

Magnify Cascades of eWOM on Social Networks: The Roles of User, Product, and Relationship Characteristics

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Abstract

Firms are increasingly relying on electronic word-of-mouth (eWOM), in the form of online reviews and social media posts, to sell their products or services. A pivotal component of managing eWOM is to understand and, potentially influence, how one consumer's eWOM can lead to another's – a process called *behavioral cascading*. While prior eWOM research has established the importance of behavioral cascading between connected users, there is little understanding of what factors could impact the likelihood of such cascades. To address this gap, we draw on the theory of competitive altruism to identify several moderators of behavioral cascading in eWOM. Our empirical tests using an online review dataset from Yelp show that eWOM cascading between a followee and a follower is less likely when the followee is a high-status member, a female, or has a strong connection with the follower; and more likely when the product in consideration is inexpensive. These findings provide valuable insights about the behavioral cascading process in eWOM and hold implications for social media platforms and sellers to facilitate the cascades of eWOM between connected consumers.

Keywords: eWOM, Behavioral Cascading, Social Media Operations, Competitive Altruism

1. Introduction

A 2022 report by Kepios reveals that approximately 4.74 billion individuals globally are active social media users, representing 59.3 percent of the total global population (DataReportal 2022). The massive popularity of social media as a hub for consumers to connect and exchange information with each other has drastically changed the landscape of firms' operations. Not only traditional firm operations (e.g., pricing, revenue management, and payment management) must consider the hyper-connectivity among customers (Candogan et al., 2012; Lu et al., 2021; Qiu and Whinston, 2017), but also consumers increasingly rely on social media information in their interactions with firms. A prominent example of social media information is electronic word-of-mouth (eWOM), in the form of online reviews, social media posts, and tweets. Online reviews, for instance, play a crucial role in consumer decision-making and have received much attention in academic literature. Numerous studies have shown that online reviews hold important implications for firm operations including supply chain coordination and sales management (Akturk et al., 2022; Dellarocas et al., 2007; Duan et al., 2008; Lee and Shin, 2014). Unsurprisingly, firms are interested in generating “buzz” about their products and increasingly incorporate the management of eWOM as part of their operations.

There are many aspects to managing eWOM. For example, prior research has considered how firms should respond to negative online reviews and complaints posted on social media platforms (Chen et al. 2019; Gunarathne et al. 2017; Ma et al. 2015; Ravichandran and Deng 2022). Research has also explored how firms can use coupons, discounts, and other financial incentives to promote positive eWOM about their products (Burtch et al. 2018). Recent research shows that eWOM occurs through “behavioral cascading” between connected users (Ke et al. 2020; Taxidou and Fischer 2014) – when a user’s followee posts a review about a product (or a service), the user may be inclined to follow up with his/her review of the same product. To manage such eWOM cascades, there needs to be an understanding of what factors may magnify behavioral cascading. For example, could the likelihood of cascade be affected by characteristics of the followee, or the relationship between the followee and the follower? Furthermore, could it be affected by the characteristics of the product, such as its price? Having such information helps sellers better coordinate their product decisions (e.g., pricing) with eWOM. It may also help social media platforms recommend the most suitable eWOM content to users to facilitate cascades among users. Despite this issue’s practical importance, it has been inadequately studied in the literature. This research aims to address the gap by investigating the following research questions: *how does the likelihood of cascade between two connected users vary with the characteristics of the followee, the product in consideration, and the relationship between the two users?* We explore these questions in the context of online review platforms where a review by a user’s followee can inspire the user to write a follow-up review of the same product. We focus on online review because it is an important form of eWOM and holds critical implications for firm operations (Cui et al. 2018; Dellarocas et al. 2007).

To answer these research questions, we first develop a theoretical framework for understanding how contextual factors may affect behavioral cascading between connected users. Our framework, which is based on theory of competitive altruism (Hardy and Vugt 2006; Henrich and Gil-White 2001; Willer 2009), holds that a contribution by a user's followee may have two effects on the user: first, the followee's contribution may draw the user's *attention* to the product, increasing the user's likelihood of trying out the product; second, the followee's contribution may also reduce the *status-enhancement* benefits of a subsequent contribution. We then explore how contextual factors may affect the attention to the product and/or status-enhancement benefits of a subsequent contribution. Using our theoretical framework, we identify several important factors that are *unexplored* in prior research. For characteristics of the followee, we mainly focus on the followee's status and gender, which are among the most notable user attributes in an online community (Levina and Arriaga 2014; Otterbacher 2013). For product characteristics, we focus on the role of product price and promotion – these factors play an important role in consumers' decision to try out the product (Liao et al. 2009; Rehman et al. 2017). Finally, we capture the strength of the relationship between two connected users by the presence of common friends. We offer hypotheses on how these may impact behavioral cascades.

We tested our hypotheses using a unique panel of 2,923 Yelp users' reviewing of 8,289 restaurants in the state of Washington over 36 weeks. We find that behavioral cascading between two connected users is less likely when the followee is a high-status member of the community, a female, or shares common friends with the follower; and is more likely when the product in consideration is inexpensive. On the other hand, we cannot draw a conclusive conclusion regarding the moderating role of promotion.

This research contributes to the literature in a few ways. First, we complement the existing behavioral cascading literature by adding several novel moderators. While prior research demonstrates the existence of behavioral cascading on social media, there is limited attention on how contextual factors may affect the process (Hong et al. 2016; Wang et al. 2018). Our research especially extends the work of Ke et al. (2020), which shows that reviews by a user's followees lead to a stronger behavioral cascading effect than those by strangers. The same study also explores the roles of two moderating factors: the follower's reviewing experience and the product's popularity, yet leaving many other factors unexplored. This research builds on and extends Ke et al. (2020) by further developing the theoretical framework for behavioral cascading in eWOM and adding novel moderators related to the characteristics of the followees (e.g., their status/gender), their relationship with the follower, and sellers' product decisions (price and promotion).

Second, we also advance the understanding of behavioral cascading in eWOM. Though behavioral cascading has been studied in many other contexts such as delinquency, criminal behavior, and private consumption (Bapna and Umyarov, 2015; Barry and Wentzel, 2006), behavioral cascading in eWOM deserves separate attention because of its distinct characteristics: writing a review, unlike focal behaviors

in most other contexts, represents a contribution to public goods, which requires a different theoretical framework, say, cascading of private consumption or adoption. Our use of competitive altruism theory reflects this distinction. Furthermore, the cascading of eWOM contributions typically consists of distinct phases: after reading a follower's review, the follower often first needs to try out the product, and then decides whether to offer a follow-up review. In this research, we have developed theoretical perspectives on how contextual factors can affect each phase.

Finally, our research offers implications for firms and social media platforms' eWOM strategies. For example, we provide insights into what kinds of eWOM content to recommend to a user to facilitate cascades of contributions, what types of users could be leveraged to generate "buzz" around a product/service, and how to magnify eWOM using pricing strategies.

2. Related Literature

This research is mainly related to two literature streams – the role of social media in firm operations and behavioral cascading on social media.

2.1. Role of Social Media in Firm Operations

The operations management literature has examined the role of social media from two perspectives: how firm operations can be shaped by social networking among customers and information produced by social media (or "social information"). Examples include how the incorporation of information on consumers' connections and social interactions can affect a firm's pricing strategy (Crapis et al. 2017; Qiu and Whinston 2017), revenue management (Allon and Zhang 2015; Candogan et al. 2012; Zhang and Allon 2015), repayment management (Lu et al. 2021), and design of social products (Gao et al. 2020). For instance, Candogan et al. (2012) study a revenue management problem when customers' consumption depends on their friends' consumption in a social network. Lu et al. (2021) study whether and how a platform can leverage borrowers' social connections and use automatic social notifications in regulating repayment behavior. Qiu and Whinston (2017) examine the optimal pricing strategies of a monopolistic firm that accounts for observational learning in social networks. Gao et al. (2020) examine an innovative social promotion design called "red packets" – a form of digital coupon that can not only be transferred within consumers' social networks but also offer different rewards based on consumers' "social network value". Our research examines how social connectivity between consumers can be leveraged to shape cascades of eWOM, which are part of a firm's overall social media operations.

