Proceedings of the Fifteenth International AAAI Conference on Web and Social Media (ICWSM 2021)

# Understanding the Invitation Acceptance in Agent-initiated Social E-commerce

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## Abstract

Recent years have witnessed the phenomenal success of a new form of social e-commerce platforms, which transforms users into agents by motivating them with monetary rewards to promote products and invite new agents through their social network. Despite their rapid growth, there is still inadequate evidence on how such agent invitation works. This research examines what factors affect the agent invitation process. We first conduct a qualitative user study, where we identify four potential mechanisms related to the agent invitation: social conformity, social enrichment, refusal avoidance, and benefit-cost trade-off. Leveraging the empirical data collected from one of the largest social e-commerce platforms in China - Beidian, we operationalize a set of behavioral indicators of these mechanisms and further develop machine learning models to predict users' reactions to invitations. We found that the identified four mechanisms contribute to the high success rate of agent invitations differently. We conclude by discussing the implications of our findings and their potential benefits to real-world applications.

## Introduction

Understanding how social influence affects economic behavior in e-commerce has been a long-standing research problem in both academia and industry (Gefen 2000). Numerous attempts have been made to promote the e-commerce platforms with social features, including adding user review functions (e.g., Amazon), facilitating group buying (e.g., Groupon), and integrating e-commerce with social media (e.g., Facebook and Twitter). Particularly, recently emerging agent-initiated social e-commerce platforms turn out to be an immediate success (e.g., Pinduoduo[1], Beidian[2]). For example, Beidian accumulated more than 10 million users within the first year it launched. Different from previous attempts of social e-commerce, agent-initiated social e-commerce platforms use monetary rewards to transform their users into agents who recommend products and invite new agents via their social networks (Xu et al. 2019a; Cao et al. 2020). As a result, agent invitation is the key to these platforms' rapid growth. For clarity, we use *followers* to denote the users who receive invitations, and *agents* denotes the users who initiate them. It is essential to better understand the mechanisms for followers to accept invitations, which might shed light on leveraging social features to facilitate the growth of e-commerce platforms.

On the one hand, the agent invitation process is similar to the customer referral program, which motivates current customers to refer new customers (Buttle 1998). Prior research suggests the inviter's personal influence plays an important role in the success of these programs (Schmitt, Skiera, and Van den Bulte 2011), which provides a promising direction towards the role of agent invitation. On the other hand, online agent invitation is also related to the research on behavior diffusion in social networks (Golub and Jackson 2010; Cheng et al. 2018), which suggest social communities strongly influence follower's behavior adoption. However, most prior studies focus on the predictions of the invitation cascade's size and structure at a macro level (Golub and Jackson 2010; Anderson et al. 2015; Cheng et al. 2018), where the micro mechanisms of follower's adoption are less investigated. As an initial effort, in this work, we aim to understand the rapid growth of agent invitation network via two research questions: (1) What factors influence the acceptance of invitations in agent-initiated social e-commerce? (2) Can we build effective computational models to predict followers' response to an invitation, i.e., accept or not?

Building on prior works, we mainly investigate a set of hypothetical mechanisms that may influence the invitation acceptance: social conformity (Katz and Kahn 1978), social enrichment (Schmitt, Skiera, and Van den Bulte 2011), e.g. followers might alter their attitudes according to their trust in the inviters, refusal avoidance (Buhrmester et al. 1988), e.g. unable to make a proper refusal, and benefit-cost trade-off, e.g. monetary reward and purchase discount for becoming agents. To this end, we employ a mixed-method approach that consists of a qualitative user study and a quantitative large-scale data analysis. Here, the online user study allows us to gain an in-depth understanding of how different proposed mechanisms affect invitation acceptance, while quantitative data analysis provides us large scale behavior pat-



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[1]https://www.pinduoduo.com

[2]https://www.beidian.com

terns that measure the influence of each mechanism on the invitation acceptance.

**Online User Study.** We first study the effects of the proposed mechanisms through a online survey. We found a large portion of survey participants mentioned one or several of those proposed mechanisms when describing why they accept the invitations. Our survey results also showed statistically significant correlations between those different mechanisms and followers' propensity to accept a referral. These findings echo previous studies in online behavior diffusion (Cheng et al. 2018; Anderson et al. 2015), suggesting the importance of social community influence on invitation acceptance. Moreover, the effect of social enrichment and refusal avoidance demonstrates that the personal influence from the inviters also plays a significant role. These results complement previous studies on customer referral programs and online behavior diffusion, suggesting that the rapid expansion of the invitation network is a joint product of the community and personal influence.

**Large-scale Data Analysis.** We augment the findings in a user study with a data-driven analysis on Beidian, one of the largest agent-initiated social e-commerce platforms with over 35 million users. By correlating users' behavioral records with their survey response, we identify several behavioral indicators that can serve as good proxies to measure the effect of each mechanism. For example, followers' expected utility in benefit-cost trade-off positively correlates with the total expense of their purchases, which is probably due to the purchase discounts they will obtain after becoming an agent. To demonstrate the effectiveness of different mechanisms, we train a machine learning model based on them that accurately predicts whether a follower will accept a specific invitation. We found that the behavioral indicators of the social conformity and social enrichment mechanisms are the most predictive factors, which reinforces our findings that both personal and community influence contributes to the efficient agent invitations.

