Rising like a Phoenix: Emerging from the Pandemic and Reshaping Human Endeavors with Digital Technologies ICIS 2023

Digital and Mobile Commerce

Dec 11th, 12:00 AM

Local Popularity: A Double-edged Tool in Platform Operation

Xingchen Ye
University of Science and Technology of China, yexc@mail.ustc.edu.cn

Andy Tao LI
University of Science and Technology of China, andytaoli@ustc.edu.cn

Ting Li
Erasmus University, tli@rsm.nl

Local Popularity: A Double-edged Tool in Platform Operation

Completed Research Paper

Xingchen Ye
School of Management, University of Science and Technology of China
Hefei, China
yexc@mail.ustc.edu.cn

Andy Tao Li
International Institute of Finance, School of Management, University of Science and Technology of China
Hefei, China
andytaoli@ustc.edu.cn

Ting Li
Rotterdam School of Management
Rotterdam, Netherlands
tli@rsm.nl

Abstract

Although displaying local popularity is wildly adopted by major platforms, the actual effect of such information cues on motivating users has not been documented. Findings from a field experiment suggest that local popularity effectively motivates users to invite more friends but surprisingly reduces users' self-participation. Social conformity theory may account for such effects: local information encourages users to invite their local friends, but such effect is limited to users from small cities since users in a relatively small community are more bonded and less likely to reject the invitation due to social pressure. Meanwhile, local information attenuates the power of popularity (e.g., fewer registered users in the local area) and ultimately discourages users' self-participation. This study deepens our understanding of displaying popularity cue in improving platform operation, based on which we suggest that practitioners should be cautious about the persuasive power of such information cues in location-based marketing.

Keywords: social referrals, location-based marketing, local popularity, field experiment

Introduction

Social referral is an effective way for platforms to accelerate the positive word-of-mouth (WOM) of existing users to attract new ones, by leveraging existing users' social networks. Previous studies have examined how platforms can provide informational persuasion cues to boost the virality of social referrals (Belo and Li 2022; Jung et al. 2020; Sun et al. 2021). A widely adopted persuasive cue is displaying popularity cue. Popularity cue is generally defined as the number of people who have participated or the number of sales accrued to a product (Xu et al. 2013). However, little is known about how different types of popularity cue affect social referrals (Chang et al. 2015). In addition, emerging location-based services enable platforms to incorporate the user's real-time location into the popularity design and provide local popularity (e.g., how many neighbors nearby the focal user have participated). Although many platforms have widely adopted such a persuasive strategy (For example, when Alipay provides coupons to nudge users to redeem the coupon and share with friends, it displays how many people in the focal user's city have redeemed the coupon. When the user moves to another city, Alipay also updates the user location and the corresponding participants in the current city.), the actual effect of displaying local popularity on social referrals is unclear, making it hard to fully utilize the power of such an innovative persuasion cue.

Prior literature on popularity suggests that displaying popularity provides a quality signal that reduces perceived risk and increases perceived value for potential users (Chen et al. 2011; Tucker and Zhang 2011), as users tend to follow the majority and participate when they find the platform is popular, which may encourage users to spread word-of-mouth referrals. As for local popularity, the displayed location reminds users of their current local community and motivates them to invite their neighbors (Zhang et al. 2015). In addition, social conformity theory implies that displaying local information will inspire users with a sense of belonging and closeness (Sedikides and Wildschut 2019), and users are more likely to align with their neighbors by mimicking their behaviors and following their suggestions implicitly and explicitly (Turner and Reynolds 2003). Therefore, local popularity might help persuade users to generate more social referrals than general popularity. Despite these theoretical predictions, empirical evidence on the effects of popularity on social referrals is scarce, especially for local popularity. Given the widespread adoption of displaying local popularity in platform operational practices, it is highly relevant to conduct a nuanced evaluation of its impacts on social referrals.

To fill this gap, we collaborated with a telecom platform and conducted a large-scale field experiment with 5,245 users in the app for almost five months to examine the causal effects of local popularity on social referrals and the underlying mechanisms. During the experiment, the app introduced a lottery program that gave participating users a lottery (a chance to receive a 5 RMB reward) and showed popularity cue to incentivize users to share the program with their friends. We implemented a between-subject randomization and allocated users randomly to one of three conditions: (1) the control group does not display the popularity; (2) the popularity group displays the total number of participants; (3) the local popularity group displays the number of participants in the focal user's city.

The results indicate that displaying general popularity does not increase social referrals compared with the control group, but displaying local popularity significantly motivates users to invite more friends. On average, displaying local popularity induces an extra 0.296 referrals compared with displaying general popularity. Thus, leveraging local popularity can help expand the number of active users on the platform. We also examine the mechanisms of why local popularity is effective and conduct fine-grained analyses based on clickstreams and user location trajectories, suggesting that social conformity might play a role. First, we decompose the referral processes and identify the recipient of each social referral. The analyses of the referral recipient's location reveal that local popularity encourages users to invite neighbors, thereby empowering platforms to create close-knit clusters in each local community. Second, in alignment with social conformity theory that suggests users in a relatively small community have a strong priming identity with the local community (Kessler and Milkman 2018), heterogeneous analyses of city size show that the effect of displaying local popularity on motivating social referrals is confined to small cities, since users in small cities are more susceptible to local information, resulting in more active in sending referrals. In addition, social conformity theory implies that referral recipients in a relatively small community are more bonded and less likely to decline the invitation due to social pressure, even if their utility of using the platform is not high enough. Our findings that the boosted registrations induced by local popularity were inactive in further participation support this explanation.

We also explore the impact on users' subsequent participation and find that displaying local popularity has an unexpected negative impact on user participation compared with general popularity. Specifically, local popularity almost offsets the positive effect of displaying popularity on users' self-participation. We then triangulate the field evidence with the actual message displayed to each participant and find that the diminished power of popularity might account for the decreased participation. Evidence shows that local information attenuates the power of popularity (e.g., fewer participated users in the local area) and ultimately discourages users' further participation.

Our study contributes to the literature in three ways. First, this study contributes to the literature on platform operation and deepens our understanding of the significant role of designing appropriate popularity cue in improving platform operation. Second, our findings shed new light on leveraging local popularity to motivate social referrals. To the best of our knowledge, we are the first study to use a large-scale field experiment to reveal the causalities and underlying mechanisms of how local popularity affects social referrals. Third, this study contributes to the literature on location-based marketing by demonstrating the persuasive power of integrating location service into the popularity design and alerting its potential threats. Our findings also offer practical insights. Local popularity is not a one-size-fits-all persuasion strategy since it promotes social referrals at the cost of discouraging user participation. The discrepancy effects between social referral and user engagement call for cautious attention in scaling local popularity in platform practice.

Theoretical Backgrounds

Social Conformity Theory and Social Referrals

Social conformity theory primarily explores how individuals adapt to and comply with the norms, beliefs, and behavioral patterns of the surrounding social groups (Cialdini and Goldstein 2004). One significant application of this theory is to understand and influence public behavior. According to social conformity theory, users often experience the driving forces of informational social influence and normative social influence when facing group influences (Li et al. 2022; Toelch and Dolan 2015). Informational social influence arises from individuals' uncertainty about the correct course of action. When individuals are unsure of how to act, they tend to observe and imitate the behavior of others (Deutsch and Gerard 1955), believing that these behaviors are correct. This behavior of seeking correct information from the group is a natural psychological response and is sometimes referred to as the "bandwagon effect." Normative social influence stems from individuals' desire for social acceptance and approval. In order to avoid rejection or criticism, individuals may conform to the norms and expectations of their social group to gain social approval, even if these behaviors contradict their own beliefs and values (Cialdini and Goldstein 2004). This influence can lead individuals to abandon their own views and beliefs in certain situations to fit the group's expectations.

