with the individual-specific characteristics. More specifically, $\boldsymbol{X_i}$ is an individual-specific vector representing the characteristics of consumer *i* (i.e., age, gender, income level, credit card type, first-time visitor, phone type, etc.); $\Pi^{\boldsymbol{\beta}}$ is a coefficients matrix that measures how the individual social utility $U_{ik}^{Social}$ varies with observed individual characteristics.

$$\boldsymbol{\beta_i} = \begin{bmatrix} \overline{\beta_{0i}} \\ \overline{\beta_{1i}} \\ \overline{\beta_{2i}} \\ \overline{\beta_{3i}} \end{bmatrix} + \Pi^{\boldsymbol{\beta}} \boldsymbol{X_i} + \begin{bmatrix} \sigma_{0i} \\ \sigma_{1i} \\ \sigma_{2i} \\ \sigma_{3i} \end{bmatrix}. \tag{5}$$

We modeled the unobserved error terms to be correlated in the following way:

$$[\sigma_{0i} \quad \sigma_{1i} \quad \sigma_{2i} \quad \sigma_{3i}]' \sim MVN\left(0, \textstyle\sum^{\beta}\right), \tag{6}$$

where $\sum^{\beta}$ is a 4×4 covariance matrix.

Meanwhile, we modeled the probability of consumer *i* redeeming a mobile promotion under social context *k* as

$$q_{ik} = \frac{e^{U_{ik}^{Redeem}}}{1+e^{U_{ik}^{Redeem}}}, \tag{7}$$

where $U_{ik}^{Redeem}$ is the utility of consumer *i* redeeming a mobile coupon under social context *k*. It could be modeled as

$$U_{ik}^{Redeem} = \overline{U_{ik}^{R}} + \omega_{ik} = \theta_{0i} + \theta_{1i}\boldsymbol{T}_i + \theta_{2i}\boldsymbol{S}_k + \theta_{3i}\boldsymbol{T}_i \times \boldsymbol{S}_k + \theta_{4i}\boldsymbol{AD_i} + \theta_{5i}\boldsymbol{AD_i} \times \boldsymbol{S}_k + \omega_{ik}, \tag{8}$$

where $\boldsymbol{AD_i}$ is a control vector indicating the type of mobile promotion design. We considered the following five types of mobile promotion: *regular individual discount* (e.g., "50% off"), *social discount* (e.g., "buy one get one free"), *mobile trajectory-based*, *current-location-based*, and *random-based*.

Similarly, to capture the unobserved individual heterogeneity, we modeled all coefficients $\boldsymbol{\theta_i}$ as individual-specific random coefficients with subscript *i*. We assumed that each random coefficient to vary along its population mean and with the individual-consumer-specific characteristics.

$$\boldsymbol{\theta_i} = \begin{bmatrix} \overline{\theta_{0i}} \\ \overline{\theta_{1i}} \\ \cdots \\ \overline{\theta_{5i}} \end{bmatrix} + \Pi^{\boldsymbol{\theta}} \boldsymbol{X_i} + \begin{bmatrix} \tau_{0i} \\ \tau_{1i} \\ \cdots \\ \tau_{5i} \end{bmatrix}, \tag{9}$$

where $\Pi^{\boldsymbol{\theta}}$ is a coefficients matrix that measures how the individual redemption utility $U_{ik}^{Redeem}$ varies with observed individual characteristics $\boldsymbol{X_i}$. We modeled the unobserved error terms to be correlated in the following way:

$$[\tau_{0i} \quad \tau_{1i} \quad \cdots \quad \tau_{5i}]' \sim MVN\left(0, \textstyle\sum^{\theta}\right), \tag{10}$$

where $\sum^{\theta}$ is a 6×6 covariance matrix.

Finally, to capture the unobserved co-variation and potential endogenous relationship between consumers' shopping social contexts and their mobile coupon redemption decisions, we assume the two error terms in equations (4) and (8) to be correlated as follows:

$$[\varepsilon_{ik}, \omega_{ik}]' \sim MVN(0, \Omega_{ik}), \tag{11}$$

where $\Omega_{ik}$ is a 2×2 covariance matrix.