Our research is also related to the stream of research on how firms should handle eWOM on social media. Existing research on firms' eWOM management has primarily focused on two aspects. One aspect is the firms' responses to negative reviews and complaints (Chen et al. 2019; Gunarathne et al. 2017; Ma et al. 2015; Ravichandran and Deng 2022). Gunarathne et al. (2017) empirically investigate whose and what complaints on social media are more likely to receive responses from firms and have happier

resolutions. Ravichandran and Deng (2022) study the effects of firms' responses to negative reviews on future review valence and complaints. The other aspect is how firms can motivate eWOM creation. Prior research in this stream has studied the variety of approaches and factors such as financial incentives, showing users the volume of contribution, and social networks that affect content creation (Burtch et al., 2018; Chen et al., 2010; Yang et al., 2019). Yang et al., (2019) study how eWOM content (e.g., the valence of the post and type of complaints) can affect the number of likes and comments received by a post on Facebook business pages. Burtch et al., (2018) find that showing users aggregate contribution cues increases review length but not volume. However, when combining financial incentives with aggregate-contribution cues, one could increase both review length and the volume of reviews. We differentiate from existing work by focusing on eWOM creation via behavioral cascading, providing a nuanced perspective on the dynamics of eWOM creation.

2.2. Cascading on Social Media

Our research belongs to a stream of research that examines cascading on social media, including cascades of sentiment (i.e., *valence* of contribution) and cascades of behaviors (i.e., *whether* to contribute). The former focuses on whether the valence of follow-up contribution is affected by that of the original contribution. This stream has identified several factors that can moderate cascades of sentiment, including the reciprocity of social ties (Rishika and Ramaprasad 2019), the individualism of users (Hong et al. 2016), the volume of friend content (Lee et al. 2015), the popularity of topic (Wang et al. 2018), and popularity of users (Zeng and Wei 2013). These studies focus on the valence of contribution rather than on whether to contribute, which our research belongs to.

Our study is closer to a few studies of behavioral cascading in contexts such as delinquency, criminal behavior, and private consumption (Bapna and Umyarov, 2015; Barry and Wentzel, 2006). We differentiate from existing work by focusing on behavioral cascading in eWOM that the behavior of writing a review is a form of contribution to public goods. Within this stream, our study is most close to Ke et al. (2020) which studies the question of whether friend reviews can result in behavioral cascading and induce higher quality follow-up reviews. While this paper draws on the same dataset as Ke et al. (2020), the research questions pursued in this study is distinct. Specifically, the present study extends Ke et al. (2020) by delving into a novel set of moderating factors that are not studied in Ke et al. (2020), including the status and gender of followees, firms' product decisions in the form of price and promotion, and the relationship between followees and followers (i.e., whether they have common friends).

3. Theoretical Background and Hypotheses

Posting an online review constitutes an altruistic contribution to public goods since it primarily benefits consumers as a whole rather than the contributor. One relevant theory for explaining such altruistic behavior in a community context is the theory of *competitive altruism*, which suggests that individuals often engage

in altruistic behaviors to enhance their status within a community (Henrich and Gil-White 2001; McAndrew 2002; Smith and Bliege Bird 2000). When a member of a community makes outstanding altruistic contributions that benefit the community, the member is often granted high status, which brings certain long-term benefits (Henrich and Gil-White 2001; McAndrew 2002; Smith and Bliege Bird 2000). At Yelp, for example, the user community grants elite status to a subset of users who make high-quantity and high-quality contributions every year (Yelp Inc. 2012). Even for ordinary members of the Yelp user community, maintaining a high status in the community can also lead to benefits such as being invited to parties or garnering more responses for one's review request. In the following, we draw on the perspective of competitive altruism to explain how contextual factors may affect a user's tendency to write a review after a followee's review of the same.

When a user's *followee* contributes a review, there could be two effects on the user (the *follower*)'s contribution decision: on one hand, there may be *increased attention* on the product – the followee's review draws attention to the product and signals the desirability of reviewing the product. Prior research suggests that one reason behavioral cascading occurs is that prior behavior makes a user aware that he/she could do the same (Costello and Zozula 2018). In our context, when a user posts a review about a restaurant, it may draw his/her follower's attention to the restaurant and motivate him/her to try it out and subsequently write a review for it. This could happen because connections in online review communities are often based on shared interests (Dey 1997; Moretti 2011). Knowing that, the platform tends to facilitate this process: on Yelp, for example, when a user's followee reviews a restaurant, the review will appear in the user's "activity stream" and be featured on top when the user visits the restaurant's review page. Therefore, as users browse the restaurants on the platform, they are more likely to encounter reviews written by their followees.

On the other hand, there may be *reduced status benefits* from contributing a review. From the lens of competitive altruism, a user contributes an online review because such an altruistic action can enhance his/her status in the community, which can lead to some long-term benefits. The amount of status enhancement derived from a review contribution depends on how much the consumers and community peers value such a contribution. As more reviews are written about a product, subsequent review contributions add less value to the collective welfare and are less status-enhancing (Andreoni 1989, 1990). As a result, a prior contribution by a user's followee could reduce the status benefit the user can derive from his/her contribution.

The relative strength of the increased attention and reduced status benefits may depend on the circumstance. In the following, we explore how the characteristics of the followee, the product, and the relationship between the followee and the follower could influence the strengths of these effects and thus the likelihood of behavioral cascading between connected users.

3.1. The Followee's Status

A user's *status* refers to one's standing in a social hierarchy as determined by respect, deference, and social influence (Ridgeway and Walker 1995). Prior research has documented that high status confers upon an individual more power and a greater level of authority (Keltner et al. 2003; Nahapiet 1998). In the context of online reviews, a review contributed by a high-status member tends to be of higher quality and more authoritative compared with those by a low-status member (Levina and Arriaga 2014). On many online review platforms, contributions by high-status users are prominently featured and receive disproportional attention. This implies that contributions following a high-status contribution will likely get less attention and thus are less useful for enhancing one's status (Chen, Ho, et al. 2010; Yang et al. 2008). Meanwhile, because a high-status member's contribution tends to set a higher bar for review quality, it will be more costly for the subsequent contributor to make an acceptable contribution. Therefore, we expect that, after a contribution by a high-status followee, a follow-up contribution has reduced status benefits and thus is less likely to occur.

One could contend that reviews by high-status followees may also have a stronger attention effect. We argue, however, that while it is important to draw a user's attention to a product, it is even more critical for a user to gain enough status benefits to offset the cost of an altruistic contribution. A low-status followee's contribution may draw less attention to the product, but perhaps still more than a stranger's contribution. More importantly, a contribution by a low-status followee could offer much higher potential for making a status-enhancing follow-up contribution. Thus, we hypothesize:

H1: *A user is less likely to make a follow-up contribution after a contribution is made by a high-status followee than by a low-status followee.*

3.2. The Followee's Gender

Gender differences impact economic and social outcomes (Ahuja and Thatcher 2005; Li et al. 2021). We expect the followee's gender to play a role in the behavioral cascading between two connected users. Past research on eWOM has shown that reviews written by female users differ from those of male users in terms of stylistic features and content (Otterbacher 2013). Female-authored messages tended to seek social harmony (i.e., were more inclusive, and expressed emotions), and male-authored messages tended to be more competitive and assertive (Herring 2003). Such differences tend to disfavor female users: their postings receive fewer responses from others and exert less influence on the topic or the terms of the discussion (Herring et al. 1995). Similarly, in the domain of eWOM, studies have revealed that reviews written by female users are seen as less helpful and receive fewer votes (Kwok and Xie, 2016; Otterbacher, 2013). These suggest that a female followee's contribution may have a disadvantage in drawing attention to a product and establishing the desirability of reviewing the product.

One might argue that a contribution by a female followee may present a greater opportunity for a follow-up contribution. We argue, however, that because a female followee has a disadvantage in driving interest in the product, the focal user may have doubts about whether such a review contribution is desirable; in such a case, a greater potential for a follow-up contribution may not matter to the focal user. Indeed, prior research has shown that in online forums, women's ideas and statements are often overlooked or not given due attention compared to men's (Balka 1993; Camp 1996; Herring 1992, 2008). Therefore, we propose:

H2: *A user is less likely to make a follow-up contribution after a contribution is made by a female followee than by a male followee.*

3.3. Promotion of the Product

Behavioral cascading may be amplified by ongoing promotion of a product, such as email campaigns, social media, or TV advertising. On the one hand, ongoing promotion may augment the attention effect of followee reviews: with the promotion, the focal user is exposed to the product not only through his/her followee but also through the promotional effort. Consequently, the likelihood of the user trying out the product is enhanced (Hofstetter et al. 1992; Ren et al. 2012; Strömbäck and Shehata 2010). On the other hand, promotion may increase the status benefit of a subsequent contribution: the focal user would realize that more people would try out the product due to the promotion and thus his/her review could benefit a wider audience. From the perspective of competitive altruism, his/her review will add more value to the public welfare and thus yield stronger status-enhancing benefits (McAndrew 2002; Smith and Bliege Bird 2000). Therefore, we propose:

H3: *A user is more likely to make a follow-up contribution after a contribution made by his/her followee when the product is being promoted by the platform than when it is not.*