When considering the recommendation process, it can be broken down into the inviting behavior of the inviter and the acceptance behavior of the invitee. The behavior of the inviter may be influenced by their social influence and social motivations. For example, they may be more willing to invite individuals they believe will accept the invitation or those they perceive can help them gain social status or other benefits. The acceptance behavior of the invitee may be influenced by their social needs and social pressures. For instance, they may be more inclined to accept invitations they believe will help them fulfill their social needs or alleviate social pressures. This decomposition allows for a more nuanced understanding of the dynamics in the recommendation process and may assist in designing more effective social referral strategies. For instance, we can attempt to enhance the inviter's social influence or fulfill the invitee's social needs to increase the acceptance rate of recommendations. We can also explore increasing social pressure to boost the acceptance rate of recommendations.

The underlying premise of social referral is to accelerate the positive word-of-mouth (WOM) of existing users to attract new ones, who are also likely to benefit from adopting the service (Biyalogorsky et al. 2001). The popularity of social platforms (e.g., Facebook and Twitter) renders online WOM more convenient and enables WOM to spread rapidly through social platforms. In addition, referred users are generally more engaged (Fernández-Loría et al. 2022) and have higher customer lifetime value compared to users acquired from other channels (Schmitt et al. 2011). Thus, platforms can optimize social referral programs to boost user growth and promote platform revenue (Belo and Li 2022). Several pioneering studies show that platforms can encourage social referrals by optimizing the referral message. Sun et al. (2021a) explore the effect of shareability and scarcity of referral codes. Jung et al. (2020) examine the effect of contextual framing and find that equitable and prosocial framings are appealing for a sender to make referrals. Sun et al. (2021b) investigate the referral information of the sender's purchase status and the information about the referral reward. Users' local environment also influences the generation and direction of WOM referrals (Sun et al. 2019). Our work adds to this research stream by studying whether displaying the platform's popularity would influence social referrals.

Effect of Popularity on Social Referrals

Literature suggests several persuasive principles firms can follow to encourage users to behave in a desired way (Liu et al. 2019; Salganik et al. 2006; Zhang and Liu 2012), and demonstrating the popularity is one of the most adopted tools in business practice and has been identified as an important driver of persuasion (Cialdini 2001). Popularity refers to the prevalence of a specific behavior in other customers (e.g., an APP is wildly installed), and is often represented as the number of participating users (Burtch et al. 2018; Tucker and Zhang 2011). Observational learning theory suggests that individuals update their beliefs by observing others' behaviors (Bandura 1978; Cai et al. 2009; Chen et al. 2011), and thus, their decisions are influenced by their peers (Muchnik et al. 2013). In this way, when people are informed about the popularity of an activity, they are more likely to be persuaded about the value of that activity and also participate in such an activity. Some studies have documented the positive effects of displaying popularity in various contexts. For example, on online music platforms, people tend to listen to songs with popularity cue (Dewan et al. 2017) and download music based on popularity (Salganik et al. 2006). In e-commerce contexts, displaying popular products can attract consumers' attention (Tam and Ho 2005), and the displayed popular products are perceived as high quality and thus are more likely to be purchased (Cai et al. 2009; Chen et al. 2011). Further, several studies explore the effective boundaries and find that the positive effect of popularity cue on quality inference is moderated by live chat communication (Tan et al. 2019) and seller's quality signals (Tucker and Zhang 2011).

Several pioneering studies explore the effect of popularity cue on sharing intention. For example, Kao et al. (2017) find that popularity positively influences consumers' intention to purchase and willingness to recommend. Chang et al. (2015) find that displaying popularity is essential to encourage internet users to click like and share messages in social media marketing activities. Although previous studies reveal the power of displaying popularity in e-commerce contexts(Chang et al. 2015; Kao et al. 2017), the actual benefit of displaying popularity on number of social referrals in the field should not be taken for granted. Instead of making decisions for themselves, social referrals involve the consideration of referral recipients. In the context of social referrals, users care about their friends' satisfaction with their recommendations (Ames et al. 2004; Kornish and Li 2010) and perceive themselves as performing a good action and believe that the recipients would also judge it that way (Jung et al. 2020; Wirtz et al. 2013). However, whether the persuasive power of popularity can apply to the decision for others is rarely investigated. To the best of our knowledge, we are the first study to investigate the effect of popularity on social referrals in the field.

Considering a successful referral involves the mutual agreements of a sender's sharing decision and a recipient's accepting decision, we analyze the effect of displaying popularity from the sender's perspective and recipient's perspective, respectively. From the sender's perspective, they face great uncertainty about the activity quality in an online environment (Lee and Tan 2003), and they are not sure whether their friends would derive a positive utility from their referral invitation. In addition, senders usually have concerns about whether their friends would perceive their referral invitation as performing a good action. Thus, they rely on available information to infer and evaluate quality before sharing an activity. The displayed popularity cue can reduce uncertainty and make the activity value for recipients more salient, thereby highlighting the altruistic motives and alleviating their sharing concerns (Liu et al. 2019; Salganik et al. 2006; Zhang and Liu 2012). In other words, when users see a popular activity, it not only wants to follow the crowd to participate in this activity, they also have incentive to let their friends to follow the crowded, so make social referrals to them. From the recipient's perspective, social conformity theory suggests users tend to follow the crowd and displaying the popularity might increase the likelihood of recipients accepting the invitation. The fusion of two perspectives can make mutual acceptance, leading to an increase in social referrals. Therefore, we propose the following hypotheses:

H1: displaying popularity cue leads to more social referrals.

Local Popularity and its Effect on Social Referrals

As mobile technologies can reach users anywhere and anytime, many mobile platforms leverage location-based services to display the popularity in the user's current location (e.g., the popularity in the focal user's city). Location-based services (LBS) refer to technological tools that customize the information retrieved by the user's location (Brimicombe and Li 2006; Heo and Kim 2017). Ghose et al. (2013) suggest that there are stronger local interests for mobile users, and the incorporation of location-based service constitutes a groundbreaking and progressively significant facet of online platforms (Bauer and Strauss 2016). Literature has repeatedly demonstrated the positive effects of LBS on consumer engagement behavior in different scenarios, such as enhancing self-expression (Chen and Lin 2014), nudging music listening (Dewan et al. 2017), encouraging check-in behaviors (Liu et al. 2014), and convincing purchase decisions (Chen et al. 2015; Fang et al. 2015; Luo et al. 2014).