### 5.2.2 Likelihood Function

We modeled the consumer decision process in the following two steps: first, the consumer decides in which social context she will go shopping; second, according to that context, she will decide whether or not to respond to a given mobile promotion. Correspondingly, we expected to observe the following three types of events:

1) Consumer *i* chooses social context *k*; the probability of such an event is $p_{ik}$;
2) Consumer *i* redeems a mobile coupon in social context *k*; the probability of such an event is $p_{ik}q_{ik}$;
3) Consumer *i* does not redeem a mobile coupon in social context *k*; the probability of such an event is $p_{ik}$(1- $q_{ik}$).

Thus, we could derive the overall likelihood function as the joint probability of $M_k$ observed redemption events and $N_k$ observed non-redemption events in social context *k*, from a total number of *I* consumers as follows:

$$Likelihood = \prod_{i=1}^{I} \prod_{k=1}^{9} \{(p_{ik}q_{ik})^{M_k}[p_{ik}(1 - q_{ik})]^{N_k}\}. \tag{12}$$

### 5.2.3 Estimation Results

To estimate our model, we applied the MCMC methods using a Metropolis-Hastings algorithm with a random walk chain (Chib and Greenberg 1995). We ran the MCMC chain for 50,000 iterations and used the last 30,000 iterations to compute the mean and standard deviation of the posterior distribution of the model parameters.

We provide the main estimation results from the social context model in Table 3a. First, we found that on average, consumers were more likely to shop in groups than shop alone. When shopping in groups, they were more likely to shop in dyads and as couples. Second, we isolated an interesting trend, according to which high-income customers and older customers were less likely to shop in larger groups (i.e., triads). Meanwhile, we found that male customers relative to females were more likely to shop alone and less likely to shop with friends or children. This result indicates that the majority of shopping activities by male customers were either by themselves alone or with their significant other. Analysis of this social context model allowed us to explore the heterogeneity in the motivation of individuals' social contexts respecting shopping.

**Table 3a. Individual-Level Analysis – Social Context Model Estimation Results**

| | Mean | Age(ln) | Income(ln) | Male |
|---|---|---|---|---|
| Single | **-0.3280*<br>(0.0097)** | **0.1222*<br>(0.0208)** | 0.0639<br>(0.1112) | **0.8685*<br>(0.0178)** |
| Dyad | **0.9766*<br>(0.0228)** | **0.2799*<br>(0.0260)** | -0.0176<br>(0.0136) | 0.0599<br>(0.1218) |
| Triad | **0.1212*<br>(0.0276)** | **-0.2415*<br>(0.0026)** | **-0.1792*<br>(0.0138)** | 0.0231<br>(0.0218) |
| Couple | **0.5637*<br>(0.0122)** | **0.3572*<br>(0.0175)** | -0.0087<br>(0.0249) | 0.0447<br>(0.0398) |
| Friend | **0.2432*<br>(0.0027)** | **0.1255*<br>(0.0484)** | 0.0280<br>0.0254 | **-0.1881*<br>(0.0400)** |
| Child | **-0.1421*<br>(0.0055)** | 0.0244<br>(0.0479) | 0.1277<br>(0.2185) | **-0.7803*<br>(0.0378)** |
| *** indicates a 95% significance level.** | | | | |