3.4. Price of the Product

A lower product price may similarly amplify behavioral cascading. Prior research consistently demonstrates that consumers are more inclined to purchase inexpensive products due to the reduced perceived risk associated with them compared to expensive alternatives (Kim and Chung 2011; Kim and Krishnan 2015; Tanner and Raymond 2010). This trend can enhance the attention effect of a prior followee contribution. Specifically, when a user's followee reviews an inexpensive product, it becomes more feasible for the user to purchase and try out the product. Furthermore, the affordability could also counteract a reduction in status benefits as a result of a prior followee contribution: the follower is more motivated to contribute a review knowing that the review will reach a broader audience, and thus contributing more to his/her status in the community (Henrich and Gil-White 2001; McAndrew 2002). Consequently, we hypothesize:

H4: *A user is more likely to make a follow-up contribution after a contribution made by his/her followee when the reviewed product is less expensive.*

3.5. Strength of Relationship

When it comes to behavioral cascading between connected users, the strength of their relationship may also play a role. A key measure of a relationship's strength is whether there is "overlap", i.e., the presence of common neighbors between two users within a network (Easley and Kleinberg 2010). Extensive research has demonstrated the role of overlap in contexts such as knowledge transfer among individuals (Reagans and McEvily 2003), information-sharing dynamics (Aral and van Alstyne 2011), and contagion in the adoption of applications (Aral and Walker 2014).

When two users have a strong tie, they are more likely to have similar interests, trust each other, and possess similar ideas (Bapna et al. 2017; Easley and Kleinberg 2010; Song et al. 2019; Zhang et al. 2018). These traits could enhance the positive attention effect, given their similar interests and stronger trust in each other. However, a strong tie could also exacerbate the reduced status benefits. This is because strong ties tend to have similar opinions and ideas. This makes a subsequent contribution by the focal user more redundant, yielding less status-enhancing benefits. Prior research has found that users are less likely to contribute when they perceive their contribution is less unique (Alexandrov et al. 2013; Cheema and Kaikati 2010; Ho and Dempsey 2010; Lovett et al. 2013). Similar to our argument for H1, we consider the perceived status-enhancement benefits to be more crucial for review contribution and therefore expect the detrimental effect of a strong-tie's contribution to dominate. Hence, we hypothesize:

H5: *A user is less likely to make a follow-up contribution after a contribution made by a followee who has a strong relationship with the user than one who has a weak relationship.*

4. Research Context and Data

This study used data from Yelp, a popular online review platform with over 102.7 million unique visitors and 244.4 million reviews as of 2021. Yelp allows registered users to post reviews and photos of businesses and to vote on reviews posted by others in three dimensions: usefulness, humor, or coolness. Yelp users can request to become friends with each other. They can also follow and send compliments to one another. Each registered user has a public profile that includes his/her name, location, reviews written, friends, bookmarks, and compliments received (see Figure 1). Yelp does not notify users of new reviews written by friends but such friend reviews are highlighted: users can browse friend reviews through the "friends" section of the home screen; friend reviews are prioritized in the review page for a business.

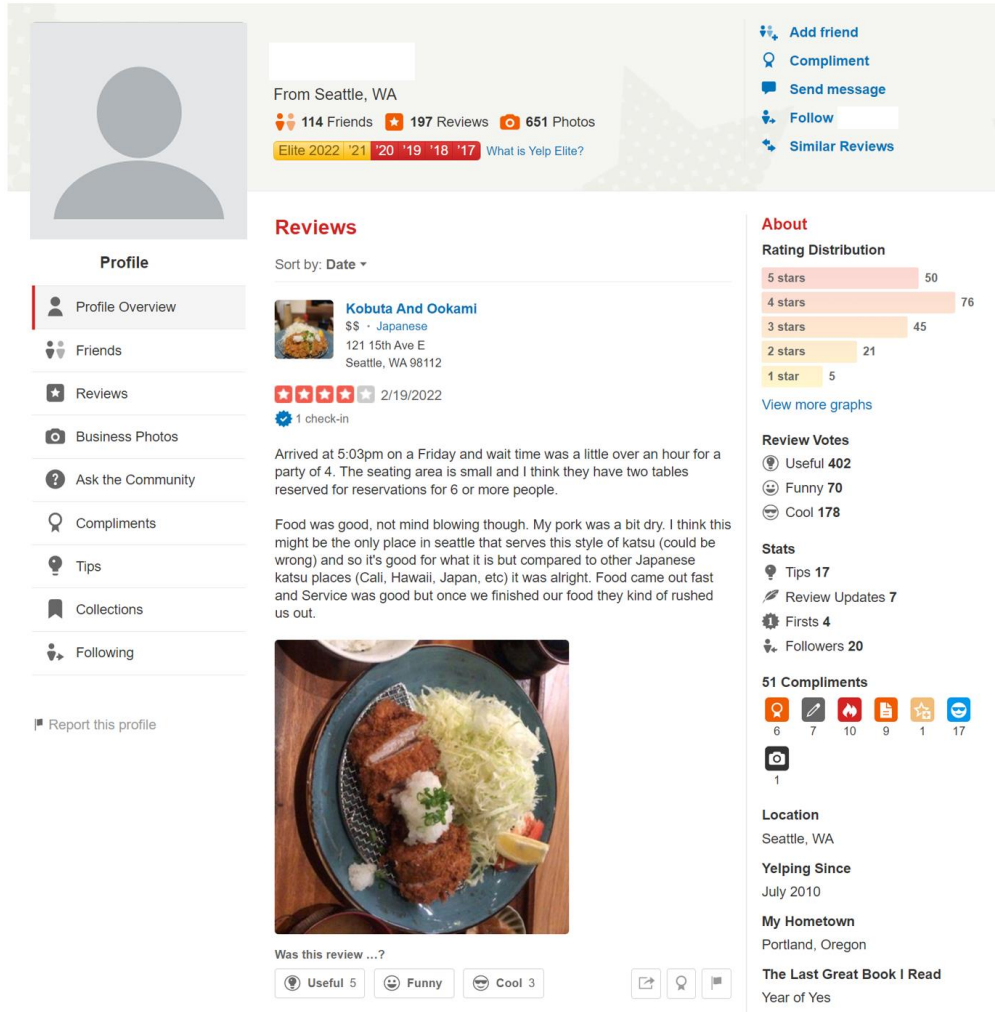


Figure 1. An Example of a Yelp User’s Public Profile Page

Each year, Yelp issues “elite” badges to users who have made extraordinary contributions to the platform. Yelp elites are chosen by Yelp’s Elite Council from candidates nominated by the community.¹ Elite users receive several benefits, such as invitations to exclusive events organized by Yelp or local businesses.²

This study focused on restaurant reviews in the state of Washington (WA), which we chose as a representative metropolitan area in the United States based on the number of restaurants and new reviews

¹ According to a blog post published by Yelp (<https://www.yelpblog.com/2012/01/what-makes-a-yelper-elite>), the criteria for selecting elite users are not publicly available. However, unofficial sources suggest that elite users are chosen based on the quantity and quality of their reviews from the previous year, as well as their engagement with the community, including activities such as sending compliments, casting votes, and answering questions. Importantly, the elite status is not permanent, and users must earn the elite badge each year.

² Yelp elite users often receive invitations to exclusive Yelp Elite events, such as visits to new businesses and dinner parties, which they can attend for free and bring guests to as well. Additionally, elite reviewers may receive regular invitations from businesses for tasting events, Yelp parties, and other perks.

per month. To compile a list of users, we first selected all 551 elite users located in Seattle, WA, and then expanded the list to include their friends, resulting in a total of 33,815 users. We then kept only the users who (1) were in WA and (2) had written at least one review on a WA restaurant during the study period. This resulted in 2,923 users. Our analysis indicated that our user sample accounted for 78% of all users who met the two criteria, suggesting the list is relatively comprehensive.³

We tracked the users’ profiles and their list of friends monthly from March 2013 to April 2014. We also collected the users’ reviews, bookmarks, and compliments received since March 2012. We collected all the reviews for the 8,289 WA restaurants posted during the study period, which resulted in 109,402 reviews – these reviews excluded fake, unhelpful, and biased reviews hidden by Yelp’s proprietary filtering and fake-review detection algorithm (Yelp Inc. 2023). We set the study period to span 36 weeks from March 2013 to November 2013 (the remaining data were used to obtain, for example, “future friends”).