To sum up, the contributions of this work are: (1) We conduct an online user study that identifies four primary mechanisms behind the agent invitation in social e-commerce: social conformity, social enrichment, refusal avoidance, and benefit-cost trade-off. We demonstrate that all four mechanisms contribute to the high acceptance rate. More importantly, we show the efficient agent invitation is a joint product of personal and community influence. (2) We validate these findings in a real-world scenario with large scale empirical data analysis. We identify several behavioral indicators that serve as good proxies for measuring the effect of these mechanisms. (3) We build a machine learning model to accurately predict the invitation acceptance based on the behavioral indicators (AUC = 0.87), with implications for real-world applications.

## Related Work

The invitation acceptance behavior in agent-initiated social e-commerce has links to social theories across multiple research areas. On the one hand, it heavily relies on the influence diffusion in social networks. On the other hand, it closely relates to a widely adopted word-of-mouth marketing strategy known as customer referral program (Buttle 1998). Therefore, we review the literature on these areas and summarize the most relevant related works as follows.

### Influence Diffusion on Social Network

Modeling the diffusion and adoption of innovations, behavior, and new products in social networks has been a longstanding problem that has attracted significant research interest (Rogers 2010; Sun et al. 2018). The rapid development of information and communication technology facilitates observations on influence diffusion events at scale (Golub and Jackson 2010). Previous works studied the online cascading behavior of influence diffusion in numerous scenarios, which included both target specific settings like email petition (Liben-Nowell and Kleinberg 2008), viral marketing (Leskovec, Adamic, and Huberman 2007) and attracting newcomers (Balali et al. 2018), and in a broadcast setting like information retweeting (Adamic et al. 2016). A particular relevant branch of research sought to understand the adoption of online services (Anderson et al. 2015; Aral, Muchnik, and Sundararajan 2009; Aral and Walker 2011). Extensive previous efforts showed the diffusive invitation processes played an important role in the adoption of emergent online services (Aral, Muchnik, and Sundararajan 2009; Aral and Walker 2011). Specifically, Anderson et al. studied the cascading invitations on Linkedin (Anderson et al. 2015). Their research found that the structure of invitation cascade exhibited a higher degree of virality than information diffusion and consisted of users with a coherent demographic. Additionally, several models of behavior contagions had been proposed to model the diffusion of online services (Centola and Macy 2007), which generally predicted users' propensity to adopt were positively correlated with the number of early adopters in their community.

Since the agent invitation in social e-commerce relies on agents to exert their influence through social connection, this is a novel type of social influence diffusion process, and hence understanding the invitation acceptance is of significant importance. Our study closely relates to the previous works in understanding the cascading invitations in online service adoption (Anderson et al. 2015). However, the agent-initiated social e-commerce differs from other online services by providing monetary incentives for successful invitations, and the new adopters are attracted by the benefits of becoming agents. Moreover, instead of modeling the structure of invitation cascades (Anderson et al. 2015), we seek to understand the governing mechanisms behind the efficient invitation acceptance.

### Customer Referral Program

The customer referral program is a well-studied marketing strategy that leverages a stimulated word-of-mouth effect to acquire new customers (Buttle 1998). Previous studies on customer referral program focused on optimizing the techniques to maximize the overall return, such as strategies on when to offer rewards (Kornish and Li 2010), how much reward should be offered (Wirtz and Chew 2002), and how to estimate the referral likelihood (Ryu and Feick 2007).

Moreover, empirical research showed increasing evidence that customer referral programs were effective and profitable because the referred customers usually contributed higher profit margins and had longer retention periods than regular customers (Guseva 2008). The personal influence that the inviters imposed on the referred customers had been identified as the determinant factor (Schmitt, Skiera, and Van den Bulte 2011) with two social mechanisms that were particularly relevant: social enrichment (Schmitt, Skiera, and Van den Bulte 2011) and refusal avoidance (Goffman 1967). On one hand, the social enrichment mechanism suggests the referred customer's emotional bond with the product is enriched because their friends are also customers of the product (Schmitt, Skiera, and Van den Bulte 2011), which is in accordance with the triadic closure effect that is widely observed in social network (Hutto, Yardi, and Gilbert 2013; Kivran-Swaine, Govindan, and Naaman 2011). On the other hand, the refusal avoidance mechanism suggests saving the sociological "faces" might be another important reason for users to accept invitations (Cheng et al. 2018). Specifically, the facework theory indicates people tend to present and preserve their public self-image in front of others (Goffman 1967). Since non-compliance with a friend's invitation is generally deemed as a face-threatening act that may translate into damage on both inviter and invitee's faces, users might accept the invitations in order to avoid that (Rao et al. 2009).