We provide the main results from the mobile promotion redemption model in Table 3b, and the interaction effects in Table 3c. First, as consistent with our group-level analyses, we found significant heterogeneity in consumer response to mobile promotions in the different social contexts. On average, a consumer was more responsive to mobile promotion when shopping in groups, especially in groups of larger size (i.e., triads). Second, we uncovered consistent evidence of significant heterogeneity in the social dynamics for the different group compositions. For example, couples were less likely to respond to mobile promotions on average; high-income customers and male customers were more likely to respond to mobile promotions when shopping alone than when shopping with others in social groups. These findings from our individual-level analyses provide support for our previous group-level analyses, and demonstrate the importance of understanding the heterogeneity in customer response to mobile interventions in various social contexts. Our third principal result was significant heterogeneity in the interaction effect between mobile promotion design and real-time social contexts. A social discount coupon (e.g., “buy one get one free”) worked more effectively than an individual price discount (e.g., “50% price off”) on average. A social discount coupon, moreover, was especially effective for groups containing couples, and this effect became even more salient with age. However, the effectiveness of a social discount coupon decreased significantly for groups with children and for solo shoppers. Fourth and finally, we found consistent results, as were also found in Ghose et al. (2016), with regard to the fact that on average, the mobile trajectory-based targeting lead to the highest mobile coupon redemption rates as compared with the existing benchmark approaches such as current-location-based mobile targeting. Interestingly, our model-estimated interaction effects indicated that mobile trajectory-based targeting became even more effective for larger real-time social groups (i.e., triads) and for groups with high income and male customers.

## 6. Conclusions and Future Work

The proliferation of mobile technologies makes it possible to leap beyond the mere snapshot of consumers’ static location and context information. In this study, we examined consumers’ behavior and decisions under different social contexts in real time. Based on the results obtained, we herein propose a methodology whereby a consumer’s real-time social context can be detected automatically by mining her GPS-based mobile trajectories using machine-learning methods. To evaluate the effectiveness of different mobile targeting strategies in various real-time social contexts, we designed a large-scale randomized field experiment in a major shopping mall in Asia based on 52,500 unique user responses from 252 stores for a 21-day period in April 2015.

We found that by extracting and incorporating the real-time social contexts and behavioral trajectory of each individual consumer, we were able to better understand the effectiveness of mobile-targeting design. In particular, our results indicated significant heterogeneity in consumer behavior among the different real-time social contexts. Interestingly, we found that couples often had attention deficits with respect to mobile interventions and were the least responsive compared with the other social groups. Besides, high-income customers and male customers were more likely to respond to mobile promotions when shopping alone than when shopping with social groups. We also find significant heterogeneity in the interaction effect between mobile-targeting design and real-time social contexts. Interestingly, mobile trajectory-based targeting became even more effective for larger-sized social groups (i.e., triads). Our study demonstrates the potential of inferring individuals' social contexts in real time from their movement trajectories. Furthermore, it demonstrates the value of leveraging real-time social dynamics for improved mobile-targeting effectiveness.

On a broader note, our paper aims to bridge the understandings of individuals' offline behavioral trajectories, offline social dynamics, and their behavior and decision making. Our work can also be viewed as a further step in the large-scale and granular-level study of the digitization of human offline behavioral traces. We demonstrate the value of leveraging mobile and sensor technologies to digitize, measure, and understand individual behavior in different social environments—specifically its potential to improve consumers' digital experiences and firms mobile marketing strategies.

Our paper has some limitations, which no doubt will serve as promising avenues of future research. First, due to the technical limitations of our GPS tracking system, we could recruit only customers who were interested in accessing Wi-Fi, which meant that approximately 80% of the mall customers could participate.[5] However, this number could potentially improve in the future with a tracking system based on more advanced sensor technologies (e.g., wearable devices). Second, currently our mobile trajectory-based recommendations are based on inter-customer similarity. In the future, we will experiment with alternative strategies, for example, recommendation based on dissimilarity between customers. Finally, due to privacy policy of the mall, we could not identify repeat customer who visited the mall multiple times during the experimental period. Instead, we treated each individual trajectory as a unique customer. In the future, it will be interesting if we can identify return customers, or the same customers visiting different shopping malls, in studying individual long-term learning behavior facilitated by mobile interventions.

[5] We obtained this percentage based on the shopping mall's statistics on its historical customer visits and WiFi usage at the daily average levels.