Yet, the extant studies have little understanding of how local popularity affects social referrals, and the actual effect of such information cues on motivating social referrals has not been documented in the literature. Displaying local information significantly influence customers' decision-making process (He and Oppewal 2018; Purohit and Srivastava 2001). Combining popularity and location dimensions may produce a new persuasive effect, and displaying local popularity might exhibit a greater persuasive power than general popularity. The combination of popularity and location dimensions into local popularity may exhibit greater persuasive power than general popularity. This is because such information allows users to gain a more direct understanding of the local activity atmosphere and engagement level. For example, Rimjhim et al. (2020) reveal that users with closer geographic locations reflect similar behaviors, and Dewan et al. (2017) demonstrate that local popularity has a larger impact on user engagement than general popularity. User's online behavior is significantly affected by the geographical locations between users and their friends (Qiu et al. 2018), and users may be less skeptical about the location-based information near them because it makes users feel more relevant and convincing.

According to social conformity theory, from the sender's perspective, in terms of informational social influence, individuals tend to compare their behavior with that of similar others to evaluate themselves (Festinger 1954). When users discover a certain number of people around them participating in an activity, they may perceive it as the correct behavior and become interested in it (Asch 1951). Users may consider the activity to be interesting or valuable, stimulating their prosocial behavior. Therefore, the number of local participants can serve as an indicator of activity quality and attractiveness, motivating users to make sharing decisions. In addition to generating informational social influence, local popularity also creates normative social influence. Friendship ties in social relationships often occur within shorter spatial distances (Laniado et al. 2018). As local popularity indicates the user's city, it triggers connections with other users in the same city. This makes users more susceptible to the opinions of those around them or social groups (Sherif 1936), fostering a sense of belonging and closeness (Sedikides and Wildschut 2019). These connections may encourage users to conform to local norms and behaviors (Asch 1951) and motivate them to establish social links (Deutsch and Gerard 1955), thereby prompting users to invite their neighbors. In order to fit into this group and demonstrate that they are part of the community, users may believe that sharing this activity will help them gain recognition and support from the community within their social circle, leading them to share the activity with local friends and obtain a certain level of social identity.

Although general popularity may involve a relatively larger number of participants compared to local popularity, this data may include many regions and populations that are irrelevant to the user, reducing the relevance of the information and creating a sense of abstraction and distance. As a result, the judgment of activity quality may be constrained (Deutsch and Gerard 1955), potentially weakening the mechanism of group pressure on user sharing behavior. Users may feel a higher need for social identity because there may be smaller geographic and cultural differences between them and other participants. Users may perceive the activity to be more exclusive and therefore more attractive (Cialdini and Goldstein 2004). Meanwhile, from the recipient's perspective, users are more likely to align with their neighbors by mimicking their behaviors and following their suggestions implicitly and explicitly (Turner and Reynolds 2003). Because nearby friends are more likely to influence each other (Qiu et al. 2018; Zhang et al. 2015), they might have difficulties to reject the invitation due to higher levels of social connectivity (Liu et al. 2019), and thus we conjecture that it is more likely to trigger an increase in social referrals due to the local popularity heuristic. Therefore, we propose the following hypotheses:

H2: displaying local popularity leads to more social referrals than displaying general popularity.

Research on social conformity theory suggests that for small communities, stimulating local identity is more effective (Kessler and Milkman 2018). Users in small communities have a stronger sense of belonging and value when they see information about their local community, which can motivate them to make recommendations even if the popularity is low. Therefore, for users in small communities, local popularity should have a stronger motivating effect on social referrals.

If social norms conflict with individual beliefs or values, social conformity strategies may lead to resistance or resistance (Brehm 1966). In large cities, people may have a low sense of identification with the city. If social conformity strategies are used, there may be limiting factors and potential negative effects. Additionally, people in large cities may value privacy rights, and displaying location information may be seen as a violation of individual privacy. Such social norms are considered to be overemphasized or used to manipulate individual behavior, leading to reactance (Clee and Wicklund 1980). Therefore, the positive impact of local popularity is limited to users in relatively smaller communities, not those in metropolitan areas. When using social conformity strategies, we need to carefully balance the relationship between social influence and individual freedom in different types of areas.

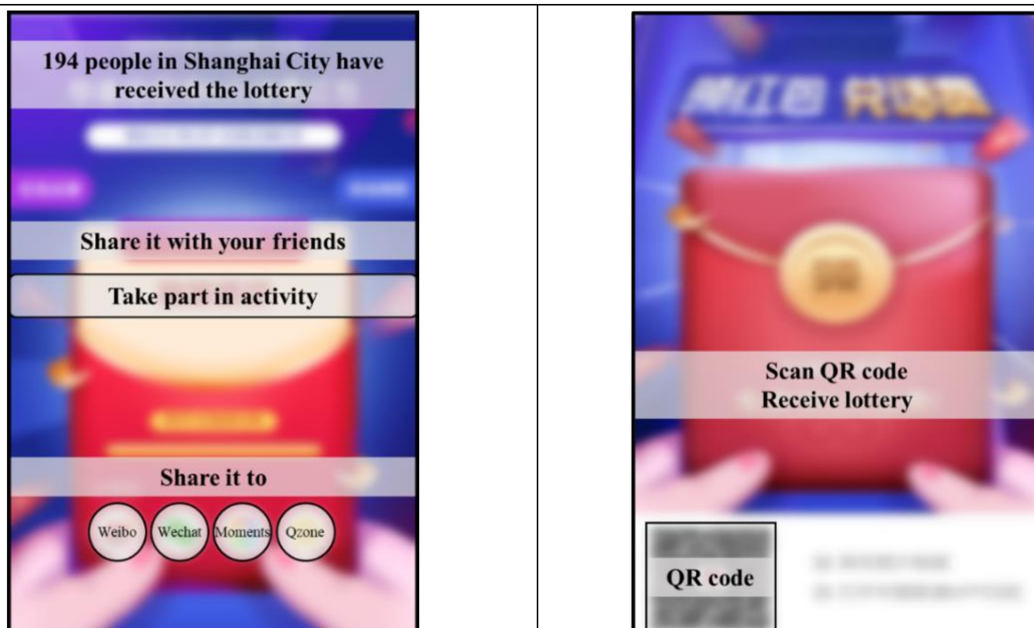
In summary, the informational social influence in social conformity theory leads users to believe in the value of the activity, thereby promoting their participation. Normative social influence, on the other hand, promotes social referrals for users in small communities in order to gain social recognition. The information on the number of participants in the city where the user is located is more relevant and can better stimulate users' informational and normative social influences. In sum, as users in smaller cities are more susceptible to local information and have a stronger sense of local community identity. Therefore, we propose the following hypotheses:

H3: The positive effect of displaying local popularity on social referrals is more pronounced in small cities compared to large cities.

Field Experiment

Research Context and Experimental Design

We collaborated with a large telecom operator company and conducted a field experiment on its mobile app. The app enables users to view and pay bills, change plans, and access other services (e.g., upgrade to 5G plans, and advertise family plans). The company, with about 300 million users, urgently needs to migrate offline users to the app and retain existing app users to save operational costs and promote online services. To increase user retention and social referrals, the company launched a lottery activity during the experimental period. The experiment was from March 11th to September 17th, 2021, lasting for 130 days. The company advertised this activity on Weibo, a popular social media platform in China. Users who clicked on the ads were redirected to the app's activity page, as shown in Panel A of Figure 1.



