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Mobile Targeting Using Customer Trajectory Patterns

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Abstract. Rapid improvements in the precision of mobile technologies now make it possible for advertisers to go beyond real-time static location and contextual information on consumers. In this paper we propose a novel "trajectory-based" targeting strategy for mobile recommendation that leverages detailed information on consumers' physical-movement trajectories using fine-grained behavioral information from different mobility dimensions. To analyze the effectiveness of this new strategy, we designed a large-scale randomized field experiment in a large shopping mall that involved 83,370 unique user responses for a 14-day period in June 2014. We found that trajectory-based mobile targeting can, as compared with other baselines, lead to higher redemption probability, faster redemption behavior, and higher transaction amounts. It can also facilitate higher revenues for the focal store as well as the overall shopping mall. Moreover, the effect of trajectory-based targeting comes not only from improvements in the efficiency of customers' current shopping processes but also from its ability to nudge customers toward changing their future shopping patterns and, thereby, generate additional revenues. Finally, we found significant heterogeneity in the impact of trajectory-based targeting. It is especially effective in influencing high-income consumers. Interestingly, however, it becomes less effective in boosting the revenues of the shopping mall during the weekends and for those shoppers who like to explore across products categories. Our overall findings suggest that highly targeted mobile promotions can have the inadvertent impact of reducing impulse-purchasing behavior by customers who are in an exploratory shopping stage. On a broader note, our work can be viewed as a first step toward the study of large-scale, fine-grained digital traces of individual physical behavior and how they can be used to predict—and market according to—individuals' anticipated future behavior.

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Keywords: mobile targeting • trajectory mining • field experiment • GPS • location-based advertising

1. Introduction

Smartphone usage is expected to exceed 6.1 billion users worldwide by 2020 (Ericsson 2014). In this context, the proliferation of mobile and sensor technologies has contributed to the rise of location-based mobile advertising. Such advertising can enable businesses to deliver, to mobile users in real time, information on offers available in close proximity to them. Recent randomized field experiments have causally shown that mobile advertisements based on location and time information can significantly increase consumers' likelihood of redeeming a geo-targeted mobile coupon (Luo et al. 2014, Fang et al. 2015, Fong et al. 2015, Molitor et al. 2015, Dubé et al. 2017b), that mobile advertisements (ads) have a synergistic relationship with personal computer (PC) ads (Ghose et al. 2013), that the validity periods of mobile coupons influence their redemption rates (Danaher et al. 2015), and that understanding consumer context, such as the crowdedness of their environment (Andrews et al. 2016) or the weather (Li et al. 2017), is essential to mobile marketing effectiveness.

Beyond the real-time snapshot of the static geographic location and consumer contextual information, the overall mobile trajectory of each individual consumer can provide even richer information about their choices. "Trajectory" hereby refers to the physical–behavioral trace of an individual's offline movement. For example, it can include information on the detailed latitude and longitude where the individual has been to in the past, at what time, and for how long, as well as the associated contexts in real time. One unique advantage of such human trace data is their *granularity*. Ubiquitous mobile devices today enable recording of detailed human behavioral data that are both large scale and fine grained (e.g., updated every minute or second). Such information provides researchers with a new lens through which to study individual decision processes that previously had gone unobserved. Especially, considering the significant search costs of consumers in the offline world, such physical–behavioral traces of individuals can be highly informative in understanding consumer choices for real-time decision making. This information is analogous to the search-click stream data that researchers have been studying in the online environment. Mobile and sensor technologies allow digitalization of such individual behavioral trajectories in the offline environment at a highly granular level. Accordingly, understanding the digital traces of consumers' offline behavior and, thus, their inherent preferences, has become increasingly critical to businesses' efforts to improve their marketing strategies.

In particular, we are interested in the following research questions: (1) Can we better understand and predict consumer behavior by analyzing the large-scale, fine-grained physical–behavioral trace data enabled by mobile sensing devices? (2) How can we leverage such information to improve firms' mobile advertising strategies?

To answer these questions, we combine machine-learning methods and a randomized field experiment. Our results enable us to propose a novel trajectory-based mobile targeting strategy that infers consumer choices by leveraging detailed, granular-level information on their offline moving trajectories in four different mobility dimensions: temporal duration, spatial dispersion, semantic information, and movement velocity. We extract these multidimensional trajectory features from large-scale user-level behavioral trace data. From that trajectory information, we analyze and predict individual behavior using statistical and machine-learning methods, such as kernel-based similarity functions, dense subgraph detection algorithms for graph-based clustering, and collaborative filtering. Finally, to determine the effectiveness of this new marketing strategy, we conducted a randomized field experiment by partnering with a major shopping mall in Asia in June 2014. For recommendation effectiveness and efficiency, we conducted, in the year preceding the experiment, trajectory mining based on a large pool of historic individual trajectories in the mall. This allowed us to identify any trajectory similarity when a new individual entered the mall. Our experiment results were validated on the basis of 83,370 unique user responses for 14 days. Our group- and individual-level analyses of the fine-grained behavioral trace data demonstrated high consistency as well as significant value.

Our main findings are the following. Trajectory-based targeting can, compared with other, more conventional forms of mobile targeting, lead to a higher mobile redemption rate, faster redemption action, and a higher satisfaction rate among customers. Additionally, trajectory-based mobile targeting increases the total focal advertising store revenues as well as overall shopping mall revenues. Interestingly, it is less effective in boosting overall shopping mall revenues during the weekends and less effective as well for those shoppers who are in the process of exploring across different product categories. This finding suggests that businesses and marketers need to be careful when implementing mobile advertising strategies according to their different business goals.

Additionally, we found that trajectory-based targeting is especially effective in attracting high-income shoppers, which fact suggests the high potential of mobile advertising for converting customers with a higher customer lifetime value. Moreover, we found that in the absence of these advertising-induced interventions, the majority of customers do not naturally change their typical shopping patterns. However, trajectory-based ads can be designed to influence customers' shopping patterns. This finding suggests that trajectory-based targeting can be used not only to increase the efficiency of customers' current shopping behavior but also to nudge them toward changing their future shopping patterns and so generate additional revenues.

Our major contribution is our demonstration of two facts: the value of the mining of large-scale, fine-grained offline mobile trajectory information to the understanding and prediction of individual consumer behavior, and the importance of leveraging such information to improve the effectiveness of mobile marketing. Our analyses based on a combination of field experiments and surveys allowed us to quantify the economic effects of the new trajectory-based mobile targeting approach from a causal perspective. Our results can help advertisers to improve the design and effectiveness of their mobile marketing strategies.

2. Theoretical Background and Research Objectives

Our study aims to build causal connections between consumers' physical movements and economic choices. To achieve our goal, we draw upon prior literature and theory in economics, psychology, marketing, and social and decision sciences. In this section, we first discuss the theoretical motivation of our study's focus on four different mobility dimensions at the granular level: spatial dispersion, temporal duration, semantic information, and movement velocity. Then we discuss the related literature.

2.1. Theoretical Motivation for Understanding Different Trajectory Dimensions

2.1.1. Spatial Dispersion/Affinity. Physical location is one of the customer–environmental cues that mobile devices identify that influence behaviors and attitudes

(Bargh and Chartrand 1999). Theoretical advancements in economics and consumer behavior suggest that consumers' location choices are indicative of their product preferences (Bettman et al. 1998, McFadden 2001). The prior literature has demonstrated the existence of a location effect in the mobile context and quantified it on the basis of the effectiveness of location-based advertising (e.g., Molitor et al. 2015). Provost et al. (2015) investigated geo-social similarity and used consumer colocation data from mobile devices to construct a geo-social network of similar users. Their work builds on the "locale-affinity" social targeting literature (Provost et al. 2009). It has been found that geographic co-occurrences between individuals are very strongly predictive of individual homophily and friendship (Crandall et al. 2010) and that the homophily (McPherson et al. 2001) that has been used to explain the effectiveness of social-network targeting is actually due largely to the constraints of location-related opportunity (Kossinets and Watts 2009). The authors found that an individual's choice is heavily constrained by geo-location. Accordingly, location similarity is a significant driver of homophily and, thereby, a determinant of the effectiveness of targeted ads (Provost et al. 2015).

2.1.2. Temporal Duration. Temporal information from mobile trajectories, such as starting and ending times and day and hour indicators, influences how individuals evaluate and respond to mobile ads (e.g., Bargh et al. 2001). These factors, the prior literature suggests, activate different goals. Time of day, for example, significantly influences consumer purchasing decisions and responses to mobile ads (e.g., Baker et al. 2014). The interaction between the spatial and temporal dimensions, meanwhile, also has a significant impact on consumer behavior. Luo et al. (2014) found an interaction effect between time and location, in that mobile ads that match consumers' mindsets are more effective. Zubcsek et al. (2016) and Molitor et al. (2014) found a colocation effect on consumers who use the same mobile app in the same area at roughly the same time. In particular, they found that consumers who attend the same venues at the same time exhibit commonalities in their preferences (Zubcsek et al. 2015, 2016). Therefore, temporal information matters, and moreover, the interaction between temporal and spatial dimensions is critical for understanding individual decisions.

2.1.3. Semantic Dimension. The prior literature suggests that consumers' broader contexts (beyond immediate location and time) affect their responses to advertising and purchasing behavior (Zhang and Katona 2012, Choi et al. 2012, Andrews et al. 2016) and that consumers use their purchasing decisions to exert control over their environment (Levav and Zhu 2009). In our study, we extracted semantic information from mobile trajectories because it captures the contexts of the individual decision-making process as well as the long-term trends of the space (e.g., visit probability and time spent at each store measures the popularity of a store; transition probability among stores captures the relationship among stores and the layout of the mall).

2.1.4. Movement Velocity. Prior psychological studies have shown that the observed speed of movement affects individuals' perception of time duration; this perception, known as "psychological time" or "subjective time" (e.g., Brown 1995, Tomassini et al. 2011, Nyman et al. 2017), in turn affects many aspects of individual cognition, action, emotion, and final decisions (e.g., Grondin 2010, Droit-Volet 2013, Van Rijn 2014, Nyman et al. 2017). In addition, prior economic theory suggests that the time value of money affects individuals' opportunity costs (Marshall 1926). An important situation factor that reflects individuals' time value of money is the observed speed of their physical movements. For example, if an individual walks very slowly in the shopping mall, it may indicate that her time is less costly and that, correspondingly, her opportunity cost is quite low during that period of time. Therefore, building on the previous psychological and economic theories, in this study we extracted the fine-grained velocity information of individual movement to better understand individual heterogeneity and, thereby, more accurately predict individual decisions.

2.2. Related Literature

As based on the aforementioned theoretical motivation, our study builds on the following four streams of research.

2.2.1. Mobile Marketing and Location-Based Advertising. Mobile and location-based advertising is closely related to our present work. Researchers using randomized field experiments have causally shown that mobile advertisements based on location and time information can significantly increase consumers' likelihood of redeeming geo-targeted mobile coupons (Luo et al. 2014, Fong et al. 2015, Molitor et al. 2015, Dubé et al. 2017b). More recently, studies have shown that understanding consumers' hyper-context, for example the crowdedness of their immediate environment, is critical to marketers' evaluation of mobile marketing effectiveness (Andrews et al. 2016). Li et al. (2017) investigated how sunny and rainy weather affects consumers' incremental purchasing responses to mobile promotions. They found that purchasing responses to promotions are faster in sunny weather relative to cloudy weather, whereas they are slower on rainy weather. Our new study is distinct from all of the earlier ones in that instead of focusing on static location, time, or contextual information, it leverages detailed historical information on consumers' offline trajectories in the temporal, spatial, semantic, and velocity dimensions to infer their preferences, formulate a recommendation system and, thereby, enable the design of targeted mobile ads in the form of carefully curated mobile coupons.

Previous studies have examined consumer perceptions and attitudes toward mobile location-based advertising (e.g., Brunner and Kumar 2007, Xu et al. 2009). Gu (2012) examined both the short- and long-term sales effects of location-based advertising. Bart et al. (2014) studied mobile advertising campaigns and found them to be effective in increasing favorable attitudes and purchasing intentions for higher- (versus lower-) involvement products as well as for utilitarian products (versus hedonic). Finally, Dubé et al. 2017a) recently focused on consumers' self-signaling and prosocial behaviors, finding that price discounts can crowd out consumer self-inference of altruism for cause marketing.

2.2.2. Spatial–Temporal Mining and Trajectory Clustering. Our study builds on the spatial–temporal mining and trajectory clustering literature from machine learning. Researchers have studied trajectories using a variety of measures, including mining of frequent trajectory patterns for activity monitoring (Liu et al. 2012), the probability function of time (Gaffney and Smyth 1999), behavior-correlation representation (Xiang and Gong 2006), density-based distance function (Nanni and Pedreschi 2006), and trajectory-uncertainty measurement (Pelekis et al. 2011). Our method, in contrast to most of the prior work, is able to 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 clustering problems. Studies have used trajectory-based clustering for different broad objectives, such as discovering common subtrajectories (Lee et al. 2007) and identifying spatial structures (Ng and Han 2002). Such work, though, is based purely on spatial locations, rendering problematic its extension to incorporate semantic, velocity, or other information that may contain 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 disjoint groups of vertices within which connections are dense, but between which connections are sparser. However, 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 detecting communities of similar users purely on the basis of their movement trajectory patterns.

2.2.3. Consumers' Physical-Path Data Analysis. Our work also is related to previous marketing studies' analysis of consumers' physical-path data (e.g., Bradlow et al. 2005; Larson et al. 2005; Hui et al. 2009a, 2009b, 2013b). Physical-path data are defined as records of consumers' movements in a spatial configuration (Hui et al. 2009b). Such data contain valuable information for marketing researchers because they describe how consumers interact with their environment and make dynamic choices. For instance, recent studies on path data have found that understanding store traffic patterns can help retailers optimize store layouts (Vrechopoulos et al. 2004), understand consumers' shopping behavior (Hui et al. 2009a), and appreciate the relationship between consumer in-store travel distance and unplanned purchasing (Hui et al. 2013b).

Our study sets itself apart from all of the previous work, in two major ways. First, we digitized and analyzed consumers' physical-path data by accounting for multiple mobility dimensions beyond the location and time dimensions to characterize consumer movement patterns at a highly granular level (we will provide more details in Section 3). A major goal of our work was to understand the incremental value of the multidimensional fine-grained mobility information yielded by smartphones and mobile sensing devices, as compared with the more traditional coarse-grained consumer behavioral information (e.g., lists of stores visited, time/money spent in stores). We aimed to identify the situations in which fine-grained mobility data become more valuable than corresponding traditional data. As for the second way in which our work is distinct from the relevant literature, our foci of interest were when and how consumers' fine-grained movement patterns can help improve personalized mobile targeting in real time, how such personalized targeting will in turn impact consumers' physical behavior in the future, and how retailers can learn from these insights to better predict individual future behavior.

2.2.4. Behavior-Based Recommendation. Finally, our work is related to the stream of literature on recommendation systems, especially behavior-based recommendation. Even though link, content, and location can be viewed as key results of users' different behaviors, there has been little previous work on trajectory clustering models that can provide recommendation. In recommender systems, behavior models are proposed for different purposes, such as behavior monitoring and perceived system benefits (Nowak and Nass 2012), navigational patterns for modeling of relationships between users (Esslimani et al. 2009), determination of the effects of context-aware recommendations on customer purchasing behavior and trust (Adomavicius et al. 2011), and economic utility-based recommendation by mining users' search behaviors (Ghose et al. 2012, 2014). Compared with previous studies, one unique feature of the present study is our aim to model individual preferences on the basis of large-scale, fine-grained information extracted from individuals' heterogeneous offline behavior using mobile trajectories and offline contexts.

2.3. Overview of Research Objectives

We had two major research goals: (1) understand consumer behavior by analyzing large-scale, fine-grained mobility trajectory data and (2) leverage such information to improve mobile advertising strategies. To achieve our goals, we drew on prior theory and literature from economics, psychology, and marketing, as well as social and decision science. For a better understanding of our research goals and their theoretical motivations, we provide an overview of our research objectives in Figure 1.