**Table 3b. Individual-Level Analysis – Redemption Model Estimation Results**

| | Mean | Age(ln) | Income(ln) | Male |
|---|---|---|---|---|
| Single | 0.0588<br>(0.0426) | 0.0698<br>(0.0208) | **0.1895***<br>**(0.0110)** | **0.0775***<br>**(0.0146)** |
| Dyad | **0.7904***<br>**(0.0282)** | **0.2335***<br>**(0.0282)** | -0.0324<br>(0.0641) | 0.0573<br>(0.0914) |
| Triad | **1.0438***<br>**(0.0389)** | 0.0498<br>(0.0732) | 0.0106<br>(0.0433) | -0.0197<br>(0.0361) |
| Couple | **-0.2144***<br>**(0.0120)** | **0.1117***<br>**(0.0203)** | 0.0399<br>(0.0501) | 0.0414<br>(0.0380) |
| Friend | **0.2764***<br>**(0.0551)** | 0.0335<br>(0.1002) | 0.0191<br>(0.0234) | -0.0501<br>(0.1337) |
| Child | -0.0164<br>(0.0129) | -0.0457<br>(0.1292) | -0.0197<br>(0.1309) | -0.1390<br>(0.2887) |
| Social Coupon | **0.3624***<br>**(0.0888)** | 0.0683<br>(0.0882) | 0.0302<br>(0.1303) | 0.0766<br>(0.0939) |
| Trajectory | **2.1907***<br>**(0.0196)** | -0.1245<br>(0.2446) | **0.5012***<br>**(0.0471)** | **0.1349***<br>**(0.0690)** |
| Location | **0.9870***<br>**(0.0478)** | **-0.2008***<br>**(0.0633)** | 0.1006<br>(0.0983) | 0.0097<br>(0.0265) |

*** indicates a 95% significance level.**
**Social coupon indicates a social discount such as "buy one get one free."**

**Table 3c. Individual-Level Analysis – Interaction Effects between Mobile-Targeting Design and Social Contexts**

| | Mean | Age(ln) | Income(ln) | Male |
|---|---|---|---|---|
| Trajectory × Single | 0.0192<br>(0.0347) | -0.1129<br>(0.0987) | **0.1015***<br>**(0.0349)** | 0.0131<br>(0.0102) |
| Trajectory × Dyad | **0.1827***<br>**(0.0102)** | 0.1972<br>(0.1201) | -0.0623<br>(0.0512) | **0.0512***<br>**(0.0043)** |
| Trajectory × Triad | **0.3492***<br>**(0.0393)** | -0.2905<br>(0.2360) | **0.1895***<br>**(0.0802)** | **0.0429***<br>**(0.0045)** |
| Social Coupon × Single | **-0.1079***<br>**(0.0056)** | -0.0235<br>(0.1193) | -0.0337<br>(0.0293) | -0.0230<br>(0.0519) |
| Social Coupon × Dyad | **0.7924***<br>**(0.0625)** | **0.0754***<br>**(0.0275)** | **0.0579***<br>**(0.0221)** | 0.0178<br>(0.0215) |
| Social Coupon × Triad | 0.1908<br>(0.1131) | -0.0509<br>(0.1036) | -0.0643<br>(0.0414) | -0.0199<br>(0.0262) |
| Social Coupon × Couple | **0.3526***<br>**(0.0619)** | **0.1024***<br>**(0.0459)** | 0.0722<br>(0.0501) | -0.0493<br>(0.0552) |
| Social Coupon × Friend | 0.1196<br>(0.0708) | -0.0371<br>(0.0698) | -0.0203<br>(0.0385) | 0.0624<br>(0.0496) |
| Social Coupon × Child | **-0.4652***<br>**(0.0521)** | -0.0270<br>(0.0342) | -0.0145<br>(0.0224) | 0.0117<br>(0.0268) |

*** indicates a 95% significance level.**
**Social coupon indicates a social discount such as "buy one get one free."**

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# Appendix A. Technical Details on Mining Mobile Trajectories for Detection of Customers' Real-Time Social Contexts

In this appendix, we discuss how we automatically detect customers' real-time social contexts by mining the individual-level mobile trajectory data.