The agent invitation in social e-commerce particularly resembles the customer referral program in the way of motivating existing agents to bring in new agents. However, the objective of agent invitation programs is to improve the acceptance rate of invitation, while the customer referral programs aim to maximize the overall return, i.e., promoting purchases and retaining acquired customers. Additionally, conventional customer referral programs are mainly carried out in an offline manner, while the agent invitation programs mostly occur in an online scenario. Therefore, it is an important research question to examine whether and how social enrichment and refusal avoidance mechanisms take effect in online agent invitations.

## Hypothesis

We aim to draw inspirations from previous related works to develop the hypotheses on the governing mechanisms behind the invitation acceptance behavior in agent-initiated social e-commerce. Specifically, the previous works on social influence diffusion suggest invitation acceptance might be subject to the influence of their social communities. Additionally, the literature on customer referral program indicates the personal influence imposed by the inviters also plays an important role. Moreover, the numerous forms of social e-commerce platforms imply that platform design might also affect user's behavior. Therefore, we investigate the invitation acceptance behavior from these three perspectives and develop the key hypotheses accordingly, which are discussed in detail as follows.

### Influence from Social Community

Accumulating empirical evidence suggest the propensity of an individual to adopt a diffusive behavior increases with the number of adopters they have been exposed to (Cialdini and Cialdini 2007). Social conformity theory is the prevalent narrative in explaining such effect, where the user's tendency to follow the crowd is rationalized as the belief of "others' interpretation of an ambiguous situation is more accurate than ours" (Katz and Kahn 1978). As a result, users tend to converge their actions to what the majority of others deem appropriate. The invitation acceptance in agent-initiated social e-commerce is a specific form of influence diffusion, where invitees can easily observe their friends' decisions on whether or not to accept invitations. Thus, it is reasonable to assume that the invitation acceptances are also significantly affected by social conformity:

***H1 Social Conformity****: Observing more friends become agents increases a user's likelihood of accepting the invitations.*

### Influence from Inviters

The social enrichment mechanism in the customer referral program predicts that a customer's propensity to purchase increases with their social tie strength with the referrers. In the context of agent-initiated social e-commerce, social enrichment indicates the user's attitude toward the invitations will be affected by her social relationship with the inviters (Xu et al. 2019b). Therefore, we make the following hypothesis:

***H2 Social Enrichment****: A user's propensity of accepting invitations increases with her/his social tie strength with the inviters.*

On the other hand, agent invitation involves a direct request from the agents to the invitees. Therefore, a social cost of non-compliance (i.e., refusal) is introduced into the process. An invitee with a neutral attitude or even one who is reluctant to become an agent may accept the invitation due to the reason of refusal avoidance. Additionally, the ability to make appropriate refusal to alleviate the social cost has long been considered as a personal trait and difficult to learn (Kwon 2004; Buhrmester et al. 1988). Therefore, it is reasonable to assume the outcomes of agent invitations are correlated with the invitee's refusal ability. Based on these considerations, we come to the following hypothesis:

***H3 Refusal Avoidance****: Users with less ability to make appropriate refusal are more likely to accept invitations.*

### Effect of Platform Design

Different from the copy-and-paste information diffusion cascade, agent invitation involves complicated benefits and costs trade-off for invitees to accept the invitations. In the context of Beidian, the platform requires users to accumulate a certain amount of purchases before becoming agents to ensure commitment, which effectively introduces a cost for joining the platform. The benefits of joining, on the other hand, include the opportunity to earn commission fees for recommending products and discounts for future purchases.

Prior works on behavior diffusion suggest the resources and effort needed for adopting a behavior play an important role in an individual's decision-making process (Marwell, Oliver, and Prahl 1988). Since individuals often only adopt it if the expected benefit exceeds the perceived costs (Oliver 1984; Cheng et al. 2018), it is effective to increase an individual's adoption likelihood by lowering the adoption cost. It is natural to assume the trade-off between benefits and costs also exists in agent invitations. Therefore, we make the following hypothesis:

***H4 Benefit-cost Trade-off****: User's propensity to accept the invitations increases with their expected utility of becoming agents.*

# User Study

## Organization of the Questionnaires

Our questionnaire is available in https://github.com/tsinghua-fib-lab/Social-Commerce. It contains four parts: namely, *demographics*, *factor quantification*, *motivation analysis*, and *open-ended questions*. For simplicity, we denote questions in agent questionnaire as AQ and questions in follower (i.e. invitee) questionnaire as FQ hereafter.

**Demographics.** We collect demographic information, including gender and age, to check the representativeness of the survey participants.

**Factor Quantification.** This part is designed to quantify the effect of each mechanism. It contains four scales for both agents and followers (AQ1-4, FQ1-3, FQ5), and we will introduce the detailed measures in the next subsection.

**Motivation Analysis.** The goal of this part is to explore the user's motivations for accepting an invitation. It contains one question for agents (AQ5) explicitly asking their primary reasons for accepting an invitation with four given options and one open-ended option, as shown in table 2. Participants can select multiple choices, and they can also report in free-text.

**Open-ended Questions.** Questions in this part are designed to collect concrete examples showing how each mechanism works and thereby deepen our understanding of the analysis results. We set an open-ended question (AQ6, FQ6) for all users asking them to provide specific situations when he or she accepted or rejected an invitation (if there were any).