3. A Machine-Learning Approach to Trajectory-Based Recommendation

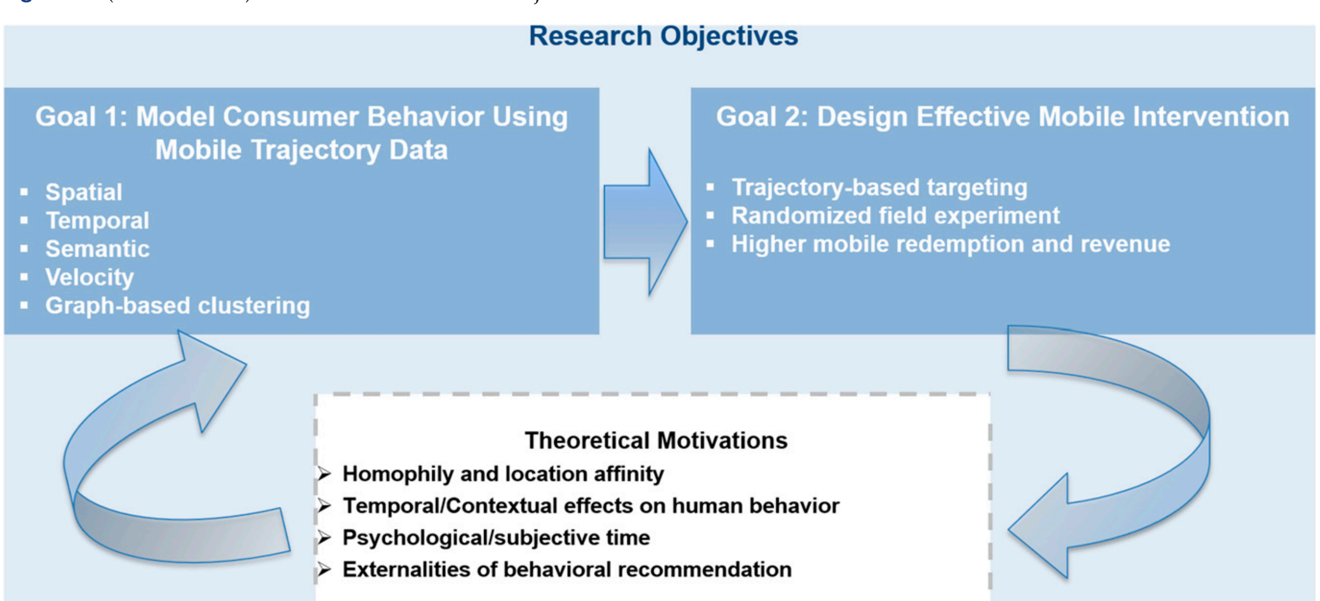
Building on the prior literature (Liu and Wang 2017), we propose a machine-learning approach to the design of a new system of trajectory-based recommendation. Our approach entails four major steps: (1) extraction of unique movement features from individuals' mobile trajectories, (2) computation of the similarity score between each two-individual pair according to the multidimensional features extracted in step 1, (3) clustering of individuals into groups according to the pair-wise similarity scores computed in step 2, and (4) offering of mobile recommendations to an individual from stores that are most frequently visited by similar individuals identified in step 3.

In the first step, we extract, from multiple dimensions, important mobility features that can better capture individuals' movement patterns in the physical environment. Building on prior theory and literature, we extract mobility features from the following four dimensions: (1) temporal information, such as time of day, day of week, weekend or holiday indicators, etc., (2) spatial information, such as pair-wise 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., and (4) velocity information, such as speed of movement over time, acceleration, etc.

In the second step, we compute the pair-wise similarity score between each two-individual pair according to the multidimensional mobility features extracted in step 1. We first compute the pair-wise similarity 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 χ^2 kernel. Then, to compute the overall pair-wise similarity score between two customers, we combine the similarity scores from all four dimensions into a weighted sum. Additional details are provided in Online Appendix A.

In the third step, we use a graph-based clustering method to detect social groups of customers according to the similarity in their 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. On the basis of the pair-wise similarity of consumers derived in the previous step, we can cluster similar individuals. The main goal of this step is to

Figure 1. (Color online) Overview of Research Objectives



identify clusters of consumers wherein the individuals are similar to each other with regard to their movement patterns but dissimilar to consumers not in the cluster. The intuition of our approach is to identify groups of similar consumers on the basis of their fine-grained mobility features.

Online Appendix A provides explanations of how, in steps 1–3, we apply spatial–temporal data mining and machine learning to extract individual mobility features, compute the pair-wise similarity scores, and cluster groups of individuals using a graph-based clustering method.

Finally, in the fourth step, we offer mobile recommendations to a customer from stores that are most frequently visited by customers with similar movement-trajectory patterns identified in the previous steps. This approach is similar to the collaborative filtering approach widely used in traditional recommender systems. Additional details on how the mobile trajectory-based recommendation is generated are provided in Online Appendix B.

4. Field Experiment

To evaluate the effectiveness of the trajectory-based mobile targeting strategy, we designed and executed a large-scale randomized field experiment in collaboration with one of the largest shopping malls in Asia in June 2014.

4.1. Experimental Setting

The shopping mall contains more than 300 stores spanning 1.3 million square feet. On average, it attracts more than 100,000 visitors daily. At the entrance of the shopping 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). At each store, when the consumer purchased a product, she was required to complete a "form B," which requested similar socio-demographic information plus the amount spent and whether the purchase was related to a mobile coupon. We cross-validated forms A and B to check the accuracy of the individual-level information. We dropped consumers whose interform information was not consistent.

Once the consumer connected to the WiFi, we were able to obtain detailed mobile trajectory information 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 she had followed the mobile recommendation, whether she wanted to follow such recommendations in 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).[1]

Additional details on data collection and indoor localization techniques are provided in Online Appendix C. Figure C.1 in Online Appendix C provides examples of movement trajectories of individual customers traveling upstairs and downstairs in the shopping mall. The trajectories contain information such as what kinds of stores the customers visited, how long they stayed in each store, the transition probability between two stores, how fast they were walking, global positioning system (GPS) location coordinates, and time and date indicators. On the basis of the four mobility-feature dimensions extracted from the trajectory information (as described in the previous section), we were able to generate mobile recommendations.

4.2. Randomized Experimental Design

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

1. Control group (C): Do not send any mobile ad;
2. Treatment group 1 (T1, Random): Send mobile ad from randomly selected store;
3. Treatment group 2 (T2, Location): Send mobile ad based on current location information;
4. Treatment group 3 (T3, Trajectory): Send mobile ad based on trajectory information.

We sent mobile coupons by short message service texts. Note that to control for the potential bias introduced by the store-level characteristics, we randomized the participation among 252 stores according to various categories, including fashion, dining, supermarket, and so on. To control for the potential bias introduced by the coupon type, 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" versus "buy one get one free") to minimize any potential bias introduced by the coupon format.[2] Moreover, to confirm that our results were comparable across groups, we considered the same set of mobile ads (in terms of both format and price discount) used in T1 as those used in T2 and T3. The only difference was that whereas the ads were tailored in T2 and T3, they were sent randomly in T1. It is also important to note that the coupons were each tied to a specific mobile phone number and could not be exchanged between individuals. This alleviated concerns about potential interference between units from possible exchanges.

Note that to design real-time location-based mobile ads (T2), we used an approach similar to that used in previous studies (e.g., Spiekermann et al. 2011, Ghose et al. 2013, 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 ad to a consumer on the basis of the store that had the shortest distance to the consumer at that time.

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

Moreover, to avoid any "cold start," we waited for a random time period (≥10 minutes) after the customer walked into the mall before sending the mobile coupon. In practice, we randomly drew, from our database for all the experimental users, a waiting time t between 10 minutes and the max time customers spent in the mall.[3] If the user was assigned to any of the three treatment groups, we implemented the corresponding intervention after t and then recorded this *critical intervention moment* (CIM) with a time stamp. If the user was assigned to the control group, we only recorded this CIM, without implementing any intervention. Note that the CIM time stamp was important to our subsequent analyses, in that it allowed us to identify the shopping transition stage of each customer upon intervention.

On each day, we randomly assigned approximately 6,000 unique consumers to one of the four groups. To account for potential daily variation in a week, we conducted the same experiment for 14 consecutive days over two weeks from June 9, 2014, through June 22, 2014. Our experiment results are based on 83,370 unique user responses for that 14-day period.[4] For better understanding of our data, we provide definitions and summary statistics for all variables in Table 1.

5. Main Results

In this section, we discuss our experimental results based on different levels of analysis. First, we present the segment profile from the trajectory-based clustering. Then, on the basis of the overall group-level analyses, we demonstrate our experimental results on the mean treatment effect. Finally, to further examine the distribution of the treatment effect at each customer level, we build individual-level models for analyses. Finally, we summarize our main findings.

5.1. Segment Profile from Trajectory-Based Clustering and Consumer Type

5.1.1. Segment Profile. First, we zoomed into each consumer segment identified from our trajectory-based clustering analysis described in Section 4.2. Our graph-based Markov Clustering Algorithm (MCL) algorithm identified a total of 10 clusters among all our experimental users according to the mobility-pattern similarity.[5] We labeled these clusters cluster 1 to cluster 10. The demographic distributions of consumer age (Shopper_Age), income (Shopper_Income), and gender (Shopper_IsMale) across the 10 clusters are illustrated in Figure 2. Interestingly, on the basis of pair-wise t-tests, we found no statistical differences in the demographic variables among a majority of the clusters.[6] This seems to suggest that the clustering results based on fine-grained trajectory data might have captured some additional, unobserved consumer heterogeneity beyond the traditional demographic dimensions of age, income, and gender.

5.1.2. Consumer Type. Second, we are interested in understanding the potential shopping "stages" of consumers. Previous marketing and psychology literature has suggested that shoppers move through different stages of deliberation during their purchasing decision processes and, further, that shopping stage can have a significant impact on purchasing decisions (e.g., Strong 1925, Howard and Sheth 1969, Lambrecht et al. 2011). This theory is grounded in information-processing theory, which postulates how consumers behave while making decisions (Bettman et al. 1998). When customers are in early shopping stages (e.g., "exploration," "awareness"), they are more likely to engage in impulse purchases (e.g., Stern 1962, Engel and Blackwell 1982). Exposure to random stimuli during exploration often creates new needs or reminds shoppers of temporarily forgotten needs, resulting, thereby, in unplanned purchases (Kollat and Willett 1967). By contrast, when customers are in later stages (e.g., "engagement," "consideration"), they are unlikely to respond to random stimuli because they tend to be more-focused shoppers.

We approximated a shopper's stage by looking into her store transition activities. The assumption was that if a shopper is currently in a "focused" shopping stage, for example, seriously searching for a size 8 pair of women's sandals, she would be more likely to visit multiple women's shoe stores in a row (e.g., hopping from Aldo, to Nine West, and then to Aerosoles). Whereas, if a shopper is currently in an "exploration" stage, she might casually look around in whatever store is near her. As a result, the customer is more likely to visit various different categories of stores in a row (e.g., hopping from Nine West to Toys R Us, and then to Starbucks). Therefore, we defined two types of shoppers according to their store transition activities at the CIM:[7] (1) single-category shopper (the most recently visited two stores belong to the *same category*, "ShopperFocus" = 1) and (2) multicategory shopper (the most

Table 1. Definitions and Summary Statistics of Variables

Variable	Definition	Mean	Standard deviation	Min	Max
C	Control group, do nothing	0.2472	0.4436	0	1
T1	Treatment group 1, random ads	0.2434	0.4291	0	1
T2	Treatment group 2, location-based ads	0.2517	0.4546	0	1
T3	Treatment group 3, trajectory-based ads	0.2577	0.4656	0	1
Sunday	Whether the visit was on Sunday	0.1416	0.3681	0	1
Monday	Whether the visit was on Monday	0.1406	0.3413	0	1
Tuesday	Whether the visit was on Tuesday	0.1433	0.3399	0	1
Wednesday	Whether the visit was on Wednesday	0.1418	0.3405	0	1
Thursday	Whether the visit was on Thursday	0.1418	0.3404	0	1
Friday	Whether the visit was on Friday	0.1431	0.3397	0	1
Saturday	Whether the visit was on Saturday	0.1477	0.3754	0	1
Morning	Whether the visit was in the morning	0.3217	0.4013	0	1
Afternoon	Whether the visit was in the afternoon	0.3407	0.4900	0	1
Evening	Whether the visit was in the evening	0.3376	0.4762	0	1
TimeElapse	Time elapse between receiving a coupon and redeeming it	11.0285	9.3735	0	36
Male	Whether the customer is male customer	0.3475	0.4762	0	1
Age	Age of the customer	37.9407	10.8149	18	64
Income	Monthly income (1,000 RMB)	16.9538	8.0364	3	33
FirstTimeVisit	Whether the customer is first-time visitor	0.0227	0.1488	0	1
Credit Type	Indicator: gold, platinum, gift card, or other	—	—	—	—
Phone Type	Indicator: iPhone, Android, or other	—	—	—	—
Shopping Alone	Whether the customer is shopping alone	0.2612	0.4395	0	1
Store Category	Indicator: fashion, beauty, home, kids, grocery, restaurant, electronics, or others	—	—	—	—
Coupon Type	Indicator for different coupon designs	—	—	—	—
ShopperFocus	Whether the customer is transit between stores with the same category upon intervention.	0.4376	0.4961	0	1
Redeem	Whether the customer redeemed the coupon	0.2484	0.4973	0	1
FutureRedeem	Whether the customer is willing to redeem the coupon in the future	0.3451	0.4754	0	1
TimeSpentStore	Total time spent in the focal advertising store (min)	16.2987	19.0283	0	51
TimeSpentMall	Total time spent in the mall (min)	60.7137	36.2377	9	273
Satisfaction	Satisfaction rate of customer	2.8813	1.7551	0	5
S_i^{store}	Customer *i*'s total spending in the focal advertising store (RMB)	45.9112	98.7585	0	5,028
S_i^{mall}	Customer *i*'s total spending in the mall (RMB)	140.8533	1,812.7680	0	15,742
R_{jt}	Store *j*'s total revenue on day *t* (RMB)	4,522.7460	30,012.1300	0	635,000
No. of users in control group (daily average)		1,472			
No. of users in treatment group 1 (daily average)		1,449			
No. of users in treatment group 2 (daily average)		1,499			
No. of users in treatment group 3 (daily average)		1,535			
Time period: 6/9/2014–6/22/2014 (14 days)					
Total no. of observations		83,370			

recently visited two stores belong to *different categories*, "ShopperFocus" = 0). For example, if at the CIM, a shopper is visiting a women's clothing store but the previous store she visited was a gift shop, she belongs to the multicategory type.[8] Interestingly, our results showed that the majority of shoppers belonged to that type, which means that, at the CIM, most shoppers were transiting between stores from different categories. Note that the purpose of considering the shopper type at the CIM is to better control for potential time-varying consumer heterogeneity upon treatment. The identification of these two types of shoppers has implications for our following discussion on the heterogeneity of treatment effects.[9]

5.2. Group-Level Analyses

5.2.1. Mean Treatment Effect. To understand the mean treatment effect, we conducted group-level analyses. We compared daily group means (14-day average) according to consumer coupon-redemption rate, time elapsed until redemption, money and time spent in store, total money spent, and time spent in the mall. To examine the statistical significance of the differences in group means, we first conduct a one-way analysis of variance (ANOVA) test, in which we tested the null hypothesis that the samples in all groups were drawn from populations with the same mean value. Our findings rejected the null hypothesis, indicating that not all of the group means were the same. To further

Figure 2. (Color online) Distribution of Shopper Demographics and Types Across 10 Mobility Clusters

Note. Shopper_IsMale: 1: Male, 0: Female; Shopper_FocusType: 1: Single-Category, 0: Multi-Category.