Panel A. The Activity Page | **Panel B. The Invitation Page**

Figure 1. The User Page Prototype Diagram

Users who viewed the activity page could decide whether they agreed to participate in the lottery activity. Users who agreed to participate were awarded a lottery. This lottery gives users the chance to get 5 RMB, and a subset of users will be randomly selected to receive the rewards. Users could participate in the lottery multiple times to increase the winning likelihood.

The app displayed popularity at the top of the activity page, which was defined as the number of participants based on the user's current location and updated upon each login. It also displayed four icons of common social channels in China (i.e., Weibo, WeChat Message, WeChat Moment, and QQ zone) on the activity page to encourage users to share the activity with their friends. Users could choose whether to share the activity by clicking one of the icons. When a user clicked an icon, the system generated a QR code with an invitation message and sent it to the corresponding channel, as shown in Panel B of Figure 1 (the QR code contained encrypted referral information including the inviter's ID and the sharing channel). For example, if a user clicked the Weibo icon, the system redirected them to the Weibo "Publish Post" page and automatically generated a post with the QR code. The system generated different QR codes for each sharing attempt by a user. Since a sender might share the QR code with multiple users or post it on their social media timeline, the QR code allowed for repeated use by multiple recipients. Recipients who saw this information could scan the QR code and be redirected to the app's activity page. A referral was considered successful if a recipient scanned the QR code or long-press the QR code that redirected the recipient to the app.

We designed a between-subject randomization field experiment with three treatments. The system checked whether a user was a newcomer (i.e., visiting the activity page for the first time since the beginning of the experiment). The system randomly assigned a newcomer to one of three groups with equal probability and stored their group information. The system read their group information when they returned and displayed the corresponding message, ensuring that users were exposed to only one pre-assigned condition even if they visited the platform multiple times. The activity page displayed the popularity message according to their group information: (1) no popularity for the control group; (2) the total number of participants for the popularity group; (3) the number of participants in their city for the local popularity group. Table 1 shows examples of popularity for users in different groups.

Group name	Example
Control	[Blank]
Popularity	4000 people nationwide have received the lottery
Local Popularity	40 people in Shanghai City have received the lottery

Table 1. Popularity cue for Users in Different Groups

Randomization Check

The experiment involved 5,245 valid users. The system randomly assigned 33.04% of users (1,733 users) to the control group, 33.16% of users (1,739 users) to the popularity group, and 33.80% of users (1,773 users) to the local popularity group. The number of users in the three groups was roughly equal. Due to the data privacy, we cannot observe the user characteristics. We conducted randomization checks by portraying the users' in-app behaviors before the beginning of the experiment. Specifically, the APP had an early version of referral program ("*PastReferral*" in short hereafter) and ended before the beginning of the experiment. *PastReferral* indicates whether a user participated in such a referral program. Apart from the referral program, we also compared the users' participation in other activities.

Variable	Mean			The P-value of the Pairwise Difference			The P-value of the F-test
	Control	Popularity	Local Popularity	Local Popularity – Control	Popularity – Control	Popularity – Local Popularity	Three Group Difference
PastReferral	8.0%	7.6%	8.2%	0.817	0.683	0.521	0.810
PastGame	7.2%	7.6%	6.7%	0.696	0.530	0.307	0.590

Table 2. Randomization Checks Between Three Groups

In specific, before the beginning of our experiment, the app implemented a wheel game that offered users an opportunity to play a wheel to win points ("*PastGame*" in short hereafter). The *PastGame* lasted for 30 days, and for each day, the user had one chance to spin the wheel to earn a random reward. The app did not implement any experiment variants in the *PastGame*, and the *PastGame* also ended before the beginning of our experiment. We use *PastGame* to indicate whether a user participated in a wheel game. Table 2 shows the average participation rate of each group and the p-value of the difference between any two groups. Results suggest that the three groups were similar without significant differences. Taken together, these results provide sanity checks for our experimental design.

Summary Statistics

Table 3 presents variable descriptions and summary statistics for users during the experimental period. It is imperative to elucidate that our analysis encompasses two distinctive levels of examination: "user level" and "user-day level". *Popularity* is a dummy variable that equals one if popularity is displayed and zero otherwise. *Locality* is a dummy variable that equals one if the local popularity is displayed and zero otherwise. We measure several behavioral outcomes. First, we consider the number of recipients who are successfully invited to the platform by a user (*Referrals*) (Jung et al. 2020). On average, each user successfully invited 0.368 friends during the experiment. We also pay attention to user's participation; we calculate the number of days that a user participates the lottery activity (*ParticipationDays*). On average, each user participated for 0.312 days. We also measure the number of times that the user logins (*Logins*) as an alternative indicator of user participation. Each user viewed the activity page 5.346 times on average.

Variables	Description	N	Mean	Sd	Min	Max
User-Level						
Popularity	=1 if the popularity is displayed.	5,245	0.670	0.470	0	1
Locality	=1 if the popularity of the user's city is displayed.	5,245	0.338	0.473	0	1
Referrals	The number of people invited by the user to enter the platform.	5,245	0.368	5.008	0	266
ParticipationDays	The number of days that the user participates in the lottery activity.	5,245	0.312	0.993	0	18
Logins	The number of times that the user logins.	5,245	5.346	11.890	1	191
SmallCity	=1 if the city is one of the top 10 cities in terms of population.	5,245	0.704	0.456	0	1
DiversityIndex	The proportion of the minority population in the province where the user lives.	5,245	0.039	0.065	0.003	0.372
User-day Level						
UD_IfParticipation	Whether the user participates in the lottery activity on that day.	10,207	0.158	0.365	0	1
UD_Referrals	The number of people invited by the user to enter the platform on that day.	10,207	0.172	3.183	0	266
LogDispNum	The number of participants shown on the activity page (log transformation).	6,921	7.306	2.334	2.197	9.520

Table 3. Variable Descriptions and Summary Statistics

We also included the covariates (i.e., *SmallCity* and *DiversityIndex*). Since users who live in different sizes of communities might exhibit different social connectivity, and thus we use *SmallCity* to indicate whether their city is one of the top 10 cities in terms of population. Meanwhile, ethnic diversity might also change user's social networks. Considering Han people occupy about 90% population in China, we use the proportion of the minority population to indicate the ethnic diversity in the area (*DiversityIndex*). In "user-day level" data, we counted whether the user participates in the lottery activity on that day (*UD_IfParticipation*) and the number of people invited by the user to enter the platform on that day (*UD_Referrals*). The number of participants shown on the activity page (*DispNum*) is also included.

Because the control group is not displaying *DispNum* (*DispNum* is only available in the popularity group and local popularity group), the sample size of *DispNum* will be reduced by about one-third.

Results

Model-free Evidence

Figure 2 compares the number of referrals (*Referrals*) between different groups and 95% confidence intervals. In general, there was no significant difference between the popularity group and the control group. Local popularity significantly inspired extra 0.296 referrals compared with the popularity group and 0.224 referrals compared with the control group.