## Step 1: Extracting Multi-Dimensional Mobility Features from Individual Trajectories

We first discuss how we characterize individual mobility by extracting unique movement features from the various dimensions of individuals' mobile trajectories. Building upon the literature (Liu et al. 2013), we focus on four different dimensions of mobility features: temporal duration, spatial dispersion, semantic information, and movement velocity. Through these four mobility dimensions, we aim to capture similar patterns in individuals' physical movement from different perspectives. Note that this step allows us to learn consumer behavior not only through static locational or contextual proximity information, but also through dynamic movement similarity obtained from the underlying mutual interaction or shared relationship.

### A.1 Temporal Duration

We define temporal duration as containing information on the starting and ending time of the mobile trajectory, as well as the day-of-the-week index. More specifically, for each consumer, we extract a vector with three different temporal features: the starting time of a consumer's trajectory, the ending time of this trajectory, and the day index. These temporal features aim to capture the temporal activity pattern for real-life communities. To measure the similarity between two user trajectories in their temporal dimension, we adopt a similar approach as in Liu et al. (2013), which is to say, we use a temporal kernel function.

### A.2 Spatial Dispersion

Spatial dispersion measures the spatial alignment of different user trajectories. The close alignment of two trajectories might indicate high behavioral similarity between the two users. To compute the spatial closeness ("spatial similarity") between two customers over time, we consider the spatial distance, altitude (floor level) and movement directions (compass degree from north).

Note that to account for the popularity of the location, we inversely weigh the spatial similarity in proportion to the crowdedness of a specific location. Intuitively, this approach is similar to TF-IDF in text mining (e.g., Manning et al. 2008). More specifically, our method builds on the Global Alignment Kernel (GAK) to measure the spatial similarity between two trajectories (Cuturi 2011). The intuition is to capture the spatial closeness between two individuals over time. However, the popularity of a location can potentially bias the GAK. For example, if customers A, B, and 100 other customers are waiting in a concourse area, the spatial closeness between A and B becomes less informative of the similarity between them, because this concourse is clearly a popular location for almost everyone. However, if A and B are the only two customers in the concourse, this spatial closeness can instead reveal significant information on the similarity between them. Based on this intuition, we apply the GAK with the Inverse Proportion method (GAK-IP), which weighs the spatial similarity in inverse proportion to how many other people are co-located within the nearby area.

### A.3 Semantic Information

Semantic information aims to capture the contextual information related to the mobile trajectory. For example, it contains the stationary probabilistic distribution of individuals' visits to different stores in the mall, the time spent at each store, the time spent in transit from one store to another, and the transition probability between two stores.

More specifically, our goal is to measure the traverse statistics on the sites and to use them to measure the semantic similarity of user trajectories. If $L$ denotes the total number of spatially distinct sites, we can extract the following features of the sites visited by an individual user.

**Markov state transition.** We construct the Markov state transition matrix A $\in R^{L\times L}$, where A$(s_a, s_b)$ represents the transition probability from site $s_a$ to site $s_b$. To calculate A, we first collect all of the site transition pairs from the entire set of trajectories. Then, we count the number of occurrences of each transition pair. Finally, we perform column normalization of A, satisfying $\sum_{s_a} \mathrm{A}(s_a, s_b) = 1$.

**Temporal intervals.** We measure the time spent at each site and the time taken in transit from site $s_a$ to site $s_b$ to capture the "level of interest" shown by the users (e.g., when a shop is very "interesting," the shoppers might choose to stay longer) as well as the convenience of moving from site $s_a$ to site $s_b$, which indicates the semantic relation of the two sites.

Based on the semantic features extracted from the trajectories, we are able to compute the similarity between two user trajectories in their semantic dimension using the Histogram Intersection Kernel and the Radial Basis Function (RBF) Kernel (Liu et al. 2013).