Table 2. Group-Level Comparisons (Daily Mean, 14-Day Period)

Group	Redeem rate (%)	Future redeem rate (%)	Money spent in focal store ($)	Total money spent in mall ($)	Time elapse until redeem (minutes)	Satisfaction rate	Time spent in focal store (minutes)	Total time spent in mall (minutes)
C, Control (n = 1,472)	—	—	—	84.98	—	**2.6**	—	**46.75**
T1, Random (n = 1,449)	**16**	**21**	**23.50**	88.19	**16.43**	2.1	**28.19**	**56.72**
T2, Location (n = 1,499)	**23**	**34**	**41.25**	**166.87**	**12.83**	**3.2**	**13.24**	**63.85**
T3, Trajectory (n = 1,535)	**31**	**56**	**56.78**	**193.06**	**4.55**	**4.3**	**9.82**	**71.98**

Note. Significant values are in bold ($p < 0.05$, pair-wise t-test between each two groups).

test the statistical significance of each treatment effect as well as the difference between each two treatment effects, we then conducted a pair-wise t-test between each two groups. The results from the group-level analyses are provided in Table 2. Our findings show that the majority of the numbers (group means) are statistically different from each other at the $p < 0.05$ level (which are highlighted in bold). We found that on average, the new trajectory-based mobile targeting can lead to a statistically significant increase in coupon-redemption rate, and in fact, there was higher overall spending in the shopping mall compared with the baseline strategies. In particular, we found that on average, the trajectory-based mobile targeting strategy led to a 34.78% increase in the coupon-redemption rate when compared with the static-location-based targeting strategy, and a 93.75% increase when compared with random targeting.

Interestingly, we also found that the new strategy can lead to a significantly lower amount of time customers spend in the focal advertising store (9.82 minutes versus 13.24 minutes/28.19 minutes), but higher revenues ($56.78 versus $41.25/$23.50). This finding indicates, significantly, that trajectory-based mobile targeting can help make customers' shopping experiences more efficient. We also noted that on average, the random targeting strategy performed the worst. Such strategy can lead to lower customer satisfaction due to the potential annoying effect from the improper ads.

5.2.2. Subgroup Analyses: Shopper Demographics. To understand how treatment effects can vary across different demographic subgroups, we compared them by breaking down the overall subject population into different demographic subgroups, especially age and income. We first conducted a one-way ANOVA test to examine the statistical significances of the differences among all subgroup means. Then, we conducted a pair-wise t-test to further test the statistical significance of each treatment effect as well as the difference between each two treatment effects. Table 3 shows the average coupon-redemption rates for the different demographic subgroups.[10] Our findings show that the majority of the subgroup means are statistically different from each other at the $p < 0.05$ level (which means are highlighted in bold).

First, we found that on average, the youngest age group (i.e., 20–30 years) was more responsive to mobile targeting, whereas the oldest age group (i.e., 40–50+ years) was less responsive, regardless of the mobile ad type. Second, on average, customers with the lowest monthly income (i.e., 2k–5k RMB) were more active in redeeming mobile ads. However, they were not sensitive to ad type. This finding is reasonable, in that low-income customers are often price sensitive; accordingly, any mobile ads that offer price promotions would attract them. Contrastingly, customers with the highest monthly income (i.e., 11k–50k RMB) were, on average, not as responsive to random ads (2%) or regular

Table 3. Demographic Subgroup-Level Redemption Rate Comparisons (Daily Mean, 14-Day Period)

Group/redeem rate	Age 20–30 years (%)	Age 30–40 years (%)	Age 40–50+ years (%)	Income $2K–$5K (%)[a]	Income $6K–$10K (%)[a]	Income $11K–$50K (%)[a]
C, Control (n = 1,472)	—	—	—	—	—	—
T1, Random (n = 1,449)	25	**17**	**6**	**34**	**15**	**2**
T2, Location (n = 1,499)	24	**20**	**10**	**33**	**23**	**9**
T3, Trajectory (n = 1,535)	**21**	**23**	**15**	**32**	**27**	**36**
No. of observations	**1,436**	**1,836**	**2,208**	**1,401**	**1,755**	**2,311**

Note. Significant values are in bold ($p < 0.05$, pair-wise t-test between each two groups).
[a]Income is measured in RMB at the monthly level.

static-location-based mobile ads (9%). However, they were highly attracted by trajectory-based ads (36%). Our findings indicate the potential of trajectory-based targeting in attracting high-end customers to achieve better customer lifetime value. These high-income customers are usually the "challenging type" and, owing to high opportunity costs, are likely to be extremely sensitive to the quality of targeting (Ratchford 1982). They will not respond to a mobile ad just because it offers a lower price, unless it is carefully designed and is a good fit for their personal preferences.

5.3. Individual-Level Analyses

Our unique data set acquired from the field experiment also allowed us to conduct, beyond the group level, individual-level analyses on the effects of mobile targeting on consumer coupon redemption and purchasing behavior. In particular, we observed individual consumer characteristics, targeting responses, consumer spending in the focal advertising store, and total spending in the mall. Such data helped us to examine the distribution of the treatment effect through interaction with individual-level consumer heterogeneity.

5.3.1. Individual Mobile-Coupon-Redemption Rate. First, we aimed to examine the effects of different mobile targeting strategies (i.e., random, current-location-based, and trajectory-based) on the likelihood of consumer mobile-coupon-redemption behavior. To do so, we applied a logit model at the individual-consumer level and modeled the consumer coupon-redemption rate as a function of consumer characteristics and different mobile targeting strategies. To account for the potential variation in the effects induced by consumer heterogeneity, we considered various interaction effects between the consumer characteristics and the different mobile targeting strategies. More specifically, we modeled the utility for consumer i to redeem a mobile coupon as follows:

$$\begin{aligned} U_i &= \overline{U}_i + \varepsilon_i \\ &= \alpha + \beta \boldsymbol{X}_i + \gamma \boldsymbol{T}_i + \lambda \boldsymbol{D}_i + \delta \boldsymbol{T}_i \times \boldsymbol{X}_i \\ &\quad + \varphi \boldsymbol{T}_i \times \boldsymbol{D}_i + \varepsilon_i, \qquad \varepsilon_i \sim i.i.d.,\ EV(0,1), \end{aligned} \tag{1}$$

where $\boldsymbol{X}_i$ is an individual-specific vector representing the characteristics of consumer i (e.g., age, gender, income level, credit card type, first-time visitor, shop alone, phone type) and the shopper type (multicategory versus single-category), $\boldsymbol{T}_i$ is an individual-specific vector containing three binary indicators for the three treatment groups (T_1, Random; T_2, Location; T_3, Trajectory), $\boldsymbol{D}_i$ represents other individual-specific control variables for consumer i (e.g., day of week, time of day, coupon type, advertising store category), and ε_i is an individual stochastic error term that captures any randomness during consumer i's decision process. We assumed that the error term follows the type I extreme value distribution.

Hence, the probability of consumer i redeeming a mobile coupon is

$$Pr_i(Redeem = 1) = \frac{exp(\overline{U}_i)}{1 + exp(\overline{U}_i)}. \tag{2}$$

We conducted a series of analyses considering the different interaction effects together as well as separately and found that the results remained highly robust. The estimation results are provided in Table 4 (columns I–VII). First, we found that on average, trajectory-based mobile targeting outperformed all the baseline targeting strategies at the individual-consumer level. In particular, the mobile trajectory-based ads showed, relative to the corresponding effects by location-based ads and random ads (i.e., the baseline), the most significant and highest positive effect on the customer coupon-redemption rates.[11] Second, we found significant differences in coupon-redemption behavior at different times. On average, customers were more likely to redeem a mobile coupon during weekends than during weekdays and were more likely to respond to a mobile coupon in the afternoon and evening than in the morning.

Interestingly, our model with interaction effects demonstrated significant heterogeneity in the treatment effect. In particular, we noted that trajectory-based targeting is especially effective for male customers and high-income customers. Prior theory and literature in the fields of marketing and psychology have shown that men are more utilitarian and goal-oriented during shopping, whereas women are more hedonic-oriented (e.g., Otnes and McGrath 2001, Hansen and Jensen 2009). In other words, men see themselves as fulfilling an instrumental need (Campbell 1997) to "grab and go" (Otnes and McGrath 2001). Therefore, close behavioral targeting based on mobile trajectory is likely to meet the needs of male customers quickly, and thus too, to be perceived as more effective by male customers. Regarding the finding on heterogeneity from high-income customers, the reason trajectory-based coupons work better for such shoppers is likely that they often have high opportunity costs (e.g., Ratchford 1982). So, well-designed behavioral targeting can be more attractive to them in enabling them to save time and the associated opportunity costs.

Moreover, although mobile trajectory-based ads perform, on average, the best in increasing coupon-redemption responses, they become less effective during the weekends. In column II of Table 4, the interaction effect between Trajectory and Weekend is –0.1503 (versus 3.1132 for weekday), indicating a significantly lower effect from trajectory-based ads during weekends than during weekdays. Meanwhile, we found that trajectory-based targeting is more effective in attracting single-category than multicategory shoppers. In column VI of Table 4, the interaction effect between Trajectory and ShopperFocus (which is an indicator for single-category-type shoppers) is statistically significant and positive (1.2449).

Table 4. Logit Model Estimation Results on Consumer Redemption Probability

Variables	Coefficient I	Coefficient II	Coefficient III	Coefficient IV	Coefficient V	Coefficient VI	Coefficient VII
Random (T1)	—	—	—	—	—	—	—
Location (T2)	1.0862 (0.0507)***	1.0888 (0.0550)***	1.0441 (0.0541)***	0.9788 (0.0585)***	1.0416 (0.0641)***	2.0198 (0.0773)***	1.8070 (0.0702)***
Trajectory (T3)	3.1608 (0.0534)***	3.1132 (0.0577)***	3.2514 (0.0579)***	3.2879 (0.0790)***	3.2220 (0.0785)***	4.0649 (0.0835)***	4.2208 (0.0918)***
ShopperFocus	−2.0430 (0.0478)***	−2.0445 (0.0478)***	−2.0491 (0.0478)***	−2.0433 (0.0478)***	−2.0468 (0.0478)***	−5.3961 (0.0749)***	−5.3872 (0.0712)***
Weekend	0.0277 (0.0138)*	0.0411 (0.0155)**	0.0302 (0.0152)*	0.0276 (0.0158)*	0.0225 (0.0162)*	0.0240 (0.0133)*	0.0374 (0.0172)**
Afternoon	0.4241 (0.0152)***	0.4235 (0.0165)***	0.4051 (0.0124)***	0.3953 (0.0206)***	0.4313 (0.0189)***	0.4456 (0.0251)***	0.4511 (0.0400)***
Evening	0.2897 (0.0988)**	0.2912 (0.0960)**	0.2309 (0.1615)*	0.2199 (0.1762)*	0.2418 (0.0912)**	0.2268 (0.1072)*	0.2534 (0.1126)*
FirstTimeVisitor	0.0115 (0.0263)	0.0108 (0.0271)	0.0121 (0.0219)	0.0185 (0.0279)	0.0642 (0.0305)*	0.0115 (0.0232)	0.0532 (0.0502)
Male	−0.0968 (0.0240)***	−0.0972 (0.0240)***	−0.0828 (0.0482)*	−0.0970 (0.0240)***	−0.0992 (0.0240)***	−0.0946 (0.0243)***	−0.1034 (0.0471)**
ln(Age)	−1.0545 (0.1376)***	−1.0564 (0.1376)***	−1.0462 (0.1376)***	−1.0547 (0.1375)***	−1.0366 (0.1376)***	−1.0358 (0.1391)***	−1.0465 (0.1377)***
ln(Age)^2	0.3090 (0.0980)***	0.3231 (0.0807)***	0.2905 (0.0981)***	0.3101 (0.0808)***	0.2877 (0.0824)***	0.2823 (0.0991)***	0.2935 (0.0973)***
ln(Income)	0.7579 (0.8110)	0.7570 (0.8111)	0.7506 (0.8112)	0.7664 (0.8123)	0.7616 (0.8122)	0.7614 (0.8125)	0.7578 (0.8149)
ln(Income)^2	−0.0763 (0.1398)	−0.0762 (0.1398)	−0.0748 (0.1399)	−0.0768 (0.1414)	−0.0750 (0.1409)	−0.0742 (0.1401)	−0.0797 (0.1418)
Credit Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phone Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shopping Context	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Advertising Store Category	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coupon Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Random × Weekend	—	—	—	—	—	—	—
Location × Weekend	—	0.0076 (0.0259)	—	—	—	—	0.0029 (0.0281)
Trajectory × Weekend	—	−0.1503 (0.0383)**	—	—	—	—	−0.1108 (0.0557)*
Random × Male	—	—	—	—	—	—	—
Location × Male	—	—	−0.0523 (0.0650)	—	—	—	−0.0236 (0.0590)
Trajectory × Male	—	—	0.1230 (0.0591)**	—	—	—	0.1205 (0.0543)**
Random × Income	—	—	—	—	—	—	—
Location × Income	—	—	—	0.0383 (0.0553)	—	—	0.0641 (0.0551)
Trajectory × Income	—	—	—	0.0446 (0.0062)***	—	—	0.0346 (0.0061)***
Random × FirstTimeVisit	—	—	—	—	—	—	—
Location × FirstTimeVisit	—	—	—	—	−0.0723 (0.0918)	—	−0.0717 (0.0906)
Trajectory × FirstTimeVisit	—	—	—	—	−0.0166 (0.0542)	—	−0.0178 (0.0565)
Random × ShopperFocus	—	—	—	—	—	—	—
Location × ShopperFocus	—	—	—	—	—	0.1144 (0.2644)	0.1654 (0.2645)
Trajectory × ShopperFocus	—	—	—	—	—	1.2449 (0.0904)***	1.2454 (0.0904)***

Note. Total no. of observations: 62,762.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.001$.

This result indicates that the treatment effect from trajectory-based targeting is approximately 30.63% higher for single-category than for multicategory shoppers (the latter was estimated through the baseline coefficient of the Trajectory dummy, 4.0649). In the meantime, the negative estimate for ShopperFocus (−5.3961) indicated the baseline effect of using random targeting on the single-category shoppers. It suggested that random ads would work more effectively for multicategory than for single-category shoppers.

Our findings from the individual-level analyses are interesting. The weekend effect has long been explored in studies, which have found that individuals behave very differently during weekends than weekdays in various domains such as finance (French 1980), medicine (Cram et al. 2004), crime (Jacob and Lefgren 2003), etc. Warner and Barsky (1995) found that in the retail shopping sector, consumers become less time-sensitive and more explorative during the weekends. Customers who visit a shopping mall during the weekends or explore multiple store categories might not have a concrete purchasing plan. As a result, for such customers, being exposed to a random promotion can significantly increase the likelihood of impulse purchases. On the other hand, behavioral ads closely targeted according to mobility trajectories tend to lead customers directly to focal advertising stores. As a result, such ads might constrict the scope and physical range of exploration, thus reducing the probability of impulse purchases, especially for customers who are in an unplanned shopping stage. Previous studies have found that shorter in-store travel distance has a negative effect on consumers' in-store impulse-buying behavior (Hui et al. 2013a, b) and that historical-behavior-based targeting may lead to less variety-seeking behavior from consumers (e.g., Fleder and Hosanagar 2009). Our findings are in line with these previous studies, which fact suggests that marketers need to carefully design their targeted campaigns according to the shopping context and mental stage of customers.

To further validate our findings, we examined consumer total spending and in-mall travel distance in addition to the mobile coupon redemption rate. We found very consistent results, which we will discuss in the following subsections.

5.3.2. Individual Spending in Focal Advertising Store. In addition to the short-term promotion effect on the individual-level coupon-redemption rate, we are interested in the potential advertising effect on individual spending. We first conducted analyses on individual consumer spending in the focal advertising store. We modeled consumer i's spending in the focal advertising store, S_i^{store}, as

$$\begin{aligned} S_i^{store} &= \alpha^{store} + \beta^{store}\boldsymbol{X}_i + \gamma^{store}\boldsymbol{T}_i + \lambda^{store}\boldsymbol{D}_i \\ &\quad + \delta^{store}\boldsymbol{T}_i \times \boldsymbol{X}_i + \varphi^{store}\boldsymbol{T}_i \times \boldsymbol{D}_i + \varepsilon_i^{store}, \end{aligned} \tag{3}$$

where $\varepsilon_i^{store} \sim$ *i.i.d.*, $N(0,1)$. Again, we conducted a series of analyses by considering different interaction effects together or separately. We found that the results remained highly robust. We provide the estimation results in Table 5 (columns I–VII).