All the details of the agent questionnaire and follower questionnaire are given in the supplementary file for reference. Note that we conducted the survey initially in Chinese. To ensure the translation of our questionnaire are faithful to the original wording, authors and a native English speaker had done a forward and backward translation.

## Measures

**Social Conformity.** Prior works measured social conformity mainly by one's tendency to follow group norms in attitudes, beliefs, and behaviors (Zhou, Horrey, and Yu 2009). We took the same approach by using a 10-item scale (AQ2, FQ2) adapted from Mehrabian et al. (Mehrabian and Stefl 1995), which asked about one's conformity experiences in different situations. (e.g. "I often rely on, and act upon, the advice of others."). This scale was highly reliable with an internal consistency measured by Cronbach's alpha (Cronbach 1951) of 0.77 in our data. We denoted the average score of this scale as *social conformity score* in quantitative analysis.

**Social Enrichment.** As we discussed before, the influence of social enrichment could be measured by the strength of social ties (Wiese et al. 2011). We took a direct approach to quantify tie strength by dividing inviters into four categories, namely relatives, friends, acquaintances, and strangers, and we asked users the relationships between him/her and the inviter (AQ4, FQ5). This approach has been proven effective by Marsden et al. (Marsden and Campbell 1984).

**Refusal Avoidance.** We measured users' refusal ability by a wildly adopted 8-item scale (AQ1, FQ1) designed by Buhrmester et al. (Buhrmester et al. 1988), which asked one to assess the difficulty he or she feels when making a refusal in different situations (e.g. "Saying 'no' when a date/acquaintance asks you to do something you don't want to do."). For a reliability check, we tested the internal consistency between the 8 items with our data measured by Cronbach's alpha, and the result was 0.87, which indicated it was highly reliable. We denoted the average score of this scale as *refusal ability score* in quantitative analysis.

**Benefit-cost Trade-off.** When receiving an invitation, one natural consideration of a user is his or her expected utility, i.e., benefits over costs. In the context of Beidian, we specified four typical benefits and costs of being an agent, and we leveraged them to measure one's expected utility of accepting an invitation. We designed a 4-item, 7-point Likert scale (AQ3, FQ3) in which we asked participants to describe their degree of agreement or disagreement on the four descriptions of benefits and costs we specified (e.g. "I can have a good income by being an agent." or "The cumulative purchase needed for being an agent bothers me."). This scale was internally consistent with a Cronbach's alpha of 0.72. Note that the scores of the cost items were counted in a reversed order, and we denote the average score of this scale as *expected utility score* in quantitative analysis.

## Participants Recruitment and Responses

We recruited participants through an improved *snowball sampling method* introduced by Goodman (Goodman 1961). We first selected ten agents with different identity backgrounds as initial participants, and then we asked them to disseminate our online questionnaires to both agents and followers through their social connections. As a result, 598 agents and 237 followers fulfilled the questionnaires. To improve the survey quality, we filtered out the duplicate responses and the responses finished in less than 180s to make sure our questions have been carefully read. After filtering, there remained 486 agent responses and 176 follower responses.

## Analyses and Results

We first tested our hypotheses by applying a fixed-effects logistic regression model on all the four factors we quantified, which could both validate the effect of each mechanism on

| Variables | $\beta$ |
|---|---|
| Intercept | $-3.624^{***}$ |
| Social conformity score | $0.195^{*}$ |
| Refusal ability score | $-0.801^{***}$ |
| Trade-off between benefits and costs (expected utility score) | $1.511^{***}$ |
| Social enrichment (relatives) | $0.186^{**}$ |
| Social enrichment (friends) | $0.178^{**}$ |
| Social enrichment (acquaintances) | $-0.141$ |

Table 1: Fixed-effects logistic regression analysis (#agent=486, #follower=132) reveals the significant effect of different factors on accepting invitations. Here, p<0.001:***, p<0.01:**, p<0.05:*

| Reasons for Acceptance | N | P |
|---|---|---|
| I think it worthwhile to be an agent due to the commission fees and the extra purchase discount offering for agents. | 339 | 72.44% |
| I trust the people who invite me. | 192 | 41.03% |
| I find many of my friends have become agents, and I want to join them. | 108 | 23.08% |
| I am embarrassed to refuse the invitation. | 55 | 11.75% |

Table 2: Most common reasons for accepting invitations, and the number (N) and percentage (P) of agent participants who reported the corresponding item (Total agents = 486).

invitation acceptance and reveal the relative influence effect among different mechanisms. Then, as a complement to our regression analyses, we analyzed the self-reported motivations for accepting invitations. Finally, we report some concrete examples of invitation acceptance, showing how each mechanism takes effect on users' decisions on invitations.