5. Analyses and Results

5.1. Dataset, Model, and Variables

We constructed a user-restaurant-week panel in the following way. We began by joining the 8,289 WA restaurants and the 2,923 users to form 24,228,747 user-restaurant dyads. Of these dyads, 18,387 had positive outcomes, i.e., the user wrote a review for the restaurant during the study period. Since our data are highly unbalanced, we followed King and Zeng (2001) to under-sample negative cases: we kept all positive cases and randomly sampled five negative cases for each positive case. This resulted in a total of 110,322 user-restaurant dyads. With 36 observations (one per week) per dyad, our dataset had 3,971,592 user-restaurant-weeks. Given that a user can only submit one review per restaurant,⁴ we eliminated cases where the user had already written a review for the restaurant. Moreover, because we were interested in how prior friend reviews of the restaurant affect subsequent reviews, we removed the cases where there were no prior reviews, i.e., the focal review was the first review of the restaurant. Our final dataset had 3,624,850 user-restaurant-weeks.

Our dependent variable, $Review_{ijt}$, is a binary variable denoting whether user i wrote a review on restaurant j in period t . The problem of whether a user offers a review for a restaurant by period t is a survival problem. We therefore utilized a discrete-time survival model, which is equivalent to the logit model, for our analysis.

We measured the main user and restaurant characteristics as follows. We classified Yelp users into two categories: *high-status* (Yelp elite) and *low-status* (non-elite). We inferred users’ gender using a

³ In the course of our study, we compiled a database of all users who have written reviews on any of the 8,289 restaurants in Washington State (WA) included in our dataset, as well as any users who are friends or friends of friends of the 551 elite users. By the end of our data collection period, this resulted in a total of 3,748 users located in WA who had written at least one review on a WA restaurant during the study period.

⁴ While Yelp allows users to update their reviews later, such incidents are infrequent. Therefore, our focus in this study is on initial reviews, as we are interested in examining the decision-making process of whether to offer a review.

combination of an automated approach and human coding.⁵ We considered a restaurant as *Promoted* during period t if it was featured in Yelp’s weekly promotional emails to users during that period. The price of a restaurant had four levels, corresponding to Yelp-reported price ranges (\$ to \$\$\$\$), respectively. We classified the strength of the relationship between two Yelp friends based on whether they have common friends – if two friends share common friends, we label the two friends with common friends, otherwise no common friends.

To capture the behavioral cascading effect of friend reviews, we included the number of reviews written by current friends on restaurant j in period $t-1$ ($CurFrndReviews_{i,j,t-1}$). One of the main threats to estimating the behavioral cascading effect is homophily, i.e., a pair of Yelp friends may independently review the same restaurant due to shared preferences rather than behavioral cascading. To control for homophily, we followed the approach of Wang et al. (2018) and Ke et al. (2020) to include reviews written by “future friends” (i.e., users who became friends of the focal user later) in our analysis. Specifically, we included the number of reviews written by future friends on restaurant j in period $t-1$ ($FutFrndReviews_{i,j,t-1}$). The intuition is that future friends share similar preferences with the focal user, but since they were not friends yet, future friends’ reviews would not have a behavioral cascading effect on the focal user. If the effect of a current-friend review exceeds that of a future-friend review, we infer a cascading effect beyond homophily.

To capture the effect of followee status on behavioral cascading, we added the number of reviews written by the elite current friends on restaurant j in period $t-1$ ($EliteCurFrndReviews_{i,j,t-1}$) and the number of reviews written by elite future friends on restaurant j in period $t-1$ ($EliteFutFrndReviews_{i,j,t-1}$). Overall, our model for followee status is specified as:

$$\begin{aligned} \text{logit}(\text{Review}_{ijt}) = & \beta_0 + \beta_1 \text{EliteCurFrndReviews}_{i,j,t-1} + \beta_2 \text{EliteFutFrndReviews}_{i,j,t-1} + \\ & \beta_3 \text{CurFrndReviews}_{i,j,t-1} + \beta_4 \text{FutFrndReviews}_{i,j,t-1} + \beta_5 \text{NewReviews}_{j,t-1} + \\ & \gamma \text{Controls}_{i,j,t-1} + \varepsilon_{ijt} \end{aligned} \quad (1)$$

In this specification, our focal variables of interest are *EliteCurFrndReviews* and *EliteFutFrndReviews*, which capture the additional effect of a review written by an elite current friend

⁵ We firstly employed an automated approach based on Yelp users’ first names. Specifically, we consulted the Behind the Name database (<https://www.behindthename.com>), which reports the gender(s) associated with first names. If the name was associated with only one gender, we assigned that gender to the Yelp user. To verify the quality of automatic gender coding, we randomly sampled 100 users with automatically assigned genders and compared them with manually assigned genders based on profile photos. The accuracy of the automatic coding was 98%, which we deemed sufficient for our purposes. The automatic approach was not able to assign a gender to 134 users, because their first names were not in the database or associated with multiple genders. In those cases, we resorted to human coding. Specifically, we asked two research assistants to independently code the gender based on the profile photos. There were eight cases where the profile photos did not provide any gender information (e.g., images of food or pets). For the eight cases, two research assistants infer the gender based on review content (e.g., the user is labeled as a male if the user mentioned wife or girlfriend in his reviews). The intercoder reliability for these 134 cases was 0.95.

and an elite future friend, respectively, relative to a review written by a non-elite current/future friend. $CurFrndReviews_{i,j,t-1}$ and $FutFrndReviews_{i,j,t-1}$ capture the effect of a review written by a current or future non-elite friend, respectively. $NewReviews_{j,t-1}$, the number of new reviews in period $t-1$ on restaurant j , captures the effect of a review written by a stranger. $Controls_{i,j,t-1}$ denotes additional control variables and ε_{ijt} is an i.i.d. random component with a type-I extreme value distribution.

The models for testing the effect of followee gender and relationship strength are specified similarly as Equation (1), with $EliteCurFrndReviews/EliteFutFrndReviews$ replaced by $FemaleCurFrndReviews / FemaleFutFrndReviews$ (the number of female current-/future-friend reviews of the user) and $ComfrndCurFrndReviews / ComfrndFutFrndReviews$ (the number of current-/future-friend reviews of the user sharing friends), respectively. The interpretation of these variables is also similar.

To examine the effect of restaurants' promotion, we added interaction terms between $Promoted$ and $CurFrndReviews/ FutFrndReviews$. Specifically, we used the following model:

$$\begin{aligned}
\text{logit}(\text{Review}_{ijt}) &= \beta_0 + \beta_1 \text{Promoted}_{j,t-1} * \text{CurFrndReviews}_{i,j,t-1} + \beta_2 \text{Promoted}_{j,t-1} \\
&* \text{FutFrndReviews}_{i,j,t-1} \\
&+ \beta_3 \text{CurFrndReviews}_{i,j,t-1} + \beta_4 \text{FutFrndReviews}_{i,j,t-1} + \beta_5 \text{NewReviews}_{j,t-1} \\
&+ \beta_6 \text{Promoted}_{j,t-1} + \gamma \text{Controls}_{i,j,t-1} + \varepsilon_{ijt}. \tag{2}
\end{aligned}$$

The model for testing the effect of price is specified similarly as Equation (2), with $Promoted_{j,t-1}$ replaced by $Price_j$ (noting that a restaurant's price was time-invariant in our dataset, whereas promotion status was time-variant).

Control variables. We controlled several other user characteristics, including the user's tendency to contribute reviews, social capital, estimated income, whether the user lives in an urban area, and geographical proximity to the restaurant. Specifically, we included the number of reviews written by the user in the last period ($\#SelfReviews$) and the cumulative number of reviews written by the user up to the last period ($Log\#CumSelfReview$) as controls for the user's tendency to contribute. To control for the effect of social capital, we included the number of compliments sent and received ($Log\#Compliments$), the number of friends ($Log\#Friends$), the number of new friends made in the last month ($Log\#NewFriends$), and the number of fans ($Log\#Fans$) as control variables (Wang 2010). In addition, we included the user's estimated income, which is approximated by the median household income of the city where the user lives ($CityIncome$), and whether the user lived in an urban area as control variables ($Urban$)⁶. The follower's

⁶ We calculated this variable based on the categorization by United States Census Bureau (2010).

gender and elite status may impact the effect of cascading, so we also controlled for followers' gender (*Female*) and elite status (*Elite*). Finally, we included the distance between the user and the restaurant (*Dist*) as a control for geographical proximity.

We also included several other restaurant characteristics that may affect a user's decision to write a review. These included the valence (*AvgRatingRestaurant*), valence difference (*DiffRatingRestaurant*), variance (*AvgVariRestaurant*), and volume (*Log#CumReviews*) of existing reviews for the restaurant, as well as whether the restaurant's Yelp page has been claimed by its owner (*Claimed*). We also included dummy variables for the restaurant's category⁷ and the competition environment the restaurant faces (*Competition*). Finally, we controlled for temporal shocks to review creation by including month dummies. Please see Table 1 for summary statistics, noting that several variables were log-transformed due to the skewness of their distributions.