We found that, on average, trajectory-based mobile targeting outperformed all the baseline targeting strategies in individual consumer spending in the focal advertising store. In column I, the average effect of the trajectory-based targeting is 1.96 times that of current-location-based ads (7.8902 versus 4.0201) and 3.74 times that of random ads (7.8902 versus 2.1108). Similarly, we uncovered significant time-level and day-level heterogeneity. On average, customers tended to spend more in the focal advertising store during weekends and in the afternoon and evening. Meanwhile, we also found that on average, female customers tended to spend significantly more money than male customers at the focal store.

On the other hand, interestingly, we did not find any significant interaction effects between various mobile targeting strategies and different consumer characteristics.[12] This seems to indicate the absence of any significant heterogeneity in the *direct* effect of mobile ads on individual consumer spending at the focal advertising store. In other words, the focal advertising store always benefited from well-designed mobile ads. Trajectory-based targeting led to the highest increase in focal-store spending, followed by static-location-based targeting, and then random targeting.

5.3.3. Individual Total Spending in Shopping Mall. Meanwhile, we conducted an individual analysis on consumer total spending in the entire shopping mall. We modeled the overall spending of consumer i in the mall, S_i^{mall}, as

$$\begin{aligned} S_i^{mall} &= \alpha^{mall} + \beta^{mall}\boldsymbol{X}_i + \gamma^{mall}\boldsymbol{T}_i + \lambda^{mall}\boldsymbol{D}_i \\ &\quad + \delta^{mall}\boldsymbol{T}_i \times \boldsymbol{X}_i + \varphi^{mall}\boldsymbol{T}_i \times \boldsymbol{D}_i + \varepsilon_i^{mall}, \end{aligned} \tag{4}$$

where $\varepsilon_i^{mall} \sim$ *i.i.d.*, $N(0,1)$. Similarly, we conducted several analyses by considering different interaction effects together or separately. We found the estimation results to be highly consistent across the different models. The corresponding results are provided in Table 6 (columns I–VII).

First, we uncovered consistent evidence on the average treatment effects of mobile ads. Column I of Table 6 indicates that, on average, trajectory-based mobile targeting was the most effective in increasing consumer total spending in the shopping mall (4.8576), as compared with the corresponding effects of static-location-based ads (3.7420) and random ads (2.6783). Additionally, we found consistent and significant positive effects from weekend customers and females. We also found that income had a diminishing positive effect on consumer overall spending in the mall.

Table 5. Estimation Results on Consumer Spending (ln) in the Focal Advertising Store

Variable	Coefficient [I]	Coefficient [II]	Coefficient [III]	Coefficient [IV]	Coefficient [V]	Coefficient [VI]	Coefficient [VII]
Random (T1)	2.1108 (0.9126)**	2.1281 (0.9023)**	2.1186 (0.9123)**	2.1191 (0.9163)**	2.1211 (0.9066)**	2.1127 (0.8920)**	2.3319 (1.0016)**
Location (T2)	4.0201 (0.9033)***	4.0177 (0.8957)***	4.0181 (0.8934)***	4.0197 (0.9121)***	4.0214 (0.8873)***	4.0192 (0.9200)***	4.3246 (1.0712)***
Trajectory (T3)	7.8902 (0.8930)***	7.8841 (0.8761)***	7.8829 (0.8803)***	7.9011 (0.9002)***	7.8925 (0.8608)***	7.8256 (0.8706)***	8.1518 (1.2093)***
ShopperFocus	−0.3457 (0.1903)*	−0.3444 (0.1902)*	−0.3454 (0.1896)*	−0.3449 (0.1901)*	−0.3447 (0.1903)*	−0.3155 (0.1812)*	−0.3125 (0.1780)*
Weekend	1.0079 (0.7262)*	1.1889 (0.7865)*	1.0056 (0.7258)*	1.0062 (0.7212)*	1.0069 (0.7251)*	1.0082 (0.7183)*	1.1870 (0.7896)*
Afternoon	1.2011 (0.5101)**	1.2012 (0.5101)**	1.2010 (0.5102)**	1.2014 (0.5104)**	1.2009 (0.5101)**	1.2016 (0.5098)**	1.2018 (0.5101)**
Evening	1.7915 (0.6350)**	1.7914 (0.6349)**	1.7919 (0.6350)**	1.7916 (0.6352)**	1.7915 (0.6350)**	1.7911 (0.6353)**	1.7918 (0.6357)**
FirstTimeVisitor	0.6822 (0.5129)	0.6824 (0.5131)	0.6819 (0.5123)	0.6823 (0.5129)	0.6769 (0.5122)	0.6818 (0.5126)	0.6780 (0.5122)
Male	−0.7663 (0.3875)*	−0.7651 (0.3810)*	−0.7867 (0.3712)**	−0.7646 (0.3711)**	−0.7652 (0.3802)*	−0.7689 (0.3757)*	−0.7893 (0.3755)**
ln(Age)	0.0671 (0.2655)	0.0667 (0.2654)	0.0670 (0.2655)	0.0672 (0.2657)	0.0673 (0.2657)	0.0674 (0.2656)	0.0680 (0.2659)
ln(Age)^2	0.0063 (0.0134)	0.0060 (0.0133)	0.0058 (0.0134)	0.0059 (0.0134)	0.0060 (0.0136)	0.0058 (0.0136)	0.0055 (0.0140)
ln(Income)	−0.1495 (0.2833)	−0.1503 (0.2839)	−0.1499 (0.2841)	−0.1763 (0.2615)	−0.1511 (0.2841)	−0.1498 (0.2821)	−0.1749 (0.2637)
ln(Income)^2	0.0532 (0.1157)	0.0538 (0.1161)	0.0541 (0.1164)	0.0782 (0.1224)	0.0528 (0.1150)	0.0533 (0.1152)	0.0791 (0.1209)
Credit Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phone Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shopping Context	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Advertising Store Category	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coupon Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Random × Weekend	—	0.2835 (0.1532)*	—	—	—	—	0.3132 (0.1820)*
Location × Weekend	—	−0.0312 (0.2124)	—	—	—	—	−0.0317 (0.2128)
Trajectory × Weekend	—	0.1387 (0.2120)	—	—	—	—	−0.1277 (0.2223)
Random × Male	—	—	−0.0126 (0.0139)	—	—	—	−0.0179 (0.0181)
Location × Male	—	—	−0.0335 (0.0378)	—	—	—	−0.0235 (0.0227)
Trajectory × Male	—	—	0.0236 (0.0275)	—	—	—	0.0187 (0.0254)
Random × Income	—	—	—	0.0014 (0.0120)	—	—	−0.0017 (0.0116)
Location × Income	—	—	—	0.0738 (0.1125)	—	—	0.0723 (0.1103)
Trajectory × Income	—	—	—	−0.2285 (0.3336)	—	—	0.2051 (0.3141)
Random × FirstTimeVisit	—	—	—	—	0.0157 (0.0473)	—	0.0189 (0.0511)
Location × FirstTimeVisit	—	—	—	—	−0.0772 (0.0769)	—	−0.0725 (0.0992)
Trajectory × FirstTimeVisit	—	—	—	—	−0.1028 (0.0786)	—	−0.1293 (0.0832)
Random × ShopperFocus	—	—	—	—	—	−0.0214 (0.1283)	−0.0121 (0.1098)
Location × ShopperFocus	—	—	—	—	—	0.0987 (0.2011)	0.1022 (0.2391)
Trajectory × ShopperFocus	—	—	—	—	—	0.2893 (0.1856)*	0.3480 (0.1935)*

Note. Total no. of observations: 83,370.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.001$.

Table 6. Estimation Results on Consumer Total Spending (ln) in the Shopping Mall

Variable	Coefficient I	Coefficient II	Coefficient III	Coefficient IV	Coefficient V	Coefficient VI	Coefficient VII
Random (T1)	2.6783 (0.1168)***	2.4080 (0.1193)***	2.0711 (0.1198)***	2.5074 (0.2311)***	2.2334 (0.2326)***	2.3472 (0.1673)***	2.8003 (0.1236)***
Location (T2)	3.7420 (0.0949)***	3.8740 (0.0974)***	3.5529 (0.0992)***	3.5644 (0.2266)***	3.9938 (0.2282)***	3.5605 (0.1233)***	3.3839 (0.1017)***
Trajectory (T3)	4.8576 (0.8867)***	4.6190 (0.0917)***	4.2702 (0.0926)***	4.2106 (0.2205)***	4.6501 (0.2220)***	4.2351 (0.1133)***	4.0391 (0.2165)***
ShopperFocus	–0.2251 (0.0523)***	–0.2209 (0.0523)***	–0.2237 (0.0523)***	–0.2135 (0.0523)***	–0.2246 (0.0523)***	–0.2952 (0.0797)***	–0.2812 (0.0771)***
Weekend	1.6596 (0.0241)***	1.1758 (0.0062)***	1.6623 (0.0241)***	1.6600 (0.0241)***	1.6627 (0.0241)***	1.6592 (0.0241)***	1.1774 (0.0062)***
Afternoon	1.0128 (0.5101)*	1.0127 (0.5103)*	1.0127 (0.5102)*	1.0128 (0.5102)*	1.0126 (0.5104)*	1.0132 (0.5104)*	1.0129 (0.5102)*
Evening	1.6187 (0.6272)**	1.6065 (0.6238)**	1.6028 (0.6243)**	1.6041 (0.6241)**	1.6056 (0.6245)**	1.6078 (0.6244)**	1.6023 (0.6257)**
FirstTimeVisitor	1.1023 (0.8601)	1.0089 (0.8542)	1.1019 (0.8587)	1.1025 (0.8605)	1.1155 (0.8579)	1.1002 (0.8580)	1.1168 (0.8672)
Male	–0.7130 (0.0241)***	–0.7148 (0.0241)***	–0.8502 (0.0617)***	–0.7132 (0.0241)***	–0.7124 (0.0241)***	–0.7122 (0.0241)***	–0.8594 (0.0662)***
ln(Age)	0.9743 (0.9652)	0.9961 (0.9641)	0.9738 (0.9635)	0.9764 (0.9654)	0.9756 (0.9638)	1.0004 (0.9650)	1.0186 (0.9625)
ln(Age)^2	–0.0765 (0.1354)	–0.0801 (0.1253)	–0.0769 (0.1352)	–0.0772 (0.1355)	–0.0776 (0.1352)	–0.0802 (0.1354)	–0.0841 (0.1350)
ln(Income)	1.2194 (0.2100)***	1.1997 (0.2098)***	1.2647 (0.2097)***	1.0073 (0.2197)***	1.1907 (0.2193)***	1.2131 (0.2100)***	1.0470 (0.2191)***
ln(Income)^2	–0.1602 (0.0399)***	–0.1561 (0.0399)***	–0.1686 (0.0399)***	–0.1640 (0.0420)***	–0.1722 (0.0420)***	–0.1588 (0.0399)***	–0.1643 (0.0419)***
Credit Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phone Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Shopping Context	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Advertising Store Category	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coupon Type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Random × Weekend	—	1.1932 (0.0783)***	—	—	—	—	0.9589 (0.1782)***
Location × Weekend	—	0.0999 (0.0506)*	—	—	—	—	0.0905 (0.1762)
Trajectory × Weekend	—	–0.4133 (0.0751)***	—	—	—	—	–0.5019 (0.2610)*
Random × Male	—	—	0.0452 (0.0578)	—	—	—	0.0483 (0.0778)
Location × Male	—	—	0.0988 (0.0976)	—	—	—	0.1026 (0.0763)
Trajectory × Male	—	—	0.1790 (0.0075)***	—	—	—	0.1202 (0.0477)**
Random × Income	—	—	—	0.0828 (0.0661)	—	—	0.0291 (0.0276)
Location × Income	—	—	—	0.1037 (0.0770)	—	—	0.1057 (0.0868)
Trajectory × Income	—	—	—	0.2486 (0.0573)***	—	—	0.2809 (0.0757)***
Random × FirstTimeVisit	—	—	—	—	0.1956 (0.0865)**	—	0.1843 (0.2135)
Location × FirstTimeVisit	—	—	—	—	–0.0877 (0.1674)	—	–0.0635 (0.1980)
Trajectory × FirstTimeVisit	—	—	—	—	0.0912 (0.1277)	—	0.1101 (0.1012)
Random × ShopperFocus	—	—	—	—	—	–0.1630 (0.0294)***	–0.1201 (0.0272)***
Location × ShopperFocus	—	—	—	—	—	0.0603 (0.0345)*	0.0610 (0.0378)*
Trajectory × ShopperFocus	—	—	—	—	—	0.4513 (0.0903)***	0.4142 (0.0616)***

Note. Total no. of observations: 83,370.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.001$.

Second, interestingly, we found significant interaction effects between the various mobile targeting strategies and different consumer characteristics with respect to individual total spending at the entire mall level. This finding suggests significant heterogeneity in the *indirect* effect of mobile ads on individual consumer spending in the mall. In particular, we determined that male customers were more sensitive to well-designed behavioral mobile ads (i.e., in column III, the interaction effect between Trajectory and Male was statistically significant and positive, 0.1790). This result is in line with Underhill (1999), who concluded that men prefer better guidance while shopping. Our results suggest that well-designed mobile advertising can help provide better shopping guidance. Moreover, we found that high-income customers were more sensitive to well-designed mobile ads. Trajectory-based ads became significantly more effective for such customers than for others (i.e., in column IV, the interaction effect between Trajectory and Income was statistically significant and positive, 0.2486). This result is consistent with our previous finding from group-level analyses. It demonstrates the potential of trajectory-based mobile targeting for attracting high-end customers in achieving better customer lifetime value. In addition, as is consistent with our previous findings, we found that random ads were more effective for first-time visitors (i.e., in column V, the interaction effect between Random and FirstTimeVisit was statistically significant and positive, 0.1956, whereas the other two interaction effects were not statistically significant).

We also found consistent evidence that trajectory-based mobile targeting became less effective during the weekends, followed by static-location-based targeting. By contrast, the random targeting strategy became much more effective during the weekends. In particular, in column II, the interaction effect between Trajectory and Weekend was −0.4133 (versus 4.6190 for weekdays), that between Random and Weekend was 1.1932 (versus 2.4080 for weekdays), and that between Location and Weekend was 0.0999 (versus 3.8740 for weekdays). Therefore, the trajectory-based targeting became 8.95% less effective during the weekends, whereas the random targeting became 49.6% more effective during the weekends.

Furthermore, we noticed a similar trend, in that trajectory-based targeting worked more effectively for the single-category shoppers, whereas random ads were more attractive to the multicategory shoppers (i.e., in column VI, the interaction effect between Trajectory and ShopperFocus was 0.4513 and that between Random and ShopperFocus was −0.1630). Interestingly too, we noticed that the scale of the interaction effect between Location and ShopperFocus was very small (0.0603). This indicated that current-location-based ads demonstrated a similar level of effectiveness to both types of shoppers.

5.4. Robustness Tests

To further account for the unobserved heterogeneity and to better interpret our findings, we conducted four sets of robustness tests: (I) store-level fixed effects and random effects to control for store-level heterogeneity, (II) ad-category-level and ad-level matching to further control for store-level heterogeneity,[13] (III) separate group-level and individual-level analyses for each day to control for day-level heterogeneity, and (IV) alternative definition of "ShopperFocus" dummy by using the velocity information. We found our results remained highly consistent. Details on these tests are provided in Online Appendix D.