**Regression Analysis.** To test whether the proposed mechanisms take effect in invitation acceptance, we conducted a fixed-effects logistic regression to predict whether one was an agent, using the four factors we quantified, i.e., social conformity score, social enrichment score, refusal ability score, and tie strength. In other words, this model predicts whether one will accept an invitation or not. Note that we treated tie strength as a dummy variable due to its discrete nature, and this analysis filtered out the users who did not receive any invitations because they could be treated as neither negative samples nor positive samples. The results are shown in table 1.

As a result, we found that each factor had a significant coefficient, indicating that all of the four mechanisms have an independent effect on invitation acceptance. Specifically, the most influential mechanism was the trade-off between benefits and costs ($\beta = 1.511$, p<0.001), which suggests that on receiving an invitation, the users' prior concerns were his gain and loss. This result supports *H4*. We also found the probability of invitation acceptances negatively correlated with refusal ability score ($\beta = -0.801$, p<0.001). In other words, users with lower refusal ability have a higher chance to accept an invitation, which supports *H3*.

The effects of social conformity and social enrichment were relatively small, yet still significant. Users with a high social conformity score were more likely to accept invitations ($\beta = 0.195$, p<0.05), and users invited by their strong ties (relatives and friends) were more likely to accept invitations compared to being invited by strangers ($\beta = 0.186$, p<0.01 for relatives and $\beta = 0.178$, p<0.01 for friends). These results support our hypotheses *H1* and *H2*.

**Self-reported Motivations.** Paralleled to our regression analysis, we examined agents' self-reported motivations for accepting invitations from AQ5. As we showed in Table 2, the four given options each correspond to the effects of one mechanism on the acceptance of invitations. Specifically, the item "I think it worthwhile to be an agent due to the commission fee and the extra purchase discount offering for agents" is related to the mechanism of the trade-off between benefits and costs and it was selected by a majority of agents (72.44%) as one of their acceptance reasons. Other three items, "I trust the people who invite me" related to social enrichment, "I find many of my friends have become agents, and I want to join them" related to social conformity, and "I am embarrassed to refuse the invitation" related to refusal ability, are chosen by 41.03%, 23.08%, and 11.75% of agents respectively. The rest of the reasons reported from the open-ended option accounted for less than 3% of the total agents. These results reflect the effects affecting users' decisions on invitations from the users' perspective, and it shows both consistencies and differences from the results of our regression analysis. First, both analyses show that the effects of benefit-cost trade-off are dominant on invitation acceptance. Second, from the users' perspective, the second most influential mechanism is social enrichment, while statistical analysis identified refusal ability to be the second most important one. This difference may indicate a social desirability bias that people tend to hide their lack of refusal ability (Edwards 1958).

## Empirical Study

In order to examine how the proposed mechanisms play out in the wild, we conducted a data-driven study on the empirical user behavioral data. Specifically, we aim to identify the behavioral indicators for the effect of each mechanism. Through them, we are able to further analyze the empirical importance of different mechanisms in the agent invitations.

### Dataset

The used dataset covers all users in Beidian (2,361,659 agents and 37,262,867 followers) for about six months, i.e., from 2018/06/01 to 2018/11/27. It contains three types of data, namely *user profile data*, *purchase behavior data* and *invitation behavior data*. Specifically, the *user profile data* includes the information of user type (agent or follower), the timestamp starting to use Beidian, and user demographics (registered age, gender, and region). The *invitation behav-*

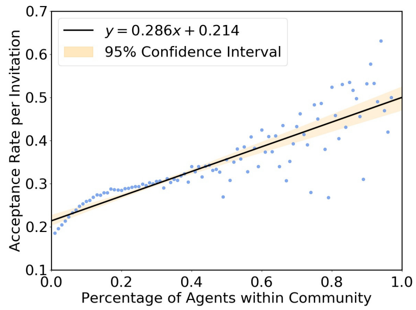



Figure 1: The empirical correlation between acceptance rate per invitation and agent percentage within a community.

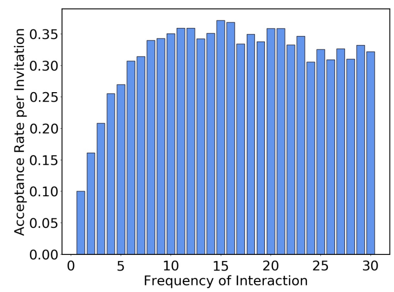



Figure 2: The empirical correlation between acceptance rate per invitation and the frequency of interactions.

*ior data* consists of the information of initiate agent's IDs, the recipient user's IDs, whether she accepts the invitations and the timestamps of events. There are 211,954 invitations records in total, and 21.75% of them are accepted. Additionally, we also collect the *purchase behavior data* to gain a full picture of the user's behavior. It includes the click records on the recommended products and the purchase records. These records consist of the follower's IDs, the product's IDs, the agent's IDs, and the timestamps of events. In total, there are 377,478,727 click records and 115,856,154 purchase records. Note that we use the interactions between users to identify the underlying social relations, since the interactions are mainly conducted via the social network. Specifically, two users are considered to have a social connection if they have at least one interaction (click, purchase, and invitation), and users that have connections with same agents are considered to be in one community. By asking the survey participants for their authorizations, we manage to link the user behavioral data with the survey responses from 44 users.