Table 1: Descriptive Statistics of Variables (N = 3,624,850)

Variables	Definition	Mean	Std. Dev	Min	Max
$Review_{ijt}$	Whether user i writes a review on restaurant j in period t : yes 1; otherwise 0	0.01	0.07	0.00	1.00
$EliteCurFrndReviews_{i,j,t-1}$	# reviews on restaurant j in period $t-1$ by user i 's elite current friends	0.00087	0.03	0.00	4.00
$FemaleCurFrndReviews_{i,j,t-1}$	# reviews on restaurant j in period $t-1$ by user i 's female current friends	0.00070	0.03	0.00	4.00
$ComfrndCurFrndReviews_{i,j,t-1}$	# reviews on restaurant j in period $t-1$ by user i 's current friends who share friends with user i	0.00095	0.03	0.00	5.00
$CurFrndReviews_{i,j,t-1}$	# reviews on restaurant j in period $t-1$ by user i 's current friends	0.00104	0.04	0.00	5.00
$EliteFutFrndReviews_{i,j,t-1}$	# reviews on restaurant j in period $t-1$ by user i 's elite future friends	0.00029	0.02	0.00	5.00
$FemaleFutFrndReviews_{i,j,t-1}$	# reviews on restaurant j in period $t-1$ by user i 's female future friends	0.00023	0.02	0.00	5.00
$ComfrndFutFrndReviews_{i,j,t-1}$	# reviews on restaurant j in period $t-1$ by user i 's future friends who share friends with user i	0.00032	0.02	0.00	5.00
$FutFrndReviews_{i,j,t-1}$	# reviews on restaurant j in period $t-1$ by user i 's future friends	0.00037	0.02	0.00	5.00
$NewReviews_{j,t-1}$	# new reviews on restaurant j in period $t-1$	0.42	1.06	0.00	38.00
$Promoted_{j,t-1}$	Whether restaurant j is promoted in period $t-1$	0.00	0.02	0.00	1.00
$Price_j$	Price range of restaurant j : 1 - least expensive; 4 - most expensive	1.63	0.56	1.00	4.00
$Elite_i$	Whether user i is an elite user	0.36	0.48	0.00	1.00
$Female_i$	Whether user i is female	0.45	0.50	0.00	1.00
$Log\#Compliments_{i,t-1}$	Log # of compliments sent and received by user i in period $t-1$	0.11	0.43	0.00	5.38

⁷ We categorized restaurants using Latent Dirichlet Allocation (LDA) topic modeling, which reduced the number of restaurant categories from over 1,000 to 16 based on word co-occurrences.

$\#SelfReviews_{i,t-1}$	# of reviews written by user i in period $t-1$	0.21	0.90	0.00	42.00
$Log\#CumSelfReview_{i,t-1}$	Log # cumulative reviews by user i up to period $t-1$	3.99	1.35	0.00	7.37
$LogTenure_{i,t-1}$	Log days elapsed since user i registered on Yelp up to period $t-1$	7.09	0.52	3.85	8.03
$Log\#Friends_{i,t-1}$	Log (1+ # friends of user i in period $t-1$)	3.52	1.08	1.10	7.00
$Log\#NewFriends_{i,t-1}$	Log (1+ # new friends of user i made in a month up to period $t-1$)	1.64	1.42	0.00	6.21
$Log\#Fans_{i,t-1}$	Log (1+ # fans of user i in period $t-1$)	2.04	0.53	1.10	5.14
$Urban_i$	Whether user i lives in an urban area	0.89	0.31	0.00	1.00
$CityIncome_i$	Median household income (thousands of dollars) of the city user i lives (time-invariant during our study period).	69.37	13.71	24.49	192.25
$Dist_{i,j}$	Miles between restaurant j and the city where user i lives	50.31	66.59	0.00	439.94
$AvgRatingRestaurant_{j,t-1}$	Cumulative average rating of restaurant j up to period $t-1$	3.59	0.67	0.50	5.00
$DiffRatingRestaurant_{j,t-1}$	Cumulative average rating of restaurant j up to period $t-1$ - Average rating of restaurant j in period $t-1$	0.00	0.31	-4.50	2.67
$AvgVariRestaurant_{j,t-1}$	Variance of cumulative ratings of restaurant j up to period $t-1$	1.07	0.29	0.00	2.00
$Log\#CumReviews_{j,t-1}$	Log # cumulative reviews of restaurant j up to period $t-1$	3.44	1.22	0.00	7.85
$Claimed_{j,t-1}$	Whether restaurant j 's business page on Yelp is claimed in period $t-1$	0.66	0.47	0.00	1.00
$Competition_{j,t-1}$	# restaurants that restaurant j shares one or more categories within 0.5 miles in period $t-1$	1.23	9.78	0.00	170.00

We omit the summary statistics of 8-month dummies and 16 restaurant-category dummies for brevity.

5.2. Results on the Effects of Status and Gender

Before estimating our models, we conducted collinearity tests and found no signs of collinearity (VIF < 3). We estimated three models: a base model that does not consider status or gender effects (Model 1), a model for status effects (Model 2), and a model for gender effects (Model 3). All models were estimated with weighting-based correction for oversampling of events, as described in King and Zeng (2001). The results of these models are presented in Table 2.

The results of Model 2 show that the odds ratio (OR) for *EliteCurFrndReviews* is less than one and significant ($OR = 0.590, p < 0.01$), while that for *EliteFutFrndReviews* is greater than 1 and significant ($OR = 2.534, p < 0.001$). An F-test comparing the coefficients for *EliteCurFrndReviews* and *EliteFutFrndReviews* is significant ($F = 19.69, p < 0.001$), suggesting that an elite followee is less likely to trigger a behavioral cascade than a nonelite followee. Thus **Hypothesis 1** is **supported**. This finding confirms the prediction of competitive altruism, which holds that contributing after an elite followee's review gets less status-enhancing benefit and, thus is less likely.

FemaleCurFrndReviews in Model 3 does not have an effect, but *FemaleFutFrndReviews* does ($OR = 2.502$, $p < 0.01$). An F-test comparing the coefficients for *FemaleCurFrndReviews* and *FemaleFutFrndReviews* is significant ($F = 6.14$, $p < 0.01$), indicating that female followees are less likely to trigger a cascade than male counterparts. Thus **Hypothesis 2** is **supported**. The finding confirms our theoretical conjecture that female followees are disadvantaged in spreading eWOM and are less likely to motivate their followers to write a follow-up review because reviews by female users tend to be disfavored by other users.

Table 2. Effects on Behavioral Cascading

Independent Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio
	(SE)	(SE)	(SE)	(SE)	(SE)	(SE)
<i>EliteCurFrndReviews</i> $i_{j,t-1}$		0.590** (0.108)				
<i>EliteFutFrndReviews</i> $i_{j,t-1}$		2.534*** (0.681)				
<i>FemaleCurFrndReviews</i> $i_{j,t-1}$			1.032 (0.206)			
<i>FemaleFutFrndReviews</i> $i_{j,t-1}$			2.502** (0.771)			
<i>Promoted</i> j_{t-1} * <i>CurFrndReviews</i> $i_{j,t-1}$				5.385** (3.230)		
<i>Promoted</i> j_{t-1} * <i>FutFrndReviews</i> $i_{j,t-1}$				- -		
<i>Price</i> j * <i>CurFrndReviews</i> $i_{j,t-1}$					0.777* (0.093)	
<i>Price</i> j * <i>FutFrndReviews</i> $i_{j,t-1}$					1.358+ (0.228)	
<i>ComfrndCurFrndReviews</i> $i_{j,t-1}$						0.893 (0.251)
<i>ComfrndFutFrndReviews</i> $i_{j,t-1}$						2.952*** (0.785)
<i>CurFrndReviews</i> $i_{j,t-1}$	2.853*** (0.232)	4.410*** (0.708)	2.786*** (0.472)	2.834*** (0.231)	4.608*** (1.170)	3.146*** (0.837)
<i>FutFrndReviews</i> $i_{j,t-1}$	1.674*** (0.256)	0.827 (0.230)	0.862 (0.267)	1.677*** (0.256)	0.941 (0.353)	0.686 (0.193)
<i>NewReviews</i> j_{t-1}	1.088*** (0.004)	1.088*** (0.004)	1.088*** (0.004)	1.088*** (0.004)	1.087*** (0.004)	1.088*** (0.004)
<i>Promoted</i> j_{t-1}	2.605*** (0.390)	2.594*** (0.388)	2.593*** (0.388)	2.565*** (0.385)	2.601*** (0.389)	2.593*** (0.388)
<i>Price</i> j	1.257*** (0.018)	1.254*** (0.018)	1.255*** (0.018)	1.257*** (0.018)	1.260*** (0.019)	1.255*** (0.018)
<i>Elite</i> i	1.723***	1.723***	1.723***	1.723***	1.723***	1.722***