5.5. Summary of Main Findings

All levels of the analyses demonstrated consistent findings. Our main results can be summarized as follows. First, we found that trajectory-based mobile targeting could significantly increase the likelihood of a consumer redeeming a mobile promotion at the focal advertising store, thus leading to the fastest redemption behavior from customers and the highest overall satisfaction rates. Second, we found that trajectory-based mobile targeting was especially effective in attracting high-income shoppers, which suggests the high potential of mobile advertising in converting customers with a higher lifetime value. We also found that trajectory-based ads were especially effective in attracting male shoppers and shoppers who are in a more focused shopping stage. Third, trajectory-based mobile targeting had a significant and positive *direct* effect on the revenues of the focal advertising store. However, regarding the *indirect* effect on the overall revenues of the shopping mall, although trajectory-based targeting had, on average, a significant and positive effect, it became less effective for weekend and multicategory shoppers. This finding suggests that trajectory-based targeting might constrict consumer exploration and reduce potential impulse-purchasing behavior. Therefore, businesses and marketers need to be careful when implementing mobile targeting strategies, according to different business scopes.

6. Value of Fine-Grained Trajectory Information

To better understand the underlying mechanism of our findings as well as to examine the value of the fine-grained trajectory information, we conducted four sets of in-depth analyses: (1) total travel distance analysis, (2) shopper behavioral-pattern change after intervention, (3) value of fine-grained information versus coarse-grained information, and (4) value from each fine-grained trajectory dimension.

6.1. In-Mall Total Travel Distance

To understand the heterogeneity in the effect of trajectory-based targeting, we looked into the in-mall total travel distance for each consumer during the weekend and weekdays. The in-mall travel distance can largely indicate a customer's mobility range. We compared the average of the individual total travel distance across all four experimental groups. The results are shown in Table 7.

First, when we looked at travel distance during the weekend, on average, an individual traveled approximately one kilometer in the shopping mall (C). Trajectory-based mobile targeting (T3) resulted in the shortest average individual travel distance, 427.2 meters, in the mall. Static-location-based targeting (T2) resulted in an average individual travel distance of 756.4 meters. By contrast, random targeting (T1) resulted in the longest individual travel distance, 1,304.1 meters, which is more than three times the distance for the trajectory-based ads group.

Second, when we compared the results from weekends with those from weekdays, we found that on average, individuals traveled significantly longer distances during the weekends than weekdays. This is reasonable, because customers are more likely to visit the mall for fun during weekends. As a result, they often do not have many purchasing plans beforehand but instead do a lot of what can be called random exploration. By contrast, customers during weekdays usually go shopping with a clear planned purchase; therefore, they are unlikely to wander the mall with no clear purpose. Besides, similarly to the case for weekends, we found that during weekdays, customers under trajectory-based targeting also tended to travel significantly less distance (404.7 meters) than did the other groups. Interestingly, however, we did not find statistically significant differences among the other groups (506.2 versus 511.4 versus 498.9 meters). This finding seems to indicate that during weekdays, customers might already know what to buy (planned purchases); therefore, less-relevant or nonspecific targeting might be simply ignored and have a very low chance of influencing customer shopping behavior. Nevertheless, a close behavioral targeting strategy (e.g., trajectory-based) can be specific enough to touch upon such planned purchases, and as such, still have an impact on reducing customer travel distances during weekdays. In the meantime, compared with trajectory-based targeting, the impact of exploratory targeting strategies (e.g., random targeting) is much larger during weekends than weekdays.

Our travel distance analysis provides further evidence to support our previous findings. It indicates that during the weekends, trajectory-based targeting indeed can significantly reduce the mobility range of customers, whereas random targeting on average can increase the total travel distance of an individual customer in the shopping mall. Interestingly, our findings demonstrate high consistency with the previous marketing research on retailing and in-store consumer behavior. Previous studies combining archival data analysis using an RFID (radio-frequency identification) in-store tracking system with a randomized field experiment have found that longer customer in-store travel distances can lead to higher probabilities of unplanned purchases (Hui et al. 2013a, b). Our results dovetail with the previous literature. Specifically, our findings indicate significant heterogeneity in the mobile advertising effect, depending on the shopping context. Targeted mobile trajectory-based ads may not always work the best. They may reduce the amount of impulse purchases from customers, especially during the weekends. Therefore, businesses must understand the heterogeneity in the effect of different mobile ads. Marketers thus should carefully take into account the business scope (e.g., revenues for a focal store versus entire shopping mall) when designing mobile advertising strategies.

Table 7. Total In-Mall Travel Distance (in Meters) During Weekends and Weekdays (Daily Mean)

Group	Weekends	Weekdays
C, Control (n = 1,472)	**1,002.8**	506.2
T1, Random (n = 1,449)	**1,304.1**	511.4
T2, Location (n = 1,499)	**756.4**	498.9
T3, Trajectory (n = 1,535)	**427.2**	**404.7**

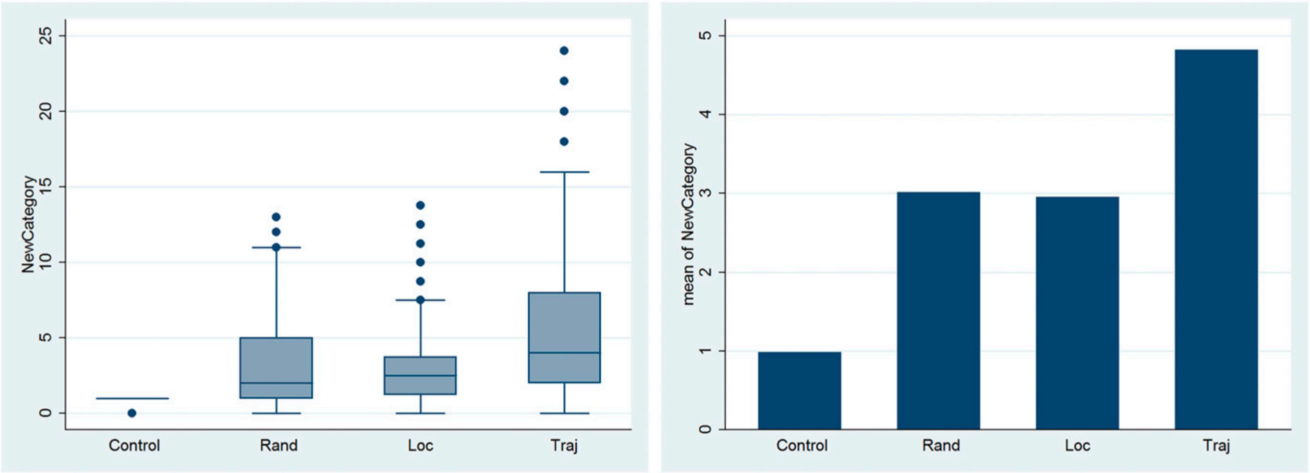
Note. Significant values are in bold ($p < 0.05$, pair-wise t-test between each two groups).

6.2. Shopper Behavioral-Pattern Change After Intervention

One interesting question is whether shoppers change their behavioral patterns after receiving the intervention. This question is important, because it will enable us to better understand what drives incremental revenue change, not to mention the advertising effect in the short run versus the long run. One possible situation is that shoppers might diverge shortly from their original behavioral patterns upon intervention (e.g., by visiting a focal advertising store from a completely new store category) but will return to their original behavioral patterns afterward. Another possibility is that shoppers will diverge permanently from their original behavioral patterns and behave differently afterward. Although in both cases the mobile advertising might bring value to the business, the underlying mechanism and the potential long-term impact can differ.

To analyze the potential change in shoppers' behavioral patterns before and after the intervention, we looked into the new store categories a customer visited after the CIM across all four experimental groups. We found that the customers from the trajectory group on average visited the highest number of new store categories, with approximately five new categories after the CIM

Figure 3. (Color online) Number of New Store Categories Visited by Users After CIM



($p > 0.05$), followed by the random group and the location group, both with an average of approximately three new store categories, and finally the control group, with an average of only one new store category. Figure 3 plots the distribution and average number of new store categories visited by customers after the CIM from each group.

Figure 3 provides evidence that the majority of customers did not seem to naturally change their shopping patterns. However, well-designed targeting such as trajectory-based targeting is more likely to change customers' behavioral patterns beyond the short-term response to focal store promotions. This finding builds on our previous group-level and individual-level analyses, wherein we showed that under trajectory-based targeting, customers shop faster and spend more in the focal advertising store while staying longer and spending more in total in the mall.

Altogether, our results seem to indicate a sign of higher enjoyment of the shopping process. Specifically, trajectory-based recommendation can lead to higher shopping efficiency as well as a higher customer satisfaction rate. Correspondingly, customers are more likely to enjoy the shopping process and, so too, to continue exploring other types of stores in the mall. Therefore, the effect of trajectory-based targeting derives not only from improvements in customers' current shopping efficiency (i.e., speed up purchases, offer good substitutes) but also from the ability to nudge customers toward changing their future shopping patterns (i.e., explore new store categories, find complements, and enlarge the shopping basket) to generate additional revenues.

Our findings are consistent with prior literature suggesting the potential externalities that behavior-based recommendations can generate to improve the diversity of customer purchases. Prior research has found that recommender systems can generate informational externalities (Bergemann and Ozmen 2006) and lead to diversity in sales (e.g., Brynjolfsson et al. 2011, Oestreicher-Singer and Sundararajan 2012). In particular, Brynjolfsson et al. (2011) found that consumers' usage of discovery tools such as recommendation engines is associated with an increase in the share of niche products. Oestreicher-Singer and Sundararajan (2012) found that categories whose products are influenced more by the recommendation have significantly flatter demand and revenue distributions, indicating higher diversity in sales patterns. Fleder and Hosanagar (2009) also found that collaborative filtering can push individuals to new products, thereby increasing the diversity of individual-level purchases. Overall, our findings are in line with this prior literature demonstrating the externalities of well-designed behavioral recommendation.

6.3. Value of Fine-Grained Information vs. Coarse-Grained Information

The two main goals of our study were to leverage the emerging source of fine-grained physical mobility trajectory data on individual consumers to understand and predict their future shopping behavior and, thereby, to influence that behavior (by changing their trajectories). One interesting and practical question for businesses is: what is the value of fine-grained trajectory data as compared with traditional "coarse-grained" behavioral indicators (such as store visits and time or money spent per store, which might be more accessible and cheaper to acquire)?

To answer this question, we conducted an additional comparison analysis. Specifically, we compared our main clustering results on the basis of the fine-grained information from the four mobility dimensions (temporal, spatial, semantic, velocity) with alternative-information-based clustering results using each of the following coarse-grained consumer behavior data:

1. List of stores visited by each customer
2. List of stores visited + time spent per store by each customer

Table 8. Pair-Wise Adjusted Rand Index (ARI) Between Different Clustering Results (I)

	Stores	Stores + Time	Stores + Money	Stores + Time + Money
Stores	1	0.8707	0.8695	0.8505
Stores + Time		1	0.8534	0.8931
Stores + Money			1	0.9002
Stores + Time + Money				1

	Full trajectory (bottom 25th percentile in length)	Full trajectory (top 25th percentile in length)	Full trajectory (all samples)
Stores	0.7812	0.1923	0.3063
Stores + Time	0.7996	0.1897	0.3153
Stores + Money	0.8185	0.2056	0.3287
Stores + Time + Money	0.8233	0.2061	0.3295

3. List of stores visited + money spent per store by each customer
4. List of stores visited + time spent per store + money spent per store by each customer

We conducted the clustering analyses on the basis of each of the above information sets using the same graph-based MCL method. Then, we compared the overlap between our original clustering results and each of the above four sets of alternative clustering results by calculating the adjusted Rand index (ARI; Hubert and Arabie 1985). The ARI is the most well-known and widely used pair-counting-based measure for comparison of agreement between two clustering results (Steinley 2004). Its value is bounded between 0 and 1; the higher the ARI value, the greater is the level of agreement between the two clustering results. We provide the pair-wise ARI results in Table 8.[14]

Our findings are as follows. First, the clusters generated according to 1, 2, 3, and 4 above did not vary significantly. We found that the pair-wise ARIs among the four clustering results were all quite high (>0.85). This finding indicates that among the traditional information dimensions, the "list of stores" is the most informative indicator. Second, the average ARI between the full-trajectory-based clustering and the traditional information-based clustering was 0.3199 (i.e., an average over 0.3063, 0.3153, 0.3287, 0.3295). Interestingly, we found that when consumers had a shorter trajectory in the mall (spent less time, visited fewer stores, or spent less money),[15] the trajectory-based clustering results had a higher likelihood of overlap with the traditional information-based clustering results (e.g., ARI = 0.7812 between trajectory-based clustering and list-of-stores-based clustering), whereas when consumers had a longer trajectory in the mall (spent longer time, visited more stores, or spent more money), the trajectory-based clustering results diverged significantly from the traditional consumer behavior-based clustering results (e.g., ARI = 0.1923 between trajectory-based clustering and list-of-stores-based clustering).

The key insight here is that when we observe longer consumer trajectories, the overall mobility information is richer. Hence, the fine-grained information derived from the trajectory becomes more precise and its value becomes more significant. However, when the trajectories are short, the fine-grained information might not be significant enough to make a difference.

6.4. Values from Different Trajectory Dimensions

We were also interested in comparing the values of fine-grained information from each of the four mobility dimensions (temporal, spatial, semantic, velocity). To do so, we conducted another set of clustering analyses based on each of these four mobility dimensions using the same MCL clustering method. Then, we again compared the agreements among these clustering results by calculating the pair-wise ARI. We provide the corresponding pair-wise ARI results in Table 9.

Our findings are as follows. First, we found that the pair-wise ARIs among the four mobility dimensions were quite low, which indicated that they are rather independent from each other in their ability to capture different perspectives of individual mobility information. Second, we computed the pair-wise ARI between the full-trajectory-based clustering results and the clustering results based on each of the four mobility dimensions. We found that within the four dimensions, "Semantic" (ARI = 0.5556) was the most informative, followed by "Temporal" (ARI = 0.4030), "Velocity" (ARI = 0.3685), and "Spatial" (ARI = 0.3178), in predicting the individual mobility patterns before the full trajectory was revealed.

Table 9. Pair-wise Adjusted Rand Index (ARI) Between Different Clustering Results (II)

	Semantic	Temporal	Spatial	Velocity	Full trajectory
Semantic	1	0.0394	0.0147	0.0590	0.5556
Temporal		1	0.0086	0.0586	0.4030
Spatial			1	0.0279	0.3178
Velocity				1	0.3685

This insight is intriguing. It suggests that location proximity alone is not sufficient for understanding and predicting consumers' physical behavior. Stronger predictors of individual future behavior are the fine-grained mobility traces, especially the semantic information (e.g., conditional and unconditional movement transition probabilities between stores) and temporal information.

7. Conclusion and Future Work

The proliferation of mobile and sensor technologies makes it possible to leap beyond the real-time snapshot of consumers' static location and contextual information. In this paper, we propose a novel mobile targeting strategy that infers consumers' preferences by leveraging detailed information on their offline moving trajectories in four different mobility dimensions. To measure the effectiveness of this new kind of mobile targeting, we conducted a large-scale randomized field experiment in a major shopping mall in Asia based on 83,370 unique user responses for a 14-day period. We found that by extracting and incorporating the overall offline behavioral trajectory of each individual consumer, we were able to significantly improve the performance of mobile targeting. In particular, our results showed that on average, trajectory-based mobile targeting could, relative to the existing baseline location-based targeting strategies, help businesses achieve higher coupon-response rates and higher revenues. Meanwhile, our study also revealed significant heterogeneity in the mobile targeting effect. Targeted mobile trajectory-based ads may not always perform the best. They may reduce the amount of impulse purchases from customers, especially during the weekends. Therefore, businesses would be better off reflecting on the heterogeneity in the effect of different kinds of mobile ads on different days of the week.

On a broader note, to our knowledge, our paper is among the first to analyze the *fine-grained* digital traces of individual physical shopping behavior and to demonstrate how they can be used to predict and influence individual future behavior. Our work can be viewed as a first step to the study of the digitization of offline behavior at a large-scale and granular level. We demonstrate the value of leveraging mobile and sensor technologies to digitize, measure, understand, and predict individual behavioral trajectories in the physical environment for improved user digital experiences and business marketing strategies.