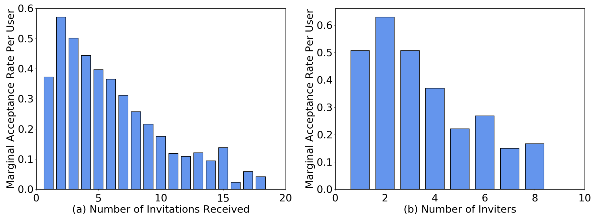
**Ethical Considerations.** We take careful steps to address the privacy issues in analyzing user data. First, the Terms of Service for Beidian include consent for research studies. Additionally, user data is accessed after privacy sanitization, where all user identifiers are replaced with anonymous hashcodes. Second, we explicitly ask the survey participants for permissions to use their responses for research purposes, with an opt-in option to gain their authorization for linking the survey result with user behavior data. Third, our research protocol has been reviewed and approved by our local institutional board. All research data is stored in a secure off-line server, with access limited to only authorized researchers bound by strict non-disclosure agreements.

## Data Analysis

Here we extract several behavioral indicators for each identified mechanism to examine their empirical predictive power for invitation acceptance. To ensure the efficacy of our results, we analyze the behavior data on basis of each invitation and compute the behavior indicators upon their arrival.

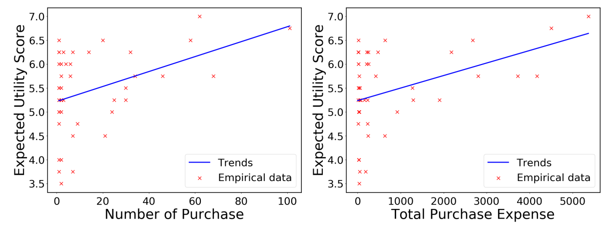
**Social Conformity.** Our user study showed that the social conformity mechanism positively contributes to the efficient agent invitations, where a notable portion of acceptances are attributed to observing friends who have become agents. To evaluate this effect in real-world scenarios, we examined the empirical correlation between the acceptance rate per invitation and the agent percentage within the community, which is shown in Figure 1. Specifically, each dot represents a data sample; the black line denotes the fitting curve, and the orange area depicts the 95% confidence interval. From the results, we observed a clear positive correlation between them, where the fitting curve suggests the acceptance rate monotonically increases from 21% to 50% as the percentage of agents increases from 0.0 to 1.0. These observations are in accordance with the hypothesis *H1* and echo previous findings in the user study. Additionally, it also indicates that the percentage of agents within the community is a good behavioral indicator for the effect of social conformity, which is likely to exhibit predictive power on the invitation acceptances.

**Social Enrichment.** The social enrichment mechanism reveals a follower's propensity to accept invitations positively correlated with her social tie strength with the inviters. Although it is hard to measure the social tie strength based on our empirical behavioral data, previous studies reveal the frequency of mutually acknowledged contacts is a good proxy (Friedkin 1980), where higher frequencies imply stronger social ties. For example, frequently mutually exchanged phone calls often indicate strong social tie strength. Inspired by these findings, we leveraged the user's clicking frequency on the agent's recommended products as the proxy of social tie strength. Specifically, each click represents a mutually acknowledged interaction, since the agent initiates the recommendation, and the follower clicks through it. We showed the empirical correlation between the acceptance rate per invitation and the interaction frequency (click through frequency between the users and the agents within the last 30 days of the invitations) in Figure 2. To avoid data sparsity and improve the stability of results, we showcased the invitations between followers and agents that have less than 30 interactions, which covered 94% of total invitations. As the frequency of interaction increases from 0 to 10, follower's propensity to accept invitations monotonically increases from around 10% to around 35% and then remains at a high level. It indicates the interaction frequency is indeed a good behavioral indicator for the invitation acceptance, which is consistent with the prediction of the social



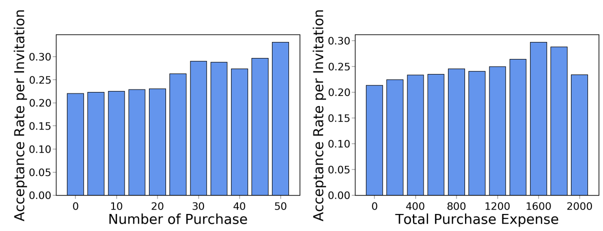

(a) Number of invitations (b) Number of inviters

Figure 3: The marginal acceptance rate with different invitation history.




(a) Number of purchase (b) Purchase expense

Figure 4: The empirical correlation between the expected utility score and users' purchase behavior.




(a) Number of purchase (b) Total purchase expenses

Figure 5: The empirical correlation between acceptance rate per invitation and users' purchase behavior.

enrichment mechanism in our previous user study.