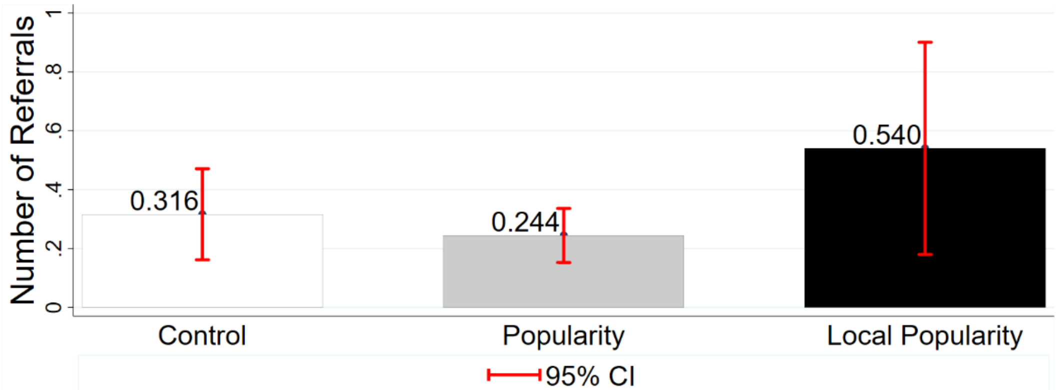


Figure 2. Model-free Results

Local Popularity Encourages Social Referrals

Then we conducted empirical models to illustrate how social referrals respond to popularity and local popularity. Specifically, we model the latent utility of an individual *i* as follows:

$$U_i = \alpha + \beta_1 \times Popularity_i + \beta_2 \times Locality_i + \lambda_i + \epsilon_i \quad (1)$$

where U_i denotes the latent utility, and we include two dummy variables (i.e., $Popularity_i$ and $Locality_i$) to represent the two experimental indicators for an individual *i*. $Popularity_i$ shows the effect of general popularity compared to the control group. $Locality_i$ shows the effect of local popularity relative to the general popularity group. λ_i captures the fixed effect of covariates (i.e., *SmallCity,* and *DiversityIndex*). The error term ϵ_i reflects the idiosyncratic variation in potential outcomes that vary across individuals.

Table 4 reports our main results. Since the number of referrals is a countable variable, we use the negative binomial model to estimate our effects in Column (1). Results show that displaying general popularity (*Popularity*) does not have a significant effect on social referrals compared to the control group. **H1 is not supported**. It seems that displaying popularity cue is not effective enough to encourage users to share with their friends. The insignificant effect of general popularity reveals a complex effect between popularity and social referrals, indicating that users do not necessarily refer very popular activities to their friends. Blindly employing popularity might not encourage users to generate more social referrals, and it also highlights the necessity to carefully design popularity cue. In contrast, displaying local popularity (*Locality*) significantly motivate users to generate more referrals. Thus, **H2 is supported**.

Then, we conduct a robustness check in Column (2) to demonstrate our results are robust to using a linear model with coefficients calculated using ordinary least squares. We also use an alternative measure of social referrals in Column (3), providing assurance that the results are not limited by a single measure. Specifically, we focus on the number of referrals of user's each participated day and conduct the analysis at the user-day level. Results show that our results are consistent across different model specifications.

We also perform a back-of-the-envelope calculation to estimate the economic value of local popularity. For instance, the telecom operator we collaborated with serves over 300 million offline customers who could be potentially to be transferred to online mode. However, only 3% of current APP users are monthly active users (logging in once a month or more), such a great discrepancy provides a huge room to optimize the social referral design. As shown in Table 4, displaying local popularity induce each user to invite extra 0.296 referrals within our experimental period (about five months). Assuming that 1% of monthly active users participate in the event, it can attract an extra 296 thousand users per month (1 million × 0.296) after scaling up this experiment to the whole APP, significantly accelerating the digital transformation.

	(1) Referrals	(2) Referrals	(3) Referrals
	User level	User level	User-day level
Popularity	-0.200 (0.24)	-0.073 (0.17)	-0.229 (0.23)
Locality	0.726*** (0.24)	0.296* (0.17)	0.564** (0.23)
Constant	-1.415*** (0.24)	0.213 (0.16)	-2.113*** (0.23)
Covariate	Included	Included	Included
N	5245	5245	10207
R^2/pseudo R^2	0.004	0.001	0.002

Table 4. Local Popularity Encourages More Social Referrals

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Columns (1) and (3) are from the negative binomial model, and Column (2) is from the ordinary least squares model.

Local Popularity Motivates Users to Invite Neighbors

We further examine the mechanisms through which popularity influences social referrals (e.g., users might select different kinds of recipients). Our arguments for the effect of local popularity are based on the notion that local popularity may be an information cue that encourages users to have a sense of local identity and inspires them to invite their neighbors. To explore this possibility, for each successful referral, we acquire the sender's location and the recipient's location and investigate whether the sender and the recipient are co-located in the same city. Table 5 shows the effect of local popularity on the number of co-located referrals.

	(1) Referrals from the Same City	(2) Referrals from the Same City	(3) Referrals from the Same City	(4) Referrals from the Same City
	User level	User level	User-day level	User-day level
Popularity	-0.296 (0.27)	-0.025 (0.03)	-0.344 (0.26)	-0.013 (0.01)
Locality	0.606** (0.27)	0.060** (0.03)	0.558** (0.25)	0.025** (0.01)
Constant	-2.523*** (0.26)	0.076*** (0.03)	-3.325*** (0.24)	0.034*** (0.01)
Covariate	Included	Included	Included	Included
N	5245	5245	10207	10207
R^2/pseudo R^2	0.004	0.002	0.004	0.002

Table 5. Local Popularity Encourages Users to Invite the Recipients in the Same City

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Columns (1) and (3) from the logit model, and Columns (2) and (4) are from the OLS model.

It reveals that local popularity will significantly encourage users to invite friends from the same city. This may reflect their awareness of nearby information and their tendency to make more targeted invitations to those around them, providing a potential mechanistic explanation: local popularity induces users to invite people in their vicinity who are more likely to accept invitations, thus enhancing the total number of referrals. This analysis is consistent with the previously proposed theory that locality is easier to digest, utilize, and promote to people in the neighborhood (Zhang et al. 2015).

Moderation Effect of City Size

Studies on social conformity theory suggest that priming local identity is more effective for small communities (Kessler and Milkman 2018). Users in smaller communities have a stronger sense of belonging and value when they see information about their local community. Therefore, the effect of local popularity should strengthen for users in small cities. Table 6 reports the results of the moderation analysis by city size. We use the *SmallCity* to indicate the size of the user's current city. In specific, *SmallCity* equals one if the city is one of the top 10 cities in terms of population, and zero otherwise. We analyzed it at both user level and user-day level. First, *SmallCity* has a significant positive impact, indicating that users in small cities are more responsive to making referrals. *Locality*×*SmallCity* has a significant positive impact, implying that local popularity in small cities is more effective in encouraging social referrals. *Popularity*×*SmallCity* has a significant negative impact, suggesting that users in smaller cities do not value popularity much when making referrals. In addition, after incorporating the interaction between *SmallCity*, the effect of local popularity (*Locality*) becomes insignificant, indicating that the positive effect of local popularity is limited to the users in relatively small cities instead of metropolitans. Thus, **H3 is supported**.

	(1) Referrals	(2) Referrals
	User level	User-day level
Popularity	0.428 (0.44)	0.430 (0.41)
Popularity× SmallCity	-0.937* (0.52)	-0.978** (0.50)
Locality	-0.029 (0.43)	-0.058 (0.42)
Locality × SmallCity	1.098** (0.51)	0.915* (0.49)
SmallCity	0.629* (0.37)	0.733** (0.35)
Constant	-1.628*** (0.31)	-2.385*** (0.30)
Covariate	Included	Included
N	5245	10207
pseudo R^2	0.005	0.004

Table 6. Moderating Effect of City Size

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Columns (1) and (2) are from the negative binomial model.