	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
<i>Female_i</i>	0.921***	0.922***	0.922***	0.921***	0.921***	0.922***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
<i>Log#Compliments_{i,t-1}</i>	1.222***	1.221***	1.222***	1.222***	1.223***	1.220***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
<i>#SelfReviews_{i,t-1}</i>	1.122***	1.122***	1.122***	1.122***	1.122***	1.122***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
<i>Log#CumSelfReview_{i,t-1}</i>	1.485***	1.485***	1.485***	1.485***	1.485***	1.485***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
<i>LogTenure_{i,t-1}</i>	0.782***	0.782***	0.782***	0.782***	0.782***	0.782***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
<i>Log#Friends_{i,t-1}</i>	0.831***	0.831***	0.831***	0.831***	0.831***	0.831***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
<i>Log#NewFriends_{i,t-1}</i>	1.198***	1.198***	1.198***	1.198***	1.198***	1.198***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
<i>Log#Fans_{i,t-1}</i>	0.952***	0.952***	0.952***	0.952***	0.952***	0.952***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
<i>Urban_{i,t-1}</i>	0.713***	0.713***	0.713***	0.713***	0.713***	0.713***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
<i>CityIncome_i</i>	0.999	0.999	0.999	0.999	0.999	0.999
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
<i>Dist_{i,j}</i>	0.981***	0.981***	0.981***	0.981***	0.981***	0.981***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
<i>AvgRatingRestaurant_{j,t-1}</i>	1.308***	1.307***	1.307***	1.308***	1.308***	1.307***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
<i>DiffRatingRestaurant_{j,t-1}</i>	0.733***	0.734***	0.734***	0.733***	0.733***	0.733***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
<i>AvgVariRestaurant_{j,t-1}</i>	0.827***	0.827***	0.826***	0.827***	0.827***	0.827***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
<i>Log#CumReviews_{j,t-1}</i>	1.604***	1.603***	1.604***	1.604***	1.604***	1.604***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
<i>Claimed_{j,t-1}</i>	1.105***	1.106***	1.106***	1.105***	1.105***	1.106***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
<i>Competition_{j,t-1}</i>	1.002***	1.002***	1.002***	1.002***	1.002***	1.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Month dummies	included	included	included	included	included	included
Restaurant category dummies	included	included	included	included	included	included
Log-Likelihood	-195,010	-194,994	-195,001	-195,007	-195,004	-194,996
Pseudo R-squared	0.081	0.081	0.081	0.081	0.081	0.081
N	3,624,850	3,624,850	3,624,850	3,624,850	3,624,850	3,624,850

DV = whether user i reviews restaurant j in period t ($Review_{ijt}$). The values in parentheses are standard errors.
+p<0.10, *p<0.05, **p<0.01, ***p<0.001. – denotes the variables are removed due to collinearity.

Our analysis also reveals several notable effects of the control variables. We find that the number of compliments received by the user (*Log#Compliments*) has a positive effect on the likelihood of writing a

review, suggesting that socially active users are more likely to contribute reviews. On the other hand, the number of friends (*Log#Friends*) has a negative impact, whereas the number of new friends (*Log#NewFriends*) has a positive impact, indicating that having more old friends leads to a lower likelihood of writing a review while having more new friends leads to a higher likelihood of writing a review. Interestingly, the number of fans (*Log#Fans*) has a negative effect, suggesting that users with more fans are less likely to contribute reviews. This is consistent with the idea that users with more fans tend to be content consumers rather than content producers, thus their primary goal is to follow other users to seek information on online review platforms. Whether the user lives in an urban area (*Urban*) has a negative impact, indicating that users who live in a rural area are more likely to contribute reviews. This may be due to the excitement for rural people to dine out and they thus are motivated to share their dining experience. The gender (*Female*) has a negative effect, whereas elite status (*Elite*) has a positive effect. This suggests that female followers are less likely to contribute but elite followers are more likely to do so.

The average rating of the restaurant (*AvgRatingRestaurant*) and the cumulative number of reviews for the restaurant (*Log#CumReviews*) both have a positive effect, suggesting that users are more likely to review highly-rated and often-reviewed restaurants. This finding is consistent with the findings of Moe and Fader (2004). In contrast, the variance of the ratings for the restaurant (*AvgVariRestaurant*) and the difference in the restaurant ratings (*DiffRatingRestaurant*) have a negative effect, indicating that users are less likely to review restaurants with very inconsistent reviews. As expected, the tenure of the follower (*LogTenure*) and the distance between the follower and the restaurant (*Dist*) negatively affect the likelihood of writing a review, while the number of reviews written by the follower in the previous period (*#SelfReviews*), the cumulative number of reviews written by the follower (*Log#CumSelfReview*), elite status, promotion, claimed status, price, and competition environment (*Competition*) the restaurant faces all have a positive effect.

5.3. Effects of Restaurants' Promotion and Price

The results of the promotion effects (Model 4) and the price effects (Model 5) are reported in Table 2. According to the results of Model 4, the odds ratio for the interaction term *Promoted * CurFrndReviews* is significant and positive ($OR = 5.385, p < 0.01$), while *Promoted * FutFrndReviews* is removed due to collinearity and we are unable to compare the two coefficients. Thus, though we find that behavioral cascades are more likely to occur when a restaurant is being promoted, we do not know how much of the observed effect is due to social influence (as opposed to homophily). Therefore, our test of **Hypothesis 3** is inconclusive and further investigations are needed.

We also find that the odds ratio for the interaction term *Price * CurFrndReviews* (Model 5 in Table 2) is less than one and significant ($OR = 0.777, p < 0.05$), while that for *Price * FutFrndReviews* is greater than 1 and significant ($OR = 1.358, p < 0.10$). An F-test comparing the two coefficients is significant ($F =$

7.06, $p < 0.01$), suggesting that the behavioral cascading effect is stronger among inexpensive restaurants than expensive ones. This finding is consistent with our theoretical argument, which holds that a less expensive product not only makes a follower more willing to try out the product but also makes their contribution more impactful (as many other users in the community can afford the product) – thus enhancing behavioral cascading. Thus, **Hypothesis 4 is supported**.

5.4. Results on the Effects of Relationship Strength

The results of the relationship-strength effects (Model 6) are reported in Table 2. We find that current followees who share friends with the focal follower do not have an effect (*OR* of *ComfrndCurFrndReviews* is insignificant and less than 1), whereas future followees do (*OR* of *ComfrndFutFrndReviews* = 2.952, $p < 0.01$). An F-test comparing the two coefficients is significant ($F = 9.49$, $p < 0.01$). This indicates that followees who shared friends with the focal user are less likely to induce the focal user to contribute compared to those who did not. Thus **Hypothesis 5 is supported**. The results validate our theoretical argument that followees who share friends are less likely to inspire their followers to write additional reviews. This is because their reviews tend to amplify the diminished status benefits resulting from the emphasis on the uniqueness of contributions, making it less probable.

5.5. Robustness Checks

5.5.1. Fixed-Effects and First-Difference Specifications

Although our main model controls for the effects of many user and restaurant characteristics, some unobservable user or restaurant factors could likely drive both followees' prior contributions and the focal user's review contribution, creating a spurious cascading effect. To further alleviate this concern, we estimated two fixed-effects models: a user-fixed-effects model and a restaurant-effects model. User- and restaurant- fixed-effect models control for unobserved, time-invariant user- and restaurant-specific characteristics that could influence both prior followee reviews and the focal follower's review, isolating the impact of prior followee reviews on subsequent contribution by their followers and reducing omitted variable bias. Similarly, the first difference models eliminate time-invariant, unobserved user-restaurant-specific characteristics that could influence both prior followee reviews and the focal follower's review, thereby facilitating the identification of the impact of prior followee reviews over time. We report abbreviated results with variables of interest in Tables 3 (for effects of status and gender), Table 4 (for effects of promotion and price), and Table 5 (for effects of relationship strength), respectively. As seen from these results, these alternative specifications yielded consistent results with our main models, further supporting our hypotheses.