**Refusal Avoidance.** Although it is hard to measure a user's social skill of refusal directly, the results in the user study indicate the majority of users find it more difficult to refuse multiple invitations. Therefore, it is reasonable to infer that multiple invitations require higher social skill to refuse properly, and hence will increase a follower's propensity to accept invitations. To examine the power of repeated invitations, we showed the marginal acceptance rate in Figure 3(a). Specifically, the marginal acceptance rate at the $t$-th invitation is computed as the number of followers who accept the $t$-th invitations divided by the total number of followers who receive at least $t$ invitations (i.e., refuse $t-1$ previous invitations), which measures the marginal effect of accumulating invitations. From the result, we found out that the marginal acceptance rate peaked at the second invitation with 58%. Additionally, the second to the fifth invitations all yield a higher marginal acceptance rate than the first invitations, which supports previous assumptions that multiple invitations increase follower's propensity to accept. However, we also observed that the marginal acceptance rate gradually decreased after the second invitations, and reduced to less than 10% after the 15-th invitation. This is probably because the remaining followers have firm attitudes toward rejecting invitations, and may perceive the accumulating invitations as spam. These findings also echo several previous studies on viral marketing, where the conversion rate peaks at the second exposure (Leskovec, Adamic, and Huberman 2007; Cheng et al. 2018).

Next, we further examined how the number of inviters affected the marginal acceptance rate, which is presented in Figure 3(b). Interestingly, the marginal acceptance rate also peaks at the second inviter. This is probably due to the joint product of the mechanisms of social conformity and refusal avoidance. Nonetheless, these results suggest adequately increasing the number of invitations and inviters are both solid methods to increase the overall acceptance rate. Additionally, the number of invitations and inviters are two promising behavioral indicators for predicting the invitation acceptance.

**Benefit-cost Trade-off.** The user study has shown that the expected utility is the primary motivation of becoming an agent, where 72% of users citing it as their reason for accepting invitations. The benefit of becoming agents includes discounts for purchasing products on the platform. Therefore, we can assume that the users with higher purchase volume have a higher expected utility of becoming agents since they can enjoy the discount for agents in their future purchases. To evaluate the validity of this assumption, we leveraged the linked user survey to examine the correlation between the purchase volume within the last 30 days and the expected utility score. As Figure 4 shows, there is a positive correlation between the expected utility score and the number of purchases as well as the total expenses of purchases. The results support the assumption that the number of purchases and the total expense of purchases can serve as the behavioral indicators of expected utility. Furthermore, we evaluated the predictive power of these behavioral indicators on invitation acceptance. Specifically, we spotlighted the invitations with less than 50 purchases and 2000 Yuan respectively to avoid data sparsity, which both covered 99.8% of the overall invitations. The empirical correlation between the acceptance rate per user and the number of purchases is presented in Figure 5(a). We observed that the acceptance rate monotonically increased from 22% to 33% as the number of purchases increased from 0 to 50. As shown in Figure 5(b), similar results are found between the acceptance rate and the total purchase expense. These validate the effectiveness of using the number of purchases and purchase expenses as behavioral indicators for accepting invitations.

## Predictive Model

To showcase the implications of our findings for real-world applications, we formulate a task to predict the result of each invitation, i.e., accepted or refused. The predictive model is built on top of the previously identified behavioral indicators of the proposed mechanisms, which aims to shed

| Feature Set | | AUC | F1-score | Overall Importance |
|---|---|---|---|---|
| *Demographics* | Age, Gender, Region | 0.569 | 0.701 | 0.096 |
| *Social Conformity* | The percentage of agent within a community | 0.750 | 0.744 | 0.569 |
| *Social Enrichment* | The number of interactions (within 7, 15, 30 days) | 0.717 | 0.683 | 0.164 |
| *Refusal Avoidance* | The number of inviters The number of invitations (within 7, 15, 30 days) | 0.600 | 0.645 | 0.148 |
| *Benefit-cost Trade-off* | The number of purchase Total expenses of purchase (within 7, 15, 30 days) | 0.618 | 0.679 | 0.022 |
| *Combined* | All Features | 0.869 | 0.790 | |

Table 3: The performance of the predictive model with different feature sets.

light on the relative importance of each indicator in explaining the invitation acceptances. We choose the demographic features as the baseline for behavior indicators, which include gender, age, and region. The demographic-based predictive models have been widely used in user behavior prediction (Justin Cheng and Cristian Danescu-Niculescu-Mizil 2017). Specifically, the selected features are summarized in Table 3. To train and evaluate our model, we first construct a benchmark dataset. We filter out the users with records less than one month from the complete dataset to avoid data sparsity. Additionally, since 78.25% of overall invitations are refused, the predictive model could generate a misleading high accuracy by always predicting refusal. Thus, to avoid unbalanced samples, we randomly downsample the positive samples and negative samples to a ratio of 1:1. Finally, we split the dataset into a training set and a test set by a ratio of 7:3. Based on the benchmark dataset, we train a random forest classifier with each set of the selected features and evaluate the predictive model with two widely adopted classification metrics, i.e., AUC and F1-score.