The Increased Referrals are Inactive in Participation

A possible explanation for the observed effects is that referral recipients in a relatively small community are more bonded and less likely to decline the invitation due to social pressure, even if their utility of using the platform is not high enough. In other words, the induced referrals that we observe may be governed by inactive recipients who are not willing to use the platform. To explore this possibility, we examine how popularity and locality influence the selection of recipients who have different levels of participation. Table 7 shows the effect on the recipients' participation.

	(1) ParticipationDays	(2) ParticipationDays
Popularity	0.580***	0.486***
	(0.12)	(0.10)
Locality	-0.599***	-0.491***
	(0.11)	(0.09)
Constant	-0.366***	0.631***
	(0.12)	(0.10)
Covariate	Included	Included
N	1159	1159
R^2/pseudo R^2	0.019	0.034

Table 7. Local Popularity Select Inactive Recipients

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Columns (1) is used the negative binomial model. Columns (2) is used the OLS model.

We find that users with local popularity tend to invite recipients who are inactive in participating on the platform. This result echoes that the invited neighbors have difficulty rejecting invitations even though they are unlikely to derive positive utility from participating on the platform, thereby exhibiting a low level of participation. Although displaying local popularity can boost social referrals by encouraging users to invite their neighbors, our results caution managers about displaying local popularity since the boosted new registrations might be inactive users with low engagement.

Additional Analysis on User Participation

Studies on popularity hold that displaying popularity affects user participation. Although local popularity has a positive impact on social referrals, it might hurt user participation. In particular, to display the popularity in a local area, the number of participating neighbors could be very small. Due to the corresponding popularity being restricted to the local area, such a restriction might diminish the power of popularity and ultimately hurt user participation. We thus investigate how local popularity affects user participation and present our results in Table 8.

	(1) ParticipationDays	(2) Logins	(3) IfParticipation
	User level	User level	User-day level
Popularity	0.232**	0.119***	0.219***
	(0.09)	(0.04)	(0.07)
Locality	-0.172*	-0.068*	-0.176***
	(0.09)	(0.04)	(0.07)
Constant	-1.033***	1.671***	-1.523***
	(0.09)	(0.04)	(0.06)
Covariate	Included	Included	Included
N	5245	5245	10207
pseudo R^2	0.003	0.000	0.006

Table 8. Local Popularity Hurts User Participation

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Columns (1) and (2) are from the negative binomial model, and Column (3) is from the logit model.

Column (1) of Table 8 shows that popularity (*Popularity*) significantly increases participation compared to the control group, which echoes the herding effect of popularity that displaying popularity cue induces users to follow the crowd (Ding and Li 2019). In contrast, local popularity (*Locality*) significantly decreases user participation compared to general popularity. We conduct several robustness checks to support that our results are robust to alternative model specifications and participation measures. We choose *Logins* (the number of times that the user logins) as an alternative measure of participation in Column (2) and find consistent results. Meanwhile, we also investigate user participation in user-day level, and we use *IfParticipation* to indicate whether the user participated on the day. We demonstrate our results by using the logit model in Column (3), respectively. Taken together, our results consistently support that displaying general popularity can increase user participation, while displaying local popularity backfires and hurts user participation.

Our results related to the analysis of participation reveals an interesting puzzle: why local popularity weakens self-participation? If the negative effect on participation is due to the decreased popularity in the local area, the effect of local popularity on participation will not be negative after controlling the displayed number of participants. To further explore the underlying mechanism of the unexpected decrease in user participation, we unpack the box of participation details and extract the displayed number of participants for each login from the APP logs. We compare user participation between the popularity group and local popularity group and present our results in Table 9 (the control group does not display the number of participants and thus is dropped in this analysis). *Locality* represents the net effect of displaying local information after controlling the popularity. Column (1) shows that the displayed number of participants (*DispNum*) is positively related to user participation, which further corroborates our findings that displaying popularity can motivate user participation. In addition, the effect of local information (*Locality*) on participation becomes positive after controlling the displayed number of participants. This reveals that although displaying local information can encourage user participation, the decrease of displayed participants in the restricted area dominates our findings, and thus the effect of local popularity on user participation becomes negative. Columns (2) – (4) presents several robustness checks for this observation. In Column (2), we use *Logins* as an alternative indicator. We add the date fixed effect in Columns (3) and (4). Results consistently show that the negative effect of displaying local popularity on participation is due to the decreased popularity in the local area, and the net effect of displaying local information is positive after controlling the displayed number of participants.

	(1) IfParticipation	(2) Logins	(3) IfParticipation	(4) Logins
	User-day level	User-day level	User-day level	User-day level
Locality	0.560** (0.23)	0.151** (0.07)	0.499** (0.25)	0.116* (0.07)
DispNum	0.171*** (0.05)	0.045*** (0.02)	0.168*** (0.06)	0.039*** (0.02)
Constant	-3.011*** (0.52)	0.598*** (0.15)	-2.140*** (0.69)	1.219*** (0.44)
Date Fixed Effect			Included	Included
Covariate	Included	Included	Included	Included
N	6921	6921	6833	6921
pseudo R^2	0.007	0.001	0.153	0.010

Table 9. The Analysis of Controlling the Displayed Number of Participates

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Columns (1) and (3) are from the logit model, and Columns (2) and (4) are from the negative binomial model.

Discussion

Incorporating local popularity is wildly adopted by major e-commerce platforms. Therefore, understanding how and why local popularity cue effectively motivates social referrals is of high relevance for IS scholars. Our randomized field experiment speaks to this potential and provides mechanisms. Specifically, we contribute to the IS literature and offer practical insights by boosting social referrals via optimized information disclosure.

Theoretical Contribution

This study makes several contributions to the literature. First, our research contributes to the IS literature on platform information disclosure and demonstrates how to improve platform operation by providing popularity and local popularity for users. Previous studies primarily focus on identifying the different effects of popularity in the lab setting. We are the first to use a large-scale field experiment to reveal the causal relationship of how popularity reshapes users' referral behaviors, which allows us to make causal inferences and has high external validity for platform operations. This study offers a holistic view of the multifaceted aspects of displaying popularity cue and provides the first evidence of how the effects of social referrals are conditioned by local popularity.

Second, this study contributes to the literature on location-based marketing by providing a new analytical framework to balance popularity and location information. The related literature has long studied people's preferences toward popularity, but there is limited evidence on how location-based services change the role of popularity (e.g., local popularity) on social referrals. Our paper is the first to document the differential effects of popularity and local popularity on social referrals. We also offer a better understanding of why this is the case. We find suggestive evidence that popularity enhances user participation, while local popularity stimulates users to make more successful referrals, but at the cost of decreasing their own participation due to lower displayed popularity numbers.

Third, the novelty of our study also lies in unpacking the underlying mechanisms by exploring the referral details: local popularity motivates users' referral selection by inviting nearby recipients, but the invited recipients are generally inactive in further participation. In addition, the power of local popularity to motivate social referrals is limited for users in small cities. Our paper answers when and how using local popularity is an effective strategy for boosting social referrals, highlighting the importance of such information in consumer decision-making and firm strategy.