Note that to implement the proposed targeting strategy in practice, the information required is fully controlled by the platform (e.g., shopping mall). The individual GPS mobility data can be automatically collected through the WiFi tracking system, which is a mature technology nowadays and has been widely used by many platforms such as in airports and malls around the world. Besides, the mall in our study had access to sales data from all of its partner vendors. This is usually the case when working with platforms in the physical setting. However, even in certain scenarios whereby such purchase data are unavailable, our proposed method can be generalized with minor extensions. For example, we can make recommendations using, in place of purchase data, store visitation information (e.g., whether visited or not and length of stay, both of which can be easily derived from GPS data).

Our paper has some limitations that will serve as promising topics for future research. First, because of the technical limitations of our GPS tracking system, we could recruit only customers who were interested in accessing WiFi, which group accounted for approximately 80% of the customers in the shopping mall.[16] However, this number could potentially be enlarged in the near future with a tracking system based on more advanced sensor technologies. Second, in the current analysis, whereas we were able to control for various observed individual characteristics such as age, income, gender, and others, individual-level unobserved heterogeneity might yet have existed. For example, because of our data limitation, we could not control for friends or family who shopped together. Future work will incorporate random coefficient models to better account for such individual-specific unobservables. Third, we acknowledge that if the mall has ex ante detailed customer demographic information, it can potentially make recommendations based on demographics, or a combination of demographics and physical mobility trajectories. In some scenarios, demographic information might be available (e.g., if the customer is a registered VIP member). Most often, however, this information is missing in such physical settings. Our experiment was a controlled setup in which demographic information became available ex post because of surveys. Our main purpose in collecting such information through the surveys was to understand the heterogeneity in the effects of the treatments, which helped us to better understand the underlying mechanism and boundary conditions of the treatment effects. Our method thus provides a conservative *lower bound* to the effectiveness of mobile targeting when businesses know nothing about the demographics of their customers. Fourth, currently our recommendations are based on similarity between customers. In the future, we could potentially experiment with alternative recommendation strategies, for example, recommendation based on dissimilarity between customers. Besides, our recommendations were designed at a random timing to control for potential time-varying effects across customers. Future studies can also explore algorithmic improvements to find the optimal intervention time for maximum effectiveness. Fifth, owing to the privacy policy of the shopping mall, we could not identify repeat customers visiting the shopping mall multiple times during the 14-day experimental period. Instead, we treated each individual trajectory as a unique customer. In the future, it would be interesting if we could identify return customers or the same customers who visit different shopping malls, to be able to study individual long-term learning behavior facilitated by mobile advertising interventions.

Finally, we acknowledge that trajectory-based targeting can be implemented in many different ways. According to the technology by which they are recorded, trajectory data are available in different forms, for example, GPS-based data, geo-social-network-based trajectory data, RFID-based data, and Wi-Fi-based data. Although the properties of these forms can vary, they have been used to address similar or related application problems using similar or related mining methods. In this study, we adopted one specific approach in attempting to understand customers' trajectory patterns in the temporal, spatial, semantic, and velocity dimensions. We aimed to determine the value of such new sources of information for mobile targeting. Our study, however, is only a first step. For generalization, future work should consider other potential mobility dimensions (such as individuals' speech, emotions, or feelings during their movement (e.g., Feng and Zhu 2016), their location-based social network(s) (Zheng 2011, 2015), additional features, such as demographics or behavioral activities if available, or other matching algorithms for recommendation (Adomavicius and Tuzhilin 2005; Adomavicius et al. 2011, 2016). We hope that our study can pave the way for future work that will achieve better understandings of individual mobility patterns and purchasing behaviors.

Acknowledgments

Author names appear in alphabetical order by last name.

Endnotes

[1] Note that in the follow-up survey, the control group was not asked the two mobile-related questions (i.e., whether the mobile recommendation was followed and whether such recommendations would be followed in the future). We used users' self-reported mobile redemption behavior from the survey to verify the redemption data we collected from the store sales. 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, needless to say, is a topic of considerable interest amongst practitioners.

[2] In a robustness check, we also ran separate logit regressions using subsamples under different coupon designs; we found that the results remained qualitatively consistent.

[3] A small number of consumers exited the mall before the randomly drawn CIM. We did not include them in our data collection.

[4] Owing to the privacy policies of the mall, we could not identify repeat customers visiting the shopping mall multiple times during the experimental period. Instead, we treated each individual trajectory as a unique customer. In reality, the proportion of customers visiting the same mall more than once in the two-week period was likely to be very small.

[5] Our algorithm detected 11 clusters originally, but we found that the size of the last cluster was very small. So we focus our discussion herein on the first 10 clusters.

[6] For each of the individual characteristic variables, we conducted a pair-wise t-test between each of the two clusters. Overall, we found no statistical differences in the means of these individual characteristics among a majority of the clusters. We did notice that some clusters presented significant differences in certain demographic variables compared with the others. For example, cluster 1 and cluster 5 both demonstrated significant differences in Age and Income from the others. However, the differences in demographic distribution were not salient among the majority of the clusters. Our detailed results are provided in Online Appendix E.

[7] Refer to Section 4.2 for the definition of CIM (critical intervention moment).

[8] We also tried alternative definitions of single- vs. multicategory shoppers. For example, instead of comparing the most recent two stores, we considered the most recent three stores. We defined single-category shoppers as those whose most recently visited three stores were from (at most) two different categories. We found that our results remained qualitatively consistent.

[9] For robustness confirmation, we also considered an alternative definition of "focused" shopping stage. Instead of the store transition category, we looked at the real-time speed of movement for each customer at the CIM. If the real-time speed at the CIM was slower than the average speed during the entire shopping trip, we considered the customer to be currently in a focused stage upon intervention. Otherwise, the customer was considered to be currently in an exploratory stage upon intervention. We found that our results remain qualitatively very consistent. The details are provided in Online Appendix D.

[10] We also conducted subgroup analyses for consumer total spending in the mall or in the focal advertising store. The heterogeneous treatment effects from these subgroup-level analyses were highly consistent with our individual-level analyses, which we will discuss in the following section. Owing to a space limitation, we will not present them here but will make them available upon request.

[11] Note that when studying the effects of mobile advertising on the coupon redemption rate, we used the "random coupon" group (T1) as the baseline, because the participants in the control group (C), by experimental design, did not receive any mobile coupon.

[12] We found that the interaction effects between Random and Weekend and between Trajectory and ShopperFocus were statistically significant at only the $p < 0.1$ level. These two effects are consistent with our previous results.

[13] To level the distribution of the exact ads served among different treatment groups, we conducted two in-depth analyses based on (i) ad (store)-level matching and (ii) subsample analysis. To match the distribution of ads between the Trajectory-based group (T3) and the two baseline treatment groups (T1: Random-based; T2: Location-based), we conducted ads matching based on the ad distribution in T3 (e.g., Imbens 2004, Stuart and Rubin 2008). In particular, we sampled from T1 and T2 (respectively) on the basis of the observed empirical distribution of the ads served in T3. We have tried sampling both with replacement and without replacement and found the results are very similar. In addition, we also conducted a subsample analysis. We focused on a subsample of popular stores with high volume of sales—whose daily sales were ranked in the top 10th percentile (25 stores) among all stores. Both analyses demonstrate strong consistency with our main findings. We provide the details in Online Appendix D.

[14] We have also tried alternative metrics such as the Rand index (RI), mutual information (MI), and adjusted mutual information (AMI;

e.g., Vinh et al. 2010). Our results remained highly consistent across the different metrics.

[15] Shorter and longer are defined as metrics within the bottom 25 and top 25 percentiles, respectively.

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

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Mobile Targeting Using Customer Trajectory Patterns

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Online Appendix A. Technical Details on Mining Mobile Trajectories

In this appendix, we discuss how we automatically identify similar customers 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 prior theory and literature discussed in Section 2, 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.

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 and Wang (2017), using a temporal kernel function.

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.

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 $\mathrm{A} \in R^{L \times L}$, where $\mathrm{A}(s_a, s_b)$ 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.

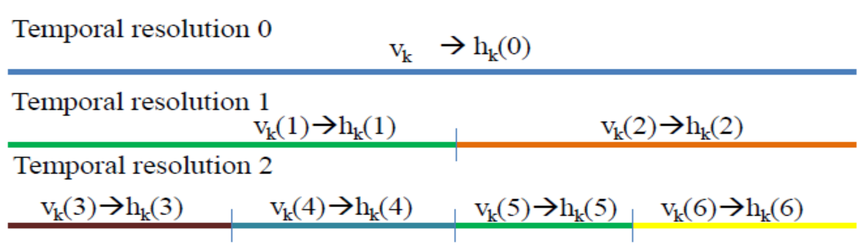
Based on the semantic features extracted from the trajectories, we are able to compute the similarity between two user trajectories in their semantic dimension using the Histogram Intersection Kernel and the Radial Basis Function (RBF) Kernel (Liu and Wang 2017).

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 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, to analyze the velocity similarity of the trajectories, we design a Temporal Pyramid Kernel by considering different temporal resolutions and non-uniform lengths of the individual trajectories. In particular, each trajectory is initially associated with a raw velocity vector with unequal lengths. Each value in the velocity vector is a speed value measured at a certain time. First, we uniformly quantize the velocity into L levels. Then, given a trajectory k and its initial velocity vector V_k with a specific 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 with $l_k\,/2$. We then calculate the normalized histogram $h_k(1)$ and $h_k(2)$ on $V_k(1)$ and $V_k(2)$, respectively, and normalize them so that $\Sigma\ h_k(1) + \Sigma\ h_k(2) = 1$. Consequently, we further equally divide $V_k(1)$ or $V_k(2)$ into two parts again and calculate the histograms in the same way. Such process can be conducted recursively until a predefined level is achieved. Finally, we concatenate all the histograms with predefined weights.

For illustration, we provide in Figure A1 a toy example with a three-level temporal pyramid in the figure below. The three levels (i.e., 0, 1, 2) represent coarse to fine temporal resolutions, respectively. We assign weight of each level to be assigned with [1/4, 1/4, 1/2], where the bottom level is assigned with the highest weight (Liu and Wang 2017). Based on this method, we can extract a velocity histogram h_k of equal length with coarse-to-fine temporal resolution. The similarity between user trajectory k and k' can be calculated with histogram intersection or Chi-Square kernel. Our Temporal Pyramid Kernel method is a much more refined matching method than using the simple average speed. It captures the distribution of the speed over the entire trajectory with a much smoother functional curve by taking into account different levels of temporal resolutions.



$$h_k=[1/4*h_k(0),\ 1/4*h_k(1),\ 1/4*h_k(2),\ ½*h_k(3),\ ½*h_k(4),\ ½*h_k(5),\ ½*h_k(6)]$$

Figure A1. Example of A 3-Level Temporal Pyramid Kernel

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:

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

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 α_m denotes the pre-assigned weights reflecting the specific interests of the problem domain.[2] 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.

Step 3: Using Graph-based Clustering to Identify Groups of Similar 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 2000, Satuluri et al. 2010). 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 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).

More specifically, we first construct an undirected probabilistic graph of individual trajectories (an example is shown in Figure A2), where 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 from the graph where the weight on the edge between each pair of two nodes in the sub-graphs is relatively high (i.e., 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 stabilize inside the dense regions of the network after many steps. The stabilized regions shape the clustered sub-graph and reflect

[2] In this study, we obtain the weight α_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.

the intrinsic structure of the network. The sub-graphs hence represent the identified clusters of similar consumers.

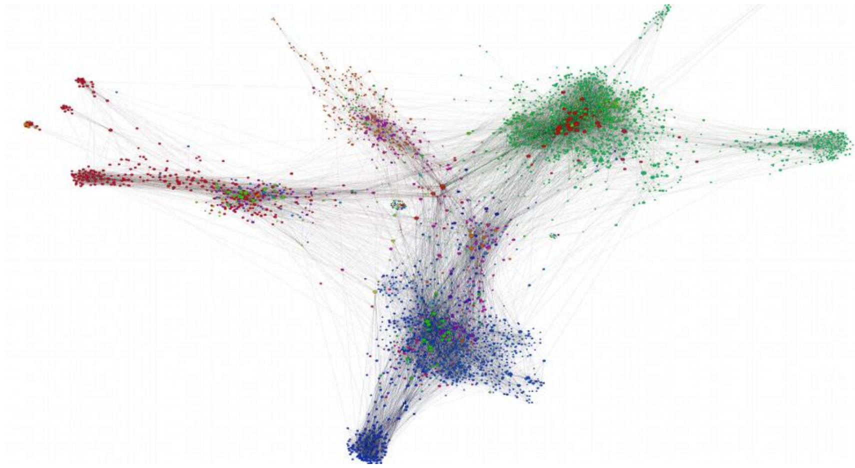


Figure A2. Example of Graph-Based Trajectory Clustering. The clustering method will find mutually exclusive partition groups of customers (sub-graphs), where within each group customers are similar to each other and between groups customers are different.

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Online Appendix B. Technical Details on Mobile Trajectory-based Recommendation

With the detected clusters of similar consumers from the previous steps, we then target mobile ads by offering recommendations to a consumer from stores that are most frequently visited by similar consumers. This approach is similar to the collaborative filtering approach widely used in traditional recommender systems.

In practice, 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 one's interest in that store. Following prior literature (e.g., Adomavicius & Tuzhilin 2005), we define the observed rating as whether or not a consumer has visited a store. Given consumer i and store j, one common approach to predict the rating $\hat{R}(i,j)$ is to average the observed ratings of similar consumers on store j weighted by their similarity information. Thus, the predicted average rating can be calculated by

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

where N_i denotes the number of similar consumers to consumer i, and $R(i',j)$ denotes 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.

References:

- Adomavicius, G. and Tuzhilin, A. 2005. Towards the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. *IEEE Transactions on Knowledge and Data Engineering*, 17(6).

Online Appendix C. Technical Details on Data Collection and Indoor Localization

Data Collection

The data in this paper were collected via smartphone's tracking of the WiFi network in the mall. Our technical methodology builds on previous work in wireless tracking and trajectory mining from computer science (e.g., Liu and Wang 2017, Guo et.al. 2014, Liu et al. 2013). More specifically, we provide more details of this collection process as follows.

At the entrance of the shopping mall, if a consumer would like to use the free WiFi (the free WiFi provided by the mall) we will collect the corresponding individual's trajectory information. Note that we only use the WiFi of the mall to collect consumer trajectory information, and only SSID of the mall's WiFi will be collected. The WiFi of the mall is dense enough (the access points are deployed around every 10 meters) to track the consumers in the mall in different stories.

When the consumer logs in the WiFi, she is required to fill a Form A (pop up when she tries to connect to the free WiFi) with information on age, gender, income range, credit card type (gold, platinum, gift card, others), phone type (iPhone, Android, others). At each store, when the consumer purchases a product, she is required to fill a Form B (sales in each store will ask her to do it during the purchase process) in store, which involves similar sociodemographic information plus whether the purchase is related to a mobile coupon and the amount of spending. We cross validate Form A and Form B to make sure the individual-level information is correct. In our experiment, we dropped those customers from our sample whose information from Form A and Form B was not consistent.

Once the consumer connects to the WiFi, we are able to in real time track the detailed mobile trajectory information during her visit in the shopping mall with precise time stamps. We leveraged RSS (Received Signal Strength) information, pre-trained signal strength map and SSID to localize each mobile phone, a.k.a., a person. The accuracy of localization is approximately 2 meters. For the transitions in Markovian state, each site (e.g., store) in the mall is defined much larger than a radius of 2 meters, hence can be very well captured in our WiFi localization.

Finally, when the consumer leaves the mall, we conduct a short follow-up survey asking whether she followed the mobile recommendation, whether she likes to follow such recommendations in future, overall satisfaction rate about the shopping experience, and additional personal information (e.g., first-time visitor or not, money spent in the focal advertising store, total money spent in the mall).

Indoor Localization

Each site (e.g., store) in the mall is defined much larger than a radius of 2 meters. Hence, it can be easily captured in our WiFi localization. Moreover, to improve the precision on detecting the boundary of the stores and to better capture store-profile information, we leveraged a crowdsourcing-based approach. In particular, aside from the mall free WiFi each store has its own secured WiFi for internal business use.