### A.4 Movement Velocity

Finally, movement velocity contains information about the speed and acceleration of customers. The information encoded in the velocity pattern of customers is critical. However, we face two challenges when modeling the velocity pattern. The first challenge is that the overall length of each individual trajectory is different, which incurs difficulty in directly measuring their pairwise similarity in the velocity aspect. The second challenge is that even within the same individual mobile trajectory, velocity can vary largely at different times and locations; therefore, performing a the direct measurement is difficult as well. To account for these challenges and to make velocity comparable across heterogeneous individual trajectories, we normalize the velocity by applying a temporal pyramid matching method. This method, as inspired by the normalization method, calculates the image similarity in image classification while accounting for the different scales of resolution (Lazebnik et al. 2006).

More specifically, each trajectory has a velocity vector $v_k$ of unequal length. We uniformly quantize the velocity into $L$ levels. Given $v_k$ with length $l_k$, we calculate the normalized histogram

$h_k(0)$ on $v_k$. Then, we equally divide $v_k$ into two parts $v_k \rightarrow [v_k(1), v_k(2)]$, where both $v_k(1)$ and $v_k(2)$ are also velocity vectors of length $l_k/2$. We then calculate the normalized histograms $h_k(1)$ and $h_k(2)$ on $v_k(1)$ and $v_k(2)$, respectively, and normalize them so that $\sum h_k(1) + \sum h_k(2) = 1$. Consequently, we further equally divide $v_k(1)$ or $v_k(2)$ into two parts and calculate the histograms in the same way.

We continue this process until we achieve a predefined level. We then concatenate all of the histograms with predefined weights. Based on this approach, we can extract a velocity histogram $h_k$ of equal length with coarse-to-fine temporal resolution.

**Step 2: Measuring Pairwise Consumer Similarity from Multiple Trajectory Dimensions**

Based on the four dimensions of mobility features extracted in Step 1, we are able to infer consumer similarity. Specifically, we calculate the pairwise similarity score between two consumers by combining the features as follows:

$$S(i, i') = \sum_{m=1}^{M} \alpha_m S_m(i, i'), \alpha_m \geq 0, \sum_{m=1}^{M} \alpha_m = 1, \quad \text{[A1]}$$

where $S(i, i')$ denotes the similarity of consumer $i$ and consumer $i'$, $M$ denotes the number of dimensions of mobility features (here $M$ = 4), $S_m(i, i')$ denotes the similarity in the *m*-th dimension of mobility features, and $\alpha_m$ denotes the pre-assigned weights reflecting the specific interests of the problem domain.[6] The similarity score $S_m(i, i')$ in the *m*-th dimension of mobility features can be calculated using different similarity functions such as cosine distance, histogram intersection or chi-square kernel (Liu e.g., 2013).

[6] In this study, we obtain the weight $\alpha_m$ using two different approaches. First, we assume an equal weight of 0.25 for each dimension. Alternatively, we are able to learn the weight using machine-learning methods. In particular, we construct a training data set by manually rating the overall pairwise similarity between two trajectories on a scale from 0 to 1. Then, we use logistic regression to learn the corresponding weights based on the training set. For model evaluation, we use 10-fold cross-validation to avoid overfitting. We find the two approaches give us very consistent results. Hence, in our experiment, we applied equal weights to the four mobility dimensions.

**Step 3: Using Graph-based Clustering to Identify Groups of Customers**

Based on the pairwise similarity scores of consumers derived from the previous step, we can cluster similar individuals according to their pairwise similarities. The main goal of this step is to identify clusters of consumers wherein individuals are similar to each other with regard to their mobile trajectories but dissimilar to consumers not in the cluster.