Practical Implications

We expect that this study offers strong implications for platform practitioners in several ways. First, our field experiment demonstrates that local popularity can be used as a powerful marketing managerial tool to improve social referrals. By simply adding local popularity cue without changing the referral design, the platform can get more registrations at a low cost. Considering that displaying popularity cue can be applied to various forms across different types of platforms, our exploratory popularity scheme is scalable to different platforms.

Second, we show that popularity and local popularity performs differently in user participation and social referrals. The promise of our findings calls for a clear recommendation of displaying popularity in platforms. However, platforms should decide which kind of popularity cue to display based on the optimization objectives. We find that displaying local popularity increases social referrals but at the cost of reducing users' self-participation. When displaying local popularity as a strategy to encourage social referrals, one needs to pay special attention to the possible negative impact on user participation. There is no one-size-fits-all rule in choosing between popularity and local popularity. The selection between popularity and local popularity depends on the trade-off between user participation and social referrals. Platform practitioners should make careful calculations or conduct a pilot test before large-scale implementation. If the platform aims to improve user participation, popularity could activate existing users, but if attracting more referrals is a pursuit in platform operations, displaying local popularity could achieve such a goal. For example, based on the growth stage of a company, leveraging social referrals to increase the user base may be the priority for a startup company. Thus, these platforms can benefit more from using local popularity. As a company grows and accumulates enough users, retaining existing users may play a more prominent role, and thus they can display general popularity to achieve the goal.

Third, firms should be cautious about the heterogeneous effect when designing popularity strategies. We show that the power of displaying local popularity is limited to users who live in a small city. In order to reap the benefit, the information could be personalized according to the user's location. Specifically, platform practitioners can display general popularity for users in large cities to stimulate user participation and display local popularity for users in small cities to attract more social referrals, thereby helping build a quick-growth and active platform ecosystem.

Limitations and Future Prospects

We acknowledge that this study has several limitations that offer opportunities for future research. First, though our theoretical framework could apply to any activity in exchange for people exerting effort, our empirical study is conducted in a specific context—a telecom app offering promotion activity. The generalizability of our findings to different types of platforms or apps and different forms of activities is worth future research. The consistent findings with different types of users lend us some confidence in the generalizability of our findings, but future research is needed to replicate the results in different contexts or to explore the boundary conditions. Second, this study explored the role of referral selection and city size to reveal the mechanism of local popularity on social referrals. Although these are two prevalent explanations in literature, we fully acknowledge that other mechanisms might also play a role. Future research could investigate other mechanisms that might drive behavioral outcomes. Third, the best way to investigate mechanisms would be to directly ask the participants how they felt when facing different ranges of popularity. Unfortunately, this was impossible for us due to privacy concerns in the field. Future studies could be sought to design experiments in such a way that they can not only measure subjects' real-life behaviors but also elicit subjects' feelings and beliefs when they are exposed to experiments. An example is to acquire detailed users' profiles via a pop-up window with a questionnaire. Fourth, we find a selection effect that displaying local popularity can encourage users to invite their nearby but inactive friends. Though the log data of users is straightforward to indicate this, some users' characteristics might also play a role in the process of senders selecting referral recipients. For instance, senders might consider recipients of different gender or age. The ideal method to test whether the inviter selects for the inviter is to consider all the recipients. However, we could not observe the users' characteristics due to the privacy in our field experiments.

References

Ames, D. R., Flynn, F. J., and Weber, E. U. 2004. "It's the Thought That Counts: On Perceiving How Helpers Decide to Lend a Hand," *Personality and Social Psychology Bulletin* (30:4), pp. 461–474.

Asch, S. E. 1951. "Effects of Group Pressure upon the Modification and Distortion of Judgments.," in *Groups, Leadership and Men; Research in Human Relations.*, Oxford, England: Carnegie Press, pp. 177–190.

Bandura, A. 1978. "Social Learning Theory of Aggression," *Journal of Communication* (28:3), pp. 12–29.

Bauer, C., and Strauss, C. 2016. "Location-Based Advertising on Mobile Devices," *Management Review Quarterly* (66:3), pp. 159–194.

Belo, R., and Li, T. 2022. "Social Referral Programs for Freemium Platforms," *Management Science* (68:12), pp. 8933–8962.

Biyalogorsky, E., Gerstner, E., and Libai, B. 2001. "Customer Referral Management: Optimal Reward Programs," *Marketing Science* (20:1), pp. 82–95.

Brehm, J. W. 1966. *A Theory of Psychological Reactance.*, A Theory of Psychological Reactance, Oxford, England: Academic Press, pp. 135.

Brimicombe, A., and Li, Y. 2006. "Mobile Space-Time Envelopes for Location-Based Services," *Transactions in GIS* (10:1), pp. 5–23.

Burtch, G., Hong, Y., Bapna, R., and Griskevicius, V. 2018. "Stimulating Online Reviews by Combining Financial Incentives and Social Norms," *Management Science* (64:5), pp. 2065–2082.

Cai, H., Chen, Y., and Fang, H. 2009. "Observational Learning: Evidence from a Randomized Natural Field Experiment," *American Economic Review* (99:3), pp. 864–882.

Chang, Y.-T., Yu, H., and Lu, H.-P. 2015. "Persuasive Messages, Popularity Cohesion, and Message Diffusion in Social Media Marketing," *Journal of Business Research* (68:4), pp. 777–782.

Chen, E. Y. I., and Lin, Y.-W. 2014. "Mobile Connection: An Examination of Antecedents to Engage Consumer in Social Network App," in *Proceedings of PICMET '14 Conference: Portland International Center for Management of Engineering and Technology, Infrastructure and Service Integration*, pp. 3184–3190.

Chen, X., Geng, R., and Phang, C. W. 2015. "The Influence of Location and Social Network on Customers' Acceptance of Mobile Marketing: Evidence from Group Buying Field Experiment," in *HCI in Business*, Lecture Notes in Computer Science, pp. 256–266.

Chen, Y., Wang, Q., and Xie, J. 2011. "Online Social Interactions: A Natural Experiment on Word of Mouth versus Observational Learning," *Journal of Marketing Research* (48:2), pp. 238–254.

Cialdini, R. 2001. "Harnessing the Science of Persuasion," *Harvard Business Review* (79:9), pp. 72–81.

Cialdini, R. B., and Goldstein, N. J. 2004. "Social Influence: Compliance and Conformity," *Annual Review of Psychology* (55:1), pp. 591–621.

Clee, M. A., and Wicklund, R. A. 1980. "Consumer Behavior and Psychological Reactance," *Journal of Consumer Research* (6:4), Oxford University Press, pp. 389–405.

Deutsch, M., and Gerard, H. B. 1955. "A Study of Normative and Informational Social Influences upon Individual Judgment.," *The Journal of Abnormal and Social Psychology* (51:3), US: American Psychological Association, pp. 629–636.

Dewan, S., Ho, Y.-J. (Ian), and Ramaprasad, J. 2017. "Popularity or Proximity: Characterizing the Nature of Social Influence in an Online Music Community," *Information Systems Research* (28:1), pp. 117–136.