Table 3 summaries the performances of the predictive model trained on different sets of features. We observe that the commonly used demographic features only result in mediocre performance on (AUC=0.569). Across all categories, the percentage of agents within a community notably performs best (AUC=0.750,F1-score=0.744), indicating that social conformity is most informative in predicting invitation acceptance. Additionally, features related to the social enrichment mechanism are also strong predictive signals (AUC=0.717,F1-score=0.683). Therefore, these observations further verify that both personal influence and community influence are important in invitation acceptance. The features regarding refusal avoidance mechanism (AUC=0.600,F1-score=0.645), and benefit-cost trade-off mechanism (AUC=0.618,F1-score=0.679) are slightly less informative. Finally, combining all the features, we derive an accurate predictive model (AUC=0.869,F1-score=0.794), which significantly outperforms the baseline of user demographic. Through incorporating the behavior indicators, the predictive model is able to improve the AUC by 0.3 and F1-score by 0.089. These results indicate the identified behavioral indicators indeed possess predictive power on the invitation acceptance. Asides from accuracy indicators, we also calculate the overall importance of each set of features in the complete model, which is also displayed in Table 3. Among different feature sets, social conformity is of the highest importance (0.569), which is consistent with its predictive power. Social enrichment (0.164) and refusal avoidance (0.148) share limited feature importance. Features of Benefit-cost Trade-off are less important in prediction, implying that there may exist a gap between purchase volume and perceived utility. One plausible explanation is that the perceived utility is more correlated with the expected sale volume of each user as suggested in the survey results (see AQ3 and FQ3), which is difficult to observe in user behavior data. Overall, we confirm that the indicators we identify for social enrichment, refusal ability, and social proof are effective to predict invitation acceptance in social e-commerce effectively, and more importantly, our analysis showcases the real-world applications of our findings.

## Discussion

First, our work echos previous research on the influence diffusion in online social network (Cheng et al. 2018; Rogers 2010). Prior studies demonstrate that social conformity is the primary mechanism affecting the diffusion process (Cialdini and Cialdini 2007). We extend these findings into a novel scenario, i.e., the invitation acceptance in agent-initiated social e-commerce. Specifically, there is a considerable amount of survey participants (23.08%) citing social conformity as their motivation for acceptance. Empirical data analysis also shows a user's propensity of accepting invitation increases with the number of their friends who have already accepted, which indicates users tend to converge their actions to what others deem as appropriate. These results suggest that the invitation acceptance behavior is affected by the influence of the social community.

Second, we also note that the agent invitation involves the explicit person to person interactions, which resembles customer referral programs (Buttle 1998). As a result, our study reveals that the fundamental mechanism of the customer referral program, social enrichment (Schmitt, Skiera, and Van den Bulte 2011), is also effective in the growth of agent-initiated social e-commerce networks. Specifically, 41.03% of survey participants attribute their motivation of acceptance to the reason “I trust the people who invite me”. Additionally, users are significantly more likely to accept the invitations from people that are close to them, e.g., friends and relatives. We also find out that the outcomes of invitations are also correlated with the invitee’s social skill of making an appropriate refusal. Users with less refusal ability scores are more likely to accept. Moreover, users generally find repeated refusals to be more difficult. This provides an explanation for previous research findings on the increased profit margin of repeated exposures in e-mail marketing (Leskovec, Adamic, and Huberman 2007). These findings combined suggest that personal influence is also an important factor in the growth of agent networks. Specifically, the mechanisms of social enrichment and refusal avoidance can be leveraged to promote the success rate of invitation.

Third, our work also contributes to the large research body on modeling the growth and evolution of social networks (Zang, Cui, and Faloutsos 2016). With the increasingly available empirical data, extensive research efforts have been dedicated to modeling the evolution patterns of numerous mainstream social networks, including Twitter (Stringhini et al. 2013), Flickr (Kumar, Novak, and Tomkins 2010) and Wechat (Zang, Cui, and Faloutsos 2016). Our work is particularly relevant to the study on LinkedIn, since its growth is also built on cascading invitations (Anderson et al. 2015). However, previous work mainly focuses on characterizing the arrival pattern of new users. In contrast, we contribute to the understanding of the primary mechanisms behind the users’ decisions to join the network. Additionally, we demonstrate that an accurate predictive model (AUC=0.854) on a user’s propensity of joining the network can be built based on the behavioral indicators of these discovered mechanisms.

## Conclusion

The rapid growth of agent-initiated social e-commerce is built on top of the complicated social interactions of agent invitations. This work seeks to reveal the underlying mechanisms behind the high success rate of agent invitations. Specifically, we establish four primary mechanisms through an online user study and large-scale empirical data analysis, i.e., social conformity, social enrichment, refusal avoidance, and benefit-cost trade-off. Additionally, we identify several behavioral indicators for measuring the effects of these mechanisms in real-world scenarios and leverage them to develop an accurate predictive model for the users’ responses to invitations. These results unveil the roles of the proposed mechanisms in the rapid expansion of agent-initiated social e-commerce networks.

## Acknowledgments

This work was supported in part by the National Natural Science Foundation of China under U1936217, 61971267, 61972223, 61941117, 61861136003, Beijing Natural Science Foundation under L182038, Beijing National Research Center for Information Science and Technology under 20031887521, and research fund of Tsinghua University - Tencent Joint Laboratory for Internet Innovation Technology.

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