Table 3. Fixed Effects of Status and Gender

Independent Variables	Model 2a (Restaurant-fixed Effect)	Model 2b (User-fixed Effects)	Model 2c (First Difference)	Model 3a (Restaurant-fixed Effect)	Model 3b (User-fixed Effects)	Model 3c (First Difference)
	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio
	(SE)	(SE)	(SE)	(SE)	(SE)	(SE)
<i>EliteCurFrndReviews</i> _{<i>i,j,t-1</i>}	0.625** (0.111)	0.678* (0.121)	0.650* (0.294)			
<i>EliteFutFrndReviews</i> _{<i>i,j,t-1</i>}	1.687** (0.309)	2.357*** (0.444)	4.368* (3.347)			
<i>FemaleCurFrndReviews</i> _{<i>i,j,t-1</i>}				0.868 (0.129)	0.947 (0.141)	1.430 (0.806)
<i>FemaleFutFrndReviews</i> _{<i>i,j,t-1</i>}				1.606* (0.308)	2.077*** (0.421)	6.190*** (2.929)
Month dummies	included	included	included	included	included	included
Restaurant category dummies		included			included	
Log-Likelihood	-87,096.94	-91,705.92	-203,085.31	-87,100.65	-91,711.34	-203,079.42
Pseudo R-squared	0.050	0.073	0.004	0.050	0.073	0.004
N	2,315,482	3,461,989	3,423,249	2,315,482	3,461,989	3,423,249

DV = whether user *i* reviews restaurant *j* in period *t* (*Review_{ijt}*). The values in parentheses are standard errors. +p<0.10, *p<0.05, **p<0.01, ***p<0.001. All control variables used in Table 2 are also included in Tables 3-5. Sample sizes in the restaurant-fixed-effect, user-fixed-effect, and first-difference models in Tables 3-5 are smaller because some observations are removed due to no variation within a restaurant, a user, or a user-restaurant pair, respectively.

Table 4. Fixed Effects of Promotion and Price

Independent Variables	Model 4a (Restaurant-fixed Effect)	Model 4b (User-fixed Effects)	Model 4c (First Difference)	Model 5a (Restaurant-fixed Effect)	Model 5b (User-fixed Effects)	Model 5c (First Difference)
	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio
	(SE)	(SE)	(SE)	(SE)	(SE)	(SE)
<i>Promoted</i> _{<i>j,t-1</i>} * <i>CurFrndReviews</i> _{<i>i,j,t-1</i>}	5.027** (2.102)	4.832** (1.820)	3.238* (2.134)			
<i>Promoted</i> _{<i>j,t-1</i>} * <i>FutFrndReviews</i> _{<i>i,j,t-1</i>}	- -	- -	0.047+ (0.087)			
<i>Price</i> _{<i>j</i>} * <i>CurFrndReviews</i> _{<i>i,j,t-1</i>}				0.703** (0.083)	0.656*** (0.074)	0.533* (0.172)
<i>Price</i> _{<i>j</i>} * <i>FutFrndReviews</i> _{<i>i,j,t-1</i>}				1.122 (0.276)	1.129 (0.252)	2.148 (0.829)
Month dummies	included	included	included	included	included	included
Restaurant category dummies		included			included	
Log-Likelihood	-87,103.44	-91,716.95	-203,039.00	-87,099.28	-91,709.93	-202,139.61
Pseudo R-squared	0.050	0.073	0.004	0.050	0.073	0.008
N	2,315,482	3,461,989	3,423,249	2,315,482	3,461,989	3,423,249

DV = whether user *i* reviews restaurant *j* in period *t* (*Review_{ijt}*). The values in parentheses are standard errors. +p<0.10, *p<0.05, **p<0.01, ***p<0.001. – denotes the variables are removed due to collinearity.

Table 5. Fixed Effects of Relationship Strength and Matching

Independent Variables	Model 6a	Model 6b	Model 6c	Model 4d
	(Restaurant-fixed Effect)	(User-fixed Effects)	(First Difference)	(Matched Samples)
	Odds Ratio	Odds Ratio	Odds Ratio	Odds Ratio
	(SE)	(SE)	(SE)	(SE)
<i>Promoted_{j,t-1}</i> * <i>CurFrndReviews_{i,j,t-1}</i>				10.700*
				(10.792)
<i>Promoted_{j,t-1}</i> * <i>FutFrndReviews_{i,j,t-1}</i>				-
				-
<i>ComfrndCurFrndReviews_{i,j,t-1}</i>	0.694 (0.180)	0.881 (0.231)	2.273 (3.677)	
<i>ComfrndFutFrndReviews_{i,j,t-1}</i>	1.728** (0.323)	2.442*** (0.464)	6.488*** (3.672)	
Month dummies	included	included	included	included
Restaurant category dummies		included		included
Log-Likelihood	-87,099.13	-91,707.66	-203,079.35	-1,371.05
Pseudo R-squared	0.050	0.073	0.004	0.110
N	2,315,482	3,461,989	3,423,249	10,110

DV = whether user i reviews restaurant j in period t ($Review_{ijt}$). The values in parentheses are standard errors. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. – denotes the variables are removed due to collinearity.

5.5.2. Matched Samples Based on the Propensity of Getting Promoted

Given our focus on the moderating roles of followee and restaurant attributes in behavioral cascading, there may be concerns that these followee and restaurant attributes are themselves endogenous – some other factors may affect both these attributes and the cascade. We note that the followee’s status, gender, and restaurant price were static in our dataset and therefore are not a source of endogeneity. Similarly, we did not observe much variation in the relationship strength for the same pair of Yelp friends in our dataset, and the endogeneity concern for relationship strength was not significant. In contrast, a restaurant’s promotion status changes often – it is likely that some underlying factors may drive both restaurant promotion and the cascading of online reviews of the same restaurant. To alleviate this concern, we adopted a Propensity Score Matching method: i.e., we matched restaurants based on their propensity of getting promoted using propensity score matching. Specifically, we used logistic regression to predict restaurant promotions based on several key characteristics, including review valence, valence difference, variance, volume, new reviews, and competition environment. We then used the nearest neighbor algorithm to match a promoted restaurant with five non-promoted restaurants with a similar probability of getting promoted. We performed the matching process using the ‘MatchIt’ package in R. Model 4d of Table 5 contains the results of panel regression estimations using matched samples. As seen in the table, our findings based on the matched sample were similar to our main findings.

We have also conducted additional analyses using alternative coding of user genders (by dropping 134 users whose genders cannot be determined by the Behind the Name database) and alternative coding of the price variable (by treating it as a categorical variable). These analyses yield similar results to our main findings but are omitted to due space constraint.

6. Discussion and Implications

Motivated by firms' increasing need to manage eWOM as part of their operations and a lack of understanding of what factors may magnify the cascades of eWOM among connected users on online review platforms, we examine the moderators of behavioral cascading between connected users in the context of Yelp reviews. Drawing on the theory of competitive altruism, we identify several potential moderators of behavioral cascades from a followee to a follower, including the status and gender of the followee, the price of the focal product, the ongoing promotion of the product, and the strength of the relationship between the two users. Using a rich dataset from Yelp, we find support for all moderators except the promotion of the product. Specifically, we find that behavioral cascading from a followee to a follower is less likely when the followee is a high-status member of the community, a female, or has a stronger tie with the follower (as indicated by the two having common friends). Moreover, behavioral cascading is more likely when the product in consideration is inexpensive. These findings hold several implications for theory and practice, as discussed below.

6.1. Contributions to the Academic Literature

Our findings make several contributions to academic literature. First, we contribute to the literature on the role of social media in firm operations. Prior research has focused more on how social networking between customers and how the content they generate can shape a variety of operational problems (Candogan et al. 2012; Lu et al. 2021; Qiu et al. 2017). Our research focuses more on how social media content, specifically eWOM, is generated among connected users, with implications for firms' eWOM management operations. As firms become increasingly interested in managing the "buzz" around their products/services on social media, our findings provide several useful clues on how they may facilitate the cascades of eWOM contributions between connected users (see Managerial Implications for details).

Second, we contribute to the literature on behavioral cascading by adding insights into salient factors that can magnify or attenuate the cascades in a social network. We offer both a theoretical perspective on why these contextual factors matter and empirical findings based on Yelp reviews. Our study yields a few interesting findings. For example, the common wisdom holds that high-status users tend to be strong influencers (Ridgeway and Walker 1995), we find, however, that a prior contribution by a high-status followee reduces the chance of a follower's subsequent contribution. Our explanation is that a prior high-status contribution can prevent followers from making an impactful contribution. Our study also reveals

the “strength of weak ties” in behavioral cascades: a user is more likely to make a follow-up contribution after a weak tie than a strong tie. Our explanation is that a user is more likely to make a distinct contribution after a weak tie’s contribution. Our study is also among the first to discover the disadvantage of female users in generating eWOM cascades, adding to a stream of research on how female users are disadvantaged in online social space (Rroadhurst 1993 and Herring 2003). Our findings also stress the need for coordinating firm product decisions, particularly pricing, with eWOM strategies. We show that a lower price can magnify cascades of eWOM between connected users.