Ding, A. W., and Li, S. 2019. "Herding in the Consumption and Purchase of Digital Goods and Moderators of the Herding Bias," *Journal of the Academy of Marketing Science* (47:3), pp. 460–478.

Fang, Z., Gu, B., Luo, X., and Xu, Y. 2015. "Contemporaneous and Delayed Sales Impact of Location-Based Mobile Promotions," *Information Systems Research* (26:3), pp. 552–564.

Fernández-Loría, C., Cohen, M. C., and Ghose, A. 2022. "Evolution of Referrals over Customers' Life Cycle: Evidence from a Ride-Sharing Platform," *Information Systems Research (Forthcoming)*.

Festinger, L. 1954. "A Theory of Social Comparison Processes.," *Human Relations* (7:2), US: Sage Publications, pp. 117–140.

Ghose, A., Goldfarb, A., and Han, S. P. 2013. "How Is the Mobile Internet Different? Search Costs and Local Activities," *Information Systems Research* (24:3), pp. 613–631.

He, Y., and Oppewal, H. 2018. "See How Much We've Sold Already! Effects of Displaying Sales and Stock Level Information on Consumers' Online Product Choices," *Journal of Retailing* (94:1), pp. 45–57.

Heo, J.-Y., and Kim, K.-J. 2017. "Development of a Scale to Measure the Quality of Mobile Location-Based Services," *Service Business* (11:1), pp. 141–159.

Jung, J., Bapna, R., Golden, J. M., and Sun, T. 2020. "Words Matter! Toward a Prosocial Call-to-Action for Online Referral: Evidence from Two Field Experiments," *Information Systems Research* (31:1), pp. 16–36.

Kao, K. C., Rao Hill, S., and Troshani, I. 2017. "Online Consumers' Responses to Deal Popularity as an Extrinsic Cue," *Journal of Computer Information Systems* (57:4), pp. 374–384.

Kessler, J. B., and Milkman, K. L. 2018. "Identity in Charitable Giving," *Management Science* (64:2), pp. 845–859.

Kornish, L. J., and Li, Q. 2010. "Optimal Referral Bonuses with Asymmetric Information: Firm-Offered and Interpersonal Incentives," *Marketing Science* (29:1), pp. 108–121.

Laniado, D., Volkovich, Y., Scellato, S., Mascolo, C., and Kaltenbrunner, A. 2018. "The Impact of Geographic Distance on Online Social Interactions," *Information Systems Frontiers* (20:6), pp. 1203–1218.

Lee, K. S., and Tan, S. J. 2003. "E-Retailing versus Physical Retailing: A Theoretical Model and Empirical Test of Consumer Choice," *Journal of Business Research* (56:11), pp. 877–885.

Li, W., Wang, M., Yu, M., and Zheng, X. 2022. "The Impact of Social Conformity on Adopting Decision of Shared Electric Vehicles: A Choice Experiment Analysis in China," *International Journal of Environmental Research and Public Health* (19:4).

Liu, C.-W., Gao, G. (Gordon), and Agarwal, R. 2019. "Unraveling the 'Social' in Social Norms: The Conditioning Effect of User Connectivity," *Information Systems Research* (30:4), pp. 1272–1295.

Liu, Z., Duan, J. A., and Ter Hofstede, F. 2014. "Marketing Spillovers of Location-Based Mobile Services," *Working Paper*.

Luo, X., Andrews, M., Fang, Z., and Phang, C. W. 2014. "Mobile Targeting," *Management Science* (60:7), pp. 1738–1756.

Muchnik, L., Aral, S., and Taylor, S. J. 2013. "Social Influence Bias: A Randomized Experiment," *Science* (341:6146), pp. 647–651.

Purohit, D., and Srivastava, J. 2001. "Effect of Manufacturer Reputation, Retailer Reputation, and Product Warranty on Consumer Judgments of Product Quality: A Cue Diagnosticity Framework," *Journal of Consumer Psychology* (10:3), pp. 123–134.

Qiu, L., Shi, Z. (Michael), and Whinston, A. B. 2018. "Learning from Your Friends' Check-Ins: An Empirical Study of Location-Based Social Networks," *Information Systems Research* (29:4), pp. 1044–1061.

Rimjhim, Cheke, N., Chandra, J., and Dandapat, S. K. 2020. "Understanding the Impact of Geographical Distance on Online Discussions," *IEEE Transactions on Computational Social Systems* (7:4), pp. 858–872.

Salganik, M. J., Dodds, P. S., and Watts, D. J. 2006. "Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market," *Science* (311:5762), pp. 854–856.

Schmitt, P., Skiera, B., and Van den Bulte, C. 2011. "Referral Programs and Customer Value," *Journal of Marketing* (75:1), pp. 46–59.

Sedikides, C., and Wildschut, T. 2019. "The Sociality of Personal and Collective Nostalgia," *European Review of Social Psychology* (30:1), pp. 123–173.

Sherif, M. 1936. *The Psychology of Social Norms.*, The Psychology of Social Norms., Oxford, England: Harper, pp. xii, 210.

Sun, T., Viswanathan, S., and Zheleva, E. 2021. "Creating Social Contagion Through Firm-Mediated Message Design: Evidence from a Randomized Field Experiment," *Management Science* (67:2), pp. 808–827.

Sun, T., Wei, Y., and Golden, J. 2019. "Geographical Pattern of Online Word-of-Mouth: How Offline Environment Influences Online Sharing," *Working Paper*.

Tam, K. Y., and Ho, S. Y. 2005. "Web Personalization as a Persuasion Strategy: An Elaboration Likelihood Model Perspective," *Information Systems Research* (16:3), pp. 271–291.

Tan, X. (Jane), Wang, Y., and Tan, Y. 2019. "Impact of Live Chat on Purchase in Electronic Markets: The Moderating Role of Information Cues," *Information Systems Research* (30:4), pp. 1248–1271.

Toelch, U., and Dolan, R. J. 2015. "Informational and Normative Influences in Conformity from a Neurocomputational Perspective," *Trends in Cognitive Sciences* (19:10), pp. 579–589.

Tucker, C., and Zhang, J. 2011. "How Does Popularity Information Affect Choices? A Field Experiment," *Management Science* (57:5), pp. 828–842.

Turner, J. C., and Reynolds, K. J. 2003. "The Social Identity Perspective in Intergroup Relations: Theories, Themes, and Controversies," in *Blackwell Handbook of Social Psychology: Intergroup Processes*, pp. 133–152.

Wirtz, J., den Ambtman, A., Bloemer, J., Horváth, C., Ramaseshan, B., van de Klundert, J., Gurhan Canli, Z., and Kandampully, J. 2013. "Managing Brands and Customer Engagement in Online Brand Communities," *Journal of Service Management* (24:3), pp. 223–244.

Xu, Y. (Calvin), Cai, S., and Kim, H.-W. 2013. "Cue Consistency and Page Value Perception: Implications for Web-Based Catalog Design," *Information & Management* (50:1), pp. 33–42.

Zhang, J., and Liu, P. 2012. "Rational Herding in Microloan Markets," *Management Science* (58:5), pp. 892–912.

Zhang, J., Liu, Y., and Chen, Y. 2015. "Social Learning in Networks of Friends versus Strangers," *Marketing Science* (34:4), pp. 573–589.