Building on the literature, we use a graph-based clustering method to achieve our goal. In particular, we apply the Markov Clustering Algorithm (MCL) for dense sub-graph detection (Van Dongen 2012). This is an unsupervised learning method that allows for leveraging of a network structure to extract groups of similar items. MCL has several advantages (Satuluri et al. 2010) over distance-based clustering algorithms such as k-means (MacQueen 1967) and hierarchical clustering (Eisen et al. 1998). First, MCL relative to the k-means-based algorithm is less sensitive to the initial starting conditions. Second, MCL does not take any default number of clusters as an input; instead, it allows the internal structure of the network to determine the granularity of the cluster. Third, MCL, compared with many state-of-the-art network-clustering algorithms, is more noise-tolerant and effective at discovering the cluster structure (Brohee and Helden 2006, Liu et al. 2013).

Next, we construct an undirected probabilistic graph of individual trajectories, wherein each node in the graph represents a consumer's trajectory, and the weight on each edge between two nodes represents the pairwise similarity between two consumers. Therefore, if two consumers are very similar to each other in their trajectory patterns, the weight on the edge between the two corresponding consumer nodes would be very high. Our goal is to detect a set of highly connected sub-graphs (cliques) from the graph where the weight on the edge between each pair of two nodes in the sub-graphs is relatively high (i.e., a dense sub-graph). The basic intuition of the MCL algorithm is based on the idea of a random walk. The probability of visiting a connected node is proportional to the weight on the edge. In other words, the random walk will, after many steps, stabilize a network's dense regions. Regions thus stabilized will shape the clustered sub-graph and, thereby, reflect the network's intrinsic structure. The sub-graphs accordingly represent identified groups of similar customers. Figure A1 shows an example of the detected real-time user groups based on the individual mobile trajectories.

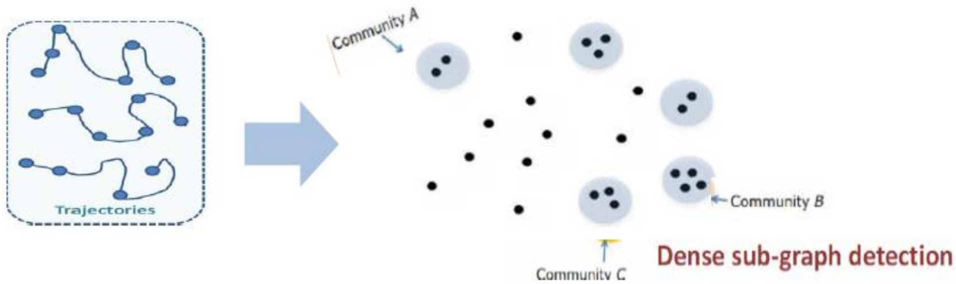


**Figure A1. Sample Groups Detected in Real Time Based on Individual Trajectories**

## Appendix B. Technical Details on Mobile Trajectory-based Targeting

For the design of mobile trajectory-based targeting, we apply a similar approach to that proposed by Ghose et al. (2016). The basic idea is to offer mobile recommendations to a customer from stores that are most frequently visited by customers with similar movement-trajectory patterns. This approach is similar to the collaborative filtering approach widely used in traditional recommender systems.

In practice, mobile recommendations are achieved by calculating the ratings of the consumers for the stores. More specifically, the rating of a consumer for a store is a measurement of her interest in that store: it is defined as the weighted sum of the time and money she spent there. Given consumer *i* and store *j*, one common approach to rating prediction is to average the ratings of similar consumers on store *j* as weighted by their similarity information. Thus, the average predicted rating can be calculated as

$$\hat{R}(i,j) = \frac{\sum_{i\prime=1}^{N_i} R(i',j)S(i,i\prime)}{\sum_{i\prime=1}^{N_i} S(i,i\prime)}, \tag{B1}$$

where $N_i$ denotes the number of consumers who are similar to consumer *i*, and $R(i', j)$ is the observed rating of consumer $i'$ on store *j*. Therefore, when generating the recommendation to consumer $i$, we will rank all of the predicted ratings between *i* and each store $j \in [1..J]$ and recommend the store that shows the highest predicted rating for consumer *i*. Note that if the consumer has already visited this store in the past, we will choose the next best store on the ranking list.