Hence, we were able to pre-generate a heat map of all the WiFi signals in the mall beforehand. When a customer carries a mobile device into a store, even though she may not connect to the store-specific WiFi, the inertial sensor readings of the mobile device can still reflect the overlapping WiFi signals inside the store. Therefore, based on the pre-generated WiFi heat map, we were able to more precisely identify the customer's location in the mall (e.g., near a store boundary) by matching the inertial sensor readings of the mobile device with the pre-generated WiFi heat map.

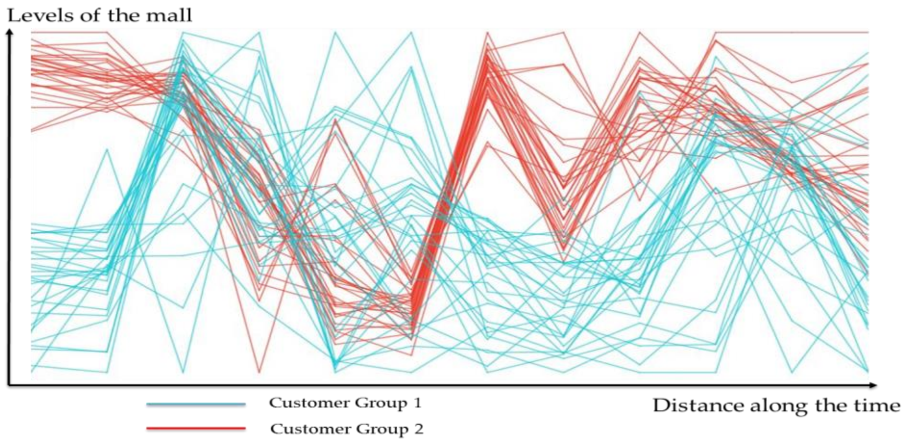


Figure C1. Example of Mobile Trajectories of Consumers in a Large Shopping Mall

Figure C1 visualizes an example of movement trajectories of individual customers traveling upstairs and downstairs in the shopping mall. Each line in the figure represents a trajectory from an individual consumer. The two colors represent two mobility clusters identified from our algorithm.

References:

- Liu, S., S. Wang. 2017. Trajectory Community Discovery and Recommendation by Multi-source Diffusion Modeling. in *IEEE Transactions on Knowledge and Data Engineering*.
- Guo, X., E. C. L. Chan, C. Liu, K. Wu, S. Liu and L. M. Ni. 2014. ShopProfiler: Profiling shops with crowdsourcing data. *IEEE INFOCOM 2014 - IEEE Conference on Computer Communications*, Toronto, ON, pp. 1240-1248.
- Liu, S., S. Wang, K. Jayarajah, A. Misra, R. Krishnan. 2013. TODMIS: mining communities from trajectories. In *Proceedings of the 22nd ACM international conference on Information & Knowledge Management (CIKM '13).* ACM, New York, NY, USA, 2109-2118.

Online Appendix D. Robustness Tests

To verify the robustness of our results, we conduct two sets of robustness tests to further account for the unobserved heterogeneity and to better interpret our findings: 1) store-level fixed effect and random effect to control for store-level heterogeneity; 2) separately conduct the group-level and individual-level analyses for each day to control for day-level heterogeneity. Overall, we find our results remain highly consistent.

Robustness Test I: Store-Level Heterogeneity Using Store-Level Fixed Effects and Random Effects

Different stores may provide different products, which may vary significantly in category, price, quality, brand affinity, and so on. In our experimental setting, we observe different stores, such as restaurants, cosmetics, supermarkets, and so forth. Randomization of store participation across different control and treatment groups in our experiment can alleviate such concerns to some extent, but potential store-level unobservables may still exist. For example, trajectory-based mobile ads could be more effective than random ads for cosmetics stores, though not necessarily for restaurants or supermarkets. To better control for the potential store-level unobservables, we conduct panel data analysis to examine daily revenues using a store-level fixed-effects model.

In particular, we model the overall revenues for store *j* on day *t* as a function of the number of different mobile ads sent by the store (N_{jt}^{T1}, N_{jt}^{T2}, N_{jt}^{T3}), a weekend dummy, interaction effects, and a store-level fixed effect (ζ_j):

$$R_{jt} = \theta_0 + \theta_1 N_{jt}^{T1} + \theta_2 N_{jt}^{T2} + \theta_3 N_{jt}^{T3} + \theta_4 Weekend_{jt} + \theta_5 N_{jt}^{T1} \times Weekend_{jt} + \theta_6 N_{jt}^{T2} \times Weekendjt + \theta_7 N_{jt}^{T3} \times Weekendjt + \zeta_j + \varepsilon_{jt} \quad [D1]$$

Table D1. Results from Store Fixed/Random Effect Models on Store Daily Revenues

Variables	Coefficient $^{\text{Fixed-Effect}}$	Coefficient $^{\text{Random-Effect}}$
# of Random Coupons	-0.1566 (.0092) ***	-0.1596 (.0091) ***
# of Location-based Coupons	0.0140 (.0081) *	0.0147 (.0080) *
# of Trajectory-based Coupons	0.1562 (.0059) ***	0.1566 (.0059) ***
Weekend	0.9149 (.0735) ***	0.9177 (.0735) ***
#Random × Weekend	0.0287 (.0145) **	0.0288 (.0145) **
#Location × Weekend	-0.0060 (.0029) *	-0.0057 (.0029) *
#Trajectory × Weekend	-0.0346 (.0096) ***	-0.0343 (.0095) ***
***** P<0.001, ** P<0.05, * P<0.1**		
Total # of Observations:	**14,112 (252 Stores * 14 Days * 4 Groups)**	

The estimation results from the store-level fixed-effects model are highly consistent with our previous findings from both group-level and individual-level analyses. The results from the store-level fixed-effects model are shown in Column 2 in Table D1. For a robustness test, we also consider a store-level random-effects model. We found the results from both fixed-effects and random-effects models stay very consistent. The results from the store-level random-effects model are shown in Column 3 in Table D1.

In particular, our analyses show that on average, trajectory-based mobile targeting has the highest positive effect on a store's daily revenues after accounting for the potential store-specific unobserved factors. Meanwhile, store revenues are significantly higher during the weekends than during the weekdays. Interestingly, we find although trajectory-based ads become less effective during the weekends compared to the weekdays, it always outperforms other targeting strategies at store level. This result also supports our previous finding that the focal advertising store always benefits from well-designed mobile ads.

Robustness Test II: Ad-Category-Level and Ad-Level Matching to Further Control for Store-Level Heterogeneity

1) Ad-Category-Level Comparison.

To look into the potential selection issue at store (ad) level, we first plotted the density distribution of ad categories served across all the three treatment groups (T1: Random-based; T2: Location-based; T3: Trajectory-based). In total, there are 15 categories of stores in the mall (Accessory, Bags, Dinning, Electronics, Entertainment, Fashion Clothes, Glasses, Household, Jewelry, Luxury, Personal Care and Cosmetology, Shoes, Sports, Grocery, Watch). Figure D1 below shows the density distribution of ads category served across the three treatment groups, where x-axis represents the store (ad) category ID and y-axis represents the frequency of category appearance. We find the distribution remains very similar across different groups.

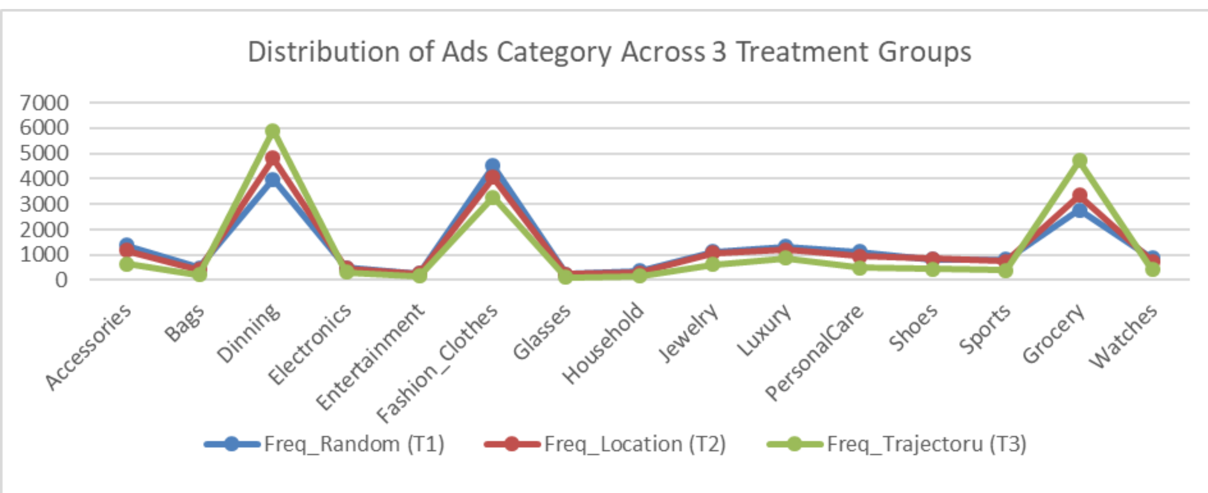


Figure D1. Distribution of Ad Categories Served in Three Treatment Groups.

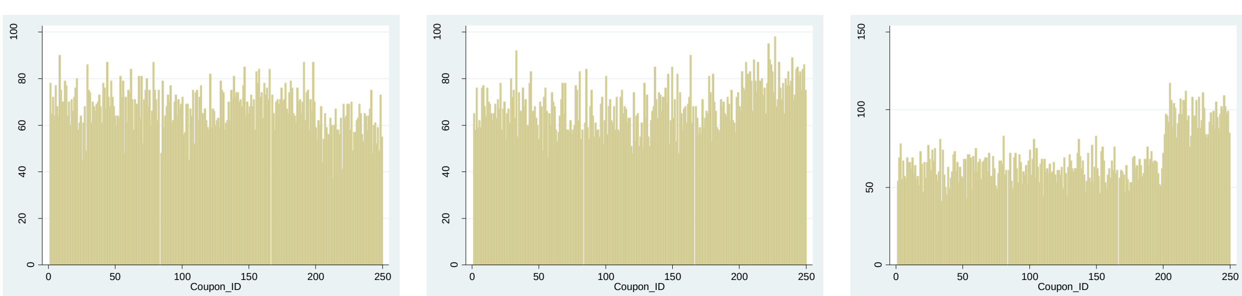
To further quantify the similarity among the three distributions, we conducted a two-sample Kolmogorov-Smirnov (KS) test for pair-wise comparison between each two treatment groups. Our pair-wise two-sample KS tests show that the max cumulative difference (CumDiff) and the corresponding p-value (p) are the following:

T1 and T2: CumDiff = 0.0280, p = 0.226
T1 and T3: CumDiff = 0.0977, p = 0.181
T2 and T3: CumDiff = 0.0775, p = 0.197

Based on the p-values from the two-sample KS tests, we cannot reject the null hypothesis that the three ad samples were drawn from the same distribution of ad categories. In other words, we didn't find significant difference in the distribution of the ad categories served among the three treatment groups. This empirical test suggests the "store selection bias" due to trajectory-based targeting is less likely a concern in our study. This is likely because of (1) the large size of the mall's historical customer pool (i.e., with all customers' mobility and purchase data over the past one year), which helped to generates recommendations with high precision; (2) the large sample size of customer population in our experiment (i.e., N_Random = 20,286, N_Location = 20,986, N_Trajectory = 21,490), which helped to cover significant heterogeneity in customer preferences. Hence, the collaborative-filtering-based recommendation was able to cover stores from a wide variety of categories (i.e., rather than focus on certain specific types of stores).

2) Ad-Level Matching.

Although we find no statistical difference in the distribution of the ad categories among the three treatment groups, we did find difference in the distribution of the exact ads served among different groups. Because we have a total of 252 different stores (ads), it is quite expected that the distribution at the exact ad level may vary among groups. Figure D2 below shows the density distribution of the exact ads served across the three treatment groups, where x-axis represents the store (ad) ID and y-axis represents the frequency of ad appearance.

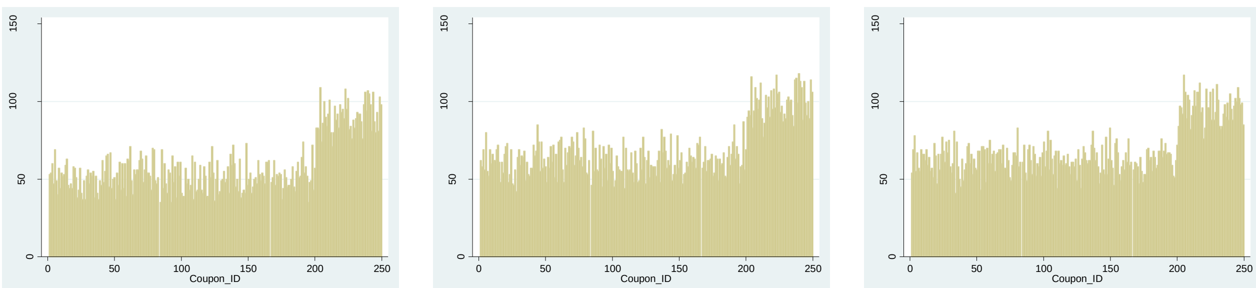


(a) T1 - Random (b) T2 - Location (c) T3 - Trajectory

Figure D2. Distribution of Ads (Pre-Matching) in (a) Random, (b) Location-based, (c) Trajectory-based Groups.

To further level the ad distribution across different treatment groups, we conducted two in-depth analyses based on: (i) Ad(Store)-Level Matching; (ii) Subsample Analysis. We discuss the former here and the latter next.

To match the distribution of ads between the Trajectory-based group (T3) and the two baseline groups (T1: Random-based; T2: Location-based), we conducted ads matching based on the ad distribution in T3 (e.g., Imbens 2004, Stuart and Rubin 2008). In particular, we sampled from T1 and T2 (respectively) based on the observed empirical distribution of the ads served in T3. We have tried sampling both with replacement and without replacement, and found the results are very similar. Figure D3 below shows the post-matching distribution of ads across the three treatment groups based on sampling with replacement, where x-axis represents the store (ad) ID and y-axis represents the frequency of ad appearance.



(a) T1 - Random (b) T2 - Location (c) T3 - Trajectory

Figure D3. Distribution of Ads (Post-Matching, Sample with Replacement) in (a) Random, (b) Location-based, (c) Trajectory-based Groups.

Based on the matched sample, we re-conducted the group-level and individual-level analyses. Our results indicate that after controlling for the distribution of the exact ads, our findings still hold consistently. Table D2 below shows the results from group-level analysis. Table D3 below shows the results from individual-level analyses for consumer redemption probability (Coefficient^{Redeem}), total spending at focal advertising store (Coefficient ^{AdStore}), and total spending at the mall (Coefficient ^{Mall}). Note that after matching the total sample size became N=85,078.

Table D2. Group-Level Results with Matched Samples (Daily Mean, 14-Day Period)

Group	Redeem Rate	Future Redeem Rate	Money Spent in Focal Store ($)	Total Money Spend in Mall ($)	Time Elapse Until Redeem	Satisfaction Rate	Time Spent in Focal Store (min)	Total Time Spent in Mall (min)
C –Control (n=1472)	--	--	--	84.98	--	**2.6**	--	**46.75**
T1-Random (n=1535)	**14%**	**20%**	**22.21**	82.26	**15.01**	**2.3**	**25.68**	**53.45**
T2-Location (n=1535)	**21%**	**31%**	**40.03**	**170.12**	**10.41**	**3.4**	**14.98**	**66.07**
T3-Trajectory (n=1535)	**31%**	**56%**	**56.78**	**193.06**	**4.55**	**4.3**	**9.82**	**71.98**
P<0.05 (pair-wise t-test between each two groups)								

Table D3. Individual-Level Results with Matched Samples

Variables	Coefficient[Redeem]	Coefficient [AdStore]	Coefficient [Mall]
Random (T1)	––	2.3053(1.0001)**	2.7043(.1202)***
Location (T2)	1.7908(.0709)***	4.2986(1.0707)***	3.3378(.1004)***
Trajectory (T3)	4.2164(.0922)***	8.1397(1.2062)***	4.0344(.2016)***
ShopperFocus	-5.3795(.0708)***	-0.2875(.1759)*	-0.2475(.0741)***
Weekend	0.0367(.0178)**	1.1720(.4796)**	1.1561(.0055)***
Afternoon	0.4421(.0429)***	1.1857(.5002)**	1.0114(.5008)**
Evening	0.2483(.1102)*	1.7285(.6221)**	1.5300(.6226)**
FirstTimeVisitor	0.0521(.0567)	0.6238(.5017)	1.1028(.8557)
Male	-0.1013(.0466)**	-0.7262(.3464)**	-0.7563(.0599)***
ln(Age)	-1.0456(.1361)***	0.0626(.2558)	1.0164(.9503)
ln(Age)^2	0.2876(.0952)***	0.0051(.0126)	-0.0740(.1441)
ln(Income)	0.7426(.8155)	-0.1609(.2651)	1.0414(.2018)***
ln(Income)^2	-0.0781(.1423)	0.0728(.1228)	-0.1446(.0412)***
Credit Type	Yes	Yes	Yes
Phone Type	Yes	Yes	Yes
Shopping Context	Yes	Yes	Yes
Advertising Store Category	Yes	Yes	Yes
Coupon Type	Yes	Yes	Yes
Random × Weekend	––	0.2881(.1603)*	0.8337(.1775)***
Location × Weekend	0.0028(.0290)	-0.0292(.2025)	0.0796(.1744)
Trajectory × Weekend	-0.1086(.0501)**	-0.1175(.2117)	-0.4417(.2098)**
Random × Male	––	-0.0165(.0199)	0.0425(.0788)
Location × Male	-0.0231(.0592)	-0.0216(.0234)	0.0903(.0769)
Trajectory × Male	0.1181(.0538)**	0.0177(.0219)	0.1058(.0468)**
Random × Income	––	-0.0012(.0141)	0.0256(.0285)
Location × Income	0.0628(.0565)	0.0698(.1080)	0.0930(.0839)
Trajectory × Income	0.0339(.0068)***	0.1887(.3356)	0.2472(.0696)***
Random × FirstTimeVisit	––	0.0193(.0521)	0.1622(.2216)
Location × FirstTimeVisit	-0.0703(.0923)	-0.0761(.0979)	-0.0559(.1996)
Trajectory × FirstTimeVisit	-0.0174(.0555)	-0.1321(.0856)	0.0969(.1021)
Random × ShopperFocus	––	-0.0128(.1067)	-0.1057(.0271)***
Location × ShopperFocus	0.1621(.2658)	0.1017(.2168)	0.0537(.0382)*
Trajectory × ShopperFocus	1.2213(.0871)***	0.3501(.1689)**	0.3645(.0587)***
Total # of Observations	**64,470**	**85,078**	**85,078**
***** P<0.001, ** P<0.05, * P<0.1**			

3) Ad-Level Subsample Analysis.

In addition to matching the overall distribution of the ads, we also conducted a subsample analysis. In particular, we focused on a subsample of popular stores with high volume of sales –

whose daily sales were ranked top 10 percentile (25 stores) among all stores. This lead to a subsample of N=27,342 observations of customer responses to ads from 25 stores.

Based on this subsample, we re-conducted the group-level and individual-level analyses. Our results demonstrate strong consistency with our main findings. Table D4 below shows the results from group-level analysis. Table D5 below shows the results from individual-level analyses for consumer redemption probability (Coefficient^{Redeem}), total spending at focal advertising store (Coefficient ^{AdStore}), and total spending at the mall (Coefficient ^{Mall}).

Table D4. Group-Level Results with Subsample of Popular Stores (Daily Mean, 14-Day Period)

Group	Redeem Rate	Future Redeem Rate	Money Spent in Focal Store ($)	Total Money Spend in Mall ($)	Time Elapse Until Redeem	Satisfaction Rate	Time Spent in Focal Store (min)	Total Time Spent in Mall (min)
C –Control (n=1472)	**--**	**--**	**--**	**84.98**	**--**	**2.6**	**--**	**46.75**
T1-Random (n=144)	**17%**	**26%**	**24.08**	**96.57**	**14.32**	**2.2**	**27.25**	**55.26**
T2-Location (n=152)	**25%**	**39%**	**44.37**	**177.28**	**10.01**	**3.4**	**17.22**	**69.34**
T3-Trajectory (n=185)	**37%**	**63%**	**59.51**	**201.55**	**4.23**	**4.5**	**11.96**	**75.61**

P<0.05 (pair-wise t-test between each two groups)

Table D5. Individual-Level Results with Subsample of Popular Stores

Variables	Coefficient^{Redeem}	Coefficient ^{AdStore}	Coefficient ^{Mall}
Random (T1)	——	2.1223(.9921)**	2.2035(.1357)***
Location (T2)	1.3480(.1143)***	4.0049(.8876)***	3.0887(.1102)***
Trajectory (T3)	2.0491(.1742)***	7.9695(1.3846)***	4.1408(.2345)***
ShopperFocus	-3.9242(.2346)***	-0.2756(.1142)**	-0.2523(.0805)***
Weekend	0.0349(.0196)**	1.0103(.4536)**	1.3674(.0064)***
Afternoon	0.3987(.0688)***	1.3981(.3898)***	1.0026(.4801)**
Evening	0.2219(.0611)***	1.5954(.5002)***	1.6980(.3321)***
FirstTimeVisitor	0.0983(.1103)	0.7866(.5570)	1.5912(1.0251)
Male	-0.0807(.0364)**	-0.6453(.3008)**	-0.8127(.0768)***
ln(Age)	-1.0136(.3519)***	0.1221(.2872)	1.2335(1.0205)
ln(Age)^2	0.2079(.1055)*	0.0120(.0204)	-0.0629(.1585)
ln(Income)	0.9928(.9052)	-0.2424(.3435)	1.0167(.2113)***
ln(Income)^2	-0.1002(.1276)	0.0733(.1141)	-0.1683(.0375)***
Credit Type	Yes	Yes	Yes
Phone Type	Yes	Yes	Yes
Shopping Context	Yes	Yes	Yes
Advertising Store Category	Yes	Yes	Yes
Coupon Type	Yes	Yes	Yes
Random × Weekend	——	0.3241(.1203)**	0.8112(.1557)***
Location × Weekend	0.0035(.0302)	-0.0255(.1875)	0.0762(.1898)
Trajectory × Weekend	-0.1107(.0463)**	-0.1098(.1991)	-0.4053(.1852)**

Random × Male	––	-0.0112(.0182)	0.0594(.0808)
Location × Male	-0.0336(.0449)	-0.0297(.0200)	0.0972(.0743)
Trajectory × Male	0.1402(.0689)**	0.0165(.0343)	0.1252(.0393)***
Random × Income	––	-0.0011(.0102)	0.0436(.0302)
Location × Income	0.0291(.0357)	0.0583(.1220)	0.1001(.0887)
Trajectory × Income	0.0514(.0120)***	0.2027(.3773)	0.2555(.0701)***
Random × FirstTimeVisit	––	0.0282(.0489)	0.1839(.2445)
Location × FirstTimeVisit	-0.0660(.0763)	-0.0834(.0887)	-0.0668(.1905)
Trajectory × FirstTimeVisit	-0.0237(.0462)	-0.1029(.0901)	0.0865(.1276)
Random × ShopperFocus	––	-0.0104(.0905)	-0.1224(.0338)***
Location × ShopperFocus	0.2009(.3130)	0.1141(.2223)	0.0626(.0225)**
Trajectory × ShopperFocus	1.5265(.3243)***	0.4245(.0968)***	0.3787(.0796)***
Total # of Observations	**6,734**	**27,342**	**27,342**
***** P<0.001, ** P<0.05, * P<0.1**			

Robustness Test III: Day-level Heterogeneity

To test the robustness of our results, we conduct additional day-level analyses by separately conducting the group-level and individual-level analyses for each day. Our day-level separate analyses show high consistency with the pooled 14-day results. In particular, we find that on average, mobile trajectory-based ads outperform all strategies across all days. Meanwhile, we observe a significant decrease in the effect of the trajectory-based ads during the weekends, compared to the corresponding effect from the weekdays. By contrast, we observe a significant increase in the effect of the random ads during the weekends.

Robustness Test IV: Alternative Definition of "ShopperFocus" Stage

For robustness check, we also considered an alternative definition of ShopperFocus dummy variable that accounts for the velocity dimension.

In particular, we looked at the real-time speed of movement for each customer at CIM (Critical Intervention Moment). If the real-time speed at CIM is slower than the average speed of that customer during the entire shopping trip, we consider the customer as currently in a focused stage (ShopperFocus = 1) upon intervention. Otherwise, the customer is currently in an exploratory stage (ShopperFocus = 0) upon intervention. This definition was inspired by R3's suggestion that when a customer spends longer time (hence incurring a slower walking speed) for a given store, it indicates his/her stronger purchase intent and focus.

Based on the new shopperFocus definition, we re-estimated our models for consumer redemption probability (CoefficientRedeem), total spending at focal advertising store (Coefficient AdStore), and total spending at the mall (Coefficient Mall). We found our results remain qualitatively very consistent. The corresponding results are provided in Table D6 below.

Table D6. Results Using Alternative Definition of ShopperFocus

Variables	Coefficient^{Redeem}	Coefficient ^{AdStore}	Coefficient ^{Mall}
Random (T1)	––	2.3321(1.0012)**	2.8007(.1234)***
Location (T2)	1.8082(.0711)***	4.3242(1.0709)***	3.3836(.1019)***
Trajectory (T3)	4.2219(.0902)***	8.1514(1.2091)***	4.0396(.2166)***
ShopperFocus	-4.1420(.1164)***	-0.4236(.1764)**	-0.3202(.0753)***
Weekend	0.0368(.0151)**	1.1872(.7895)*	1.1771(.0059)***
Afternoon	0.4549(.0442)***	1.2016(.5101)**	1.0131(.5108)*
Evening	0.2561(.1004)**	1.7915(.6354)**	1.6031(.6252)**
FirstTimeVisitor	0.0505(.0602)	0.6782(.5121)	1.1160(.8668)
Male	-0.1032(.0470)**	-0.7896(.3756)**	-0.8587(.0661)***
ln(Age)	-1.0461(.1341)***	0.0684(.2658)	1.0182(.9622)
ln(Age)^2	0.2932(.0969)***	0.0056(.0142)	-0.0843(.1344)
ln(Income)	0.7577(.8152)	-0.1743(.2634)	1.0473(.2190)***
ln(Income)^2	-0.0795(.1416)	0.0797(.1210)	-0.1639(.0417)***
Credit Type	Yes	Yes	Yes
Phone Type	Yes	Yes	Yes
Shopping Context	Yes	Yes	Yes
Advertising Store Category	Yes	Yes	Yes
Coupon Type	Yes	Yes	Yes
Random × Weekend	––	0.3131(.1820)*	0.9588(.1781)***
Location × Weekend	0.0028(.0288)	-0.0318(.2127)	0.0912(.1766)
Trajectory × Weekend	-0.1103(.0555)*	-0.1279(.2220)	-0.5021(.2613)*
Random × Male	––	-0.0179(.0180)	0.0480(.0771)
Location × Male	-0.0231(.0587)	-0.0234(.0227)	0.1029(.0772)
Trajectory × Male	0.1209(.0544)**	0.0186(.0256)	0.1211(.0480)**
Random × Income	––	-0.0018(.0118)	0.0293(.0279)
Location × Income	0.0642(.0556)	0.0722(.1108)	0.1055(.0869)
Trajectory × Income	0.0347(.0062)***	0.2052(.3142)	0.2801(.0749)***
Random × FirstTimeVisit	––	0.0189(.0512)	0.1841(.2133)
Location × FirstTimeVisit	-0.0718(.0910)	-0.0726(.0994)	-0.0639(.1977)
Trajectory × FirstTimeVisit	-0.0181(.0569)	-0.1291(.0831)	0.1103(.1013)
Random × ShopperFocus	––	-0.0203(.1121)	-0.1224(.0266)***
Location × ShopperFocus	0.1283(.2011)	0.1135(.2457)	0.0649(.0382)*
Trajectory × ShopperFocus	1.0037(.0727)***	0.3571(.1842)*	0.4417(.0601)***
Total # of Observations	**62,762**	**83,370**	**83,370**
***** P<0.001, ** P<0.05, * P<0.1**			

Online Appendix E. Segment Profile among Different Trajectory-based Clusters

First, we zoom into each consumer segment identified from our trajectory-based clustering analysis described in Subsection 4.2. Our graph-based MCL algorithm has identified a total of 10 clusters among all our experimental users based on the similarity in mobility pattern. We label these clusters from Cluster 1 to Cluster 10. The demographic distributions of consumer age (Shopper_Age), income (Shopper_Income) and gender (Shopper_IsMale) across the 10 clusters are illustrated in Figure 2. Interestingly, based on pair-wise t-tests we found no statistical difference in the demographic variables among a majority of the trajectory-based clusters.

In particular, for each individual characteristic variables (Age, Income, Gender, ShopperFocus), we conducted pairwise t-test between each two clusters. Our results are shown below in Table E1. Overall, we found no statistical difference in these individual characteristics among a majority of the clusters. We did notice some clusters present significant difference in certain demographic variables compared to the others. For example, Cluster 1 and Cluster 5 both demonstrate significant difference in Age and Income from the rest of the clusters. However, the difference in demographic distribution is not salient among the majority of the clusters. This seems to suggest that the clustering results based on fine-grained trajectory data might have captured some additional unobserved heterogeneity of consumers beyond the traditional demographic dimensions such as age, income and gender.

Table E1. Pairwise t-Test for Comparison among Different Trajectory-based Clusters

Shopper Income	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Cluster8	Cluster9	Cluster10
Cluster1										
Cluster2	**									
Cluster3	**	----								
Cluster4	**	----	----							
Cluster5	***	*	*	*						
Cluster6	**	----	----	----	*					
Cluster7	*	*	----	----	*	----				
Cluster8	*	----	----	----	**	----	----			
Cluster9	----	*	*	----	*	----	----	----		
Cluster10	*	----	----	----	*	----	----	----	----	
Results are based on pair-wise t-test. * P<0.1 ** P<0.05 *** P<0.001 ---- No Statistical Difference										

Shopper Age	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Cluster8	Cluster9	Cluster10
Cluster1										
Cluster2	*									
Cluster3	*	----								
Cluster4	----	----	----							
Cluster5	**	*	*	*						
Cluster6	**	*	*	*	----					

Cluster7	*	----	----	----	**	*				
Cluster8	----	----	----	----	**	*	----			
Cluster9	*	----	----	----	**	*	----	----		
Cluster10	**	**	**	**	*	*	*	*	*	
Results are based on pair-wise t-test. * P<0.1 ** P<0.05 *** P<0.001 ---- No Statistical Difference										

Shopper Gender	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Cluster8	Cluster9	Cluster10
Cluster1										
Cluster2	----									
Cluster3	----	----								
Cluster4	*	----	----							
Cluster5	----	----	----	----						
Cluster6	*	----	----	----	----					
Cluster7	*	----	----	----	----	----				
Cluster8	----	----	----	----	----	----	----			
Cluster9	----	----	----	----	----	----	----	----		
Cluster10	----	----	----	*	----	*	*	----	----	
Results are based on pair-wise t-test. * P<0.1 ** P<0.05 *** P<0.001 ---- No Statistical Difference										

Shopper Focus	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Cluster7	Cluster8	Cluster9	Cluster10
Cluster1										
Cluster2	**									
Cluster3	**	----								
Cluster4	**	----	----							
Cluster5	----	**	**	**						
Cluster6	**	----	----	----	**					
Cluster7	**	----	----	----	**	----				
Cluster8	**	----	----	----	**	----	----			
Cluster9	**	----	----	----	**	----	----	----		
Cluster10	**	----	----	----	**	----	----	----	----	
Results are based on pair-wise t-test. * P<0.1 ** P<0.05 *** P<0.001 ---- No Statistical Difference										