We note that our analyses of behavioral cascades occupy a unique space in rich literature (Bapna and Umyarov, 2015; Barry and Wentzel, 2006). While prior literature has identified several other mechanisms for behavioral cascading (Costello et al. 2018), few studies, except for (Ke et al, 2020), have paid attention to how a prior behavior can substitute subsequent behaviors by reducing the latter’s payoffs. We capture such tension in the context of altruistic eWOM contributions using the theory of competitive altruism and make successful predictions using the theoretical framework, suggesting that it can be useful for future studies of cascades of altruistic behaviors.

6.2. Managerial Implications

Our findings provide several practical implications for product sellers and online social platforms. For product sellers, our findings suggest that not all products are equally effective in generating behavioral cascades in social networks. Cheaper products are more likely to benefit from candidates of eWOM among connected social media users. Firms may prioritize such products when adopting an eWOM strategy that relies on the viral spread of eWOM. Correspondingly, firms can benefit from coordinating pricing discounts with eWOM campaigns. For example, when a firm is inviting social media influencers to try out their products, they may also launch a price discount to maximize the viral cascades of eWOM.

For online social platforms, our findings provide several guidelines on how to personalize eWOM recommendations. First, recommending content from high-status users can have the undesirable effect of stifling follower contribution. Therefore, platforms may want to feature more “everyday” friend contributions in users’ activity streams to inspire them to contribute. Similarly, platforms may prioritize recommending eWOM contributions authored by a user’s weak ties, as they have a higher potential to inspire follow-up contributions. Finally, knowing that female users are disadvantaged in stimulating follower contributions, the platforms may benefit from finding ways to amplify female users’ voices, especially if they make a unique contribution to eWOM.

6.3. Limitations and Future Research

This study has several limitations. First, our study uses data from Yelp and may not generalize to other eWOM platforms. Second, we focus on behavioral cascading for a single product without considering how behavioral cascading for multiple products may interact. While what we learn about behavioral cascading

for a single product may also apply to firms owning multiple products, it would be interesting to investigate the latter issue. Third, our observed effects may have alternative, non-causal explanations; though we have taken many steps to alleviate endogeneity concerns (e.g., multiple fixed effects mode, extensive list of controls, and matching), more research is needed in causal identification. Finally, we have used older data in this study. Though we believe the underlying mechanisms of our findings remain relevant today, it is still valuable to replicate our study with newer datasets and explore other factors such as inclusion of product pictures in the reviews.

References

- Alexandrov, A., Lilly, B., and Babakus, E. 2013. "The Effects of Social-and Self-Motives on the Intentions to Share Positive and Negative Word of Mouth," *Journal of the Academy of Marketing* (41:5), pp. 531–546.
- Ahuja, M. K., and Thatcher, J. B. 2005. "Moving beyond Intentions and toward the Theory of Trying: Effects of Work Environment and Gender on Post-Adoption Information Technology Use," *MIS Quarterly*, pp. 427–459.
- Akturk, M. S., Mallipeddi, R. R., and Jia, X. 2022. "Estimating Impacts of Logistics Processes on Online Customer Ratings: Consequences of Providing Technology-Enabled Order Tracking Data to Customers," *Journal of Operations Management* (68:6–7), pp. 775–811.
- Allon, G., and Zhang, DJ. 2015. "Managing Service Systems in the Presence of Social Networks." (Available at SSRN, 2673137).
- Andreoni, J. 1989. "Giving with Impure Altruism: Applications to Charity and Ricardian Equivalence," *Journal of Political Economy* (97:6), pp. 1447–1458.
- Andreoni, J. 1990. "Impure altruism and donations to public goods: A theory of warm-glow giving," *The economic journal* (100:401), pp. 464–477.
- Aral, S., and van Alstyne, M. 2011. "The Diversity-Bandwidth Trade-Off," *American Journal of Sociology* (117:1), pp. 90–171.
- Aral, S., and Walker, D. 2014. "Tie Strength, Embeddedness, and Social Influence: A Large-Scale Networked Experiment," *Management Science* (60:6), pp. 1352–1370.
- Balka, E. 1993. "Women's access to online discussions about feminism," *CPSR Internet Library*.
- Bapna, R., Gupta, A., Rice, S., and Sundararajan, A. 2017. "Trust and the Strength of Ties in Online Social Networks: An Exploratory Field Experiment," *MIS Quarterly* (41:1), pp. 115–130.
- Bapna, R., and Umyarov, A. 2015. "Do Your Online Friends Make You Pay? A Randomized Field Experiment on Peer Influence in Online Social Networks," *Management Science* (61:8), pp. 1902–1920.
- Barry, C. M. N., and Wentzel, K. R. 2006. "Friend Influence on Prosocial Behavior: The Role of Motivational Factors and Friendship Characteristics," *Developmental Psychology* (42:1), pp. 153–163.
- Broadhurst, J. 1993. "Lurkers and Flamers," *Online Access* (8:3), pp. 48–51.
- Burke, P. J., and Stets, J. E. 2009. *Identity Theory*, Oxford University Press.
- Burch, 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.

- Cha, M., Mislove, A., Adams, B., and Gummadi, K. P. 2008. "Characterizing social cascades in flickr," in *Proceedings of the first workshop on Online social networks*, pp. 13–18.
- Camp, Jean. L. 1996. "We are geeks, and we are not guys: The systers mailing list," in *Wired women: Gender and new realities in cyberspace*, L. Cherny and E. R. Weise (eds.), Seattle: Seal Press, pp. 114–125.
- Candogan, O., Bimpikis, K., and Ozdaglar, A. 2012. "Optimal Pricing in Networks with Externalities," *Operations Research* (60:4), pp. 883–905.
- Carli, L. L. 2001. "Assertiveness," in *Encyclopedia of Women and Gender: Sex Similarities and Differences and the Impact of Society on Gender* (Vol. 1), J. Worell (ed.), San Diego, California: Academic Press, pp. 157–168.
- Carpenter, J. P. 2004. "When in Rome: Conformity and the Provision of Public Goods," *Journal of Socio-Economics* (33:4), pp. 395–408.
- Cheema, A., and Kaikati, A. M. 2010. "The Effect of Need for Uniqueness on Word of Mouth," *Journal of Marketing Research* (47:3), *American Marketing Association*, pp. 553–563.
- Chen, W., Gu, B., Ye, Q., and Zhu, K. X. 2019. "Measuring and Managing the Externality of Managerial Responses to Online Customer Reviews," *Information Systems Research* (30:1), pp. 81–96.
- Chen, Y., Harper, M., Konstan, J., and Li, S. X. 2010. "Social Comparisons and Contributions to Online Communities: A Field Experiment on MovieLens," *American Economic Review* (100:4), pp. 1358–1398.
- Chen, Y., Ho, T.-H., and Kim, Y.-M. 2010. "Knowledge Market Design: A Field Experiment at Google Answers," *Journal of Public Economic Theory* (12:4), pp. 641–664.
- Costello, B. J., and Zozula, C. 2018. "Peer Influence: Mechanisms and Motivations," *Deviant Behavior* (39:1), pp. 94–110.
- Crapis, D., Ifrach, B., Maglaras, C., and Scarsini, M. 2017. "Monopoly Pricing in the Presence of Social Learning," *Management Science* (63:11), pp. 3586–3608.
- Cui, R., Gallino, S., Moreno, A., and Zhang, D. J. 2018. "The Operational Value of Social Media Information," *Production and Operations Management* (27:10), pp. 1749–1769.
- DataReportal. 2022. "GLOBAL SOCIAL MEDIA STATISTICS," *DataReportal*. (<https://datareportal.com/social-media-users>, accessed November 15, 2022).
- Dellarocas, C., Zhang, X., and Awad, N. 2007. "Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures," *Journal of Interactive Marketing* (21:4), pp. 23–45.
- Dey, E. L. 1997. "Undergraduate Political Attitudes," *The Journal of Higher Education* (68:4), pp. 398–413.
- Duan, W., Gu, B., and Whinston, A. 2008. "Do Online Reviews Matter? – An Empirical Investigation of Panel Data," *Decision Support Systems* (45:4), pp. 1007–1016.
- Easley, D., and Kleinberg, J. 2010. *Networks, Crowds, and Markets*, Cambridge, UK: Cambridge University Press.
- Gao, H., Zhao, H., Tan, Y., Lin, Y., and Wei, L. 2020. "Social Promotion: A Creative Promotional Framework on Consumers' Social Network Value," *Production and Operations Management* (29:12), pp. 2661–2678.
- Gneezy, U., Niederle, M., and Rustichini, A. 2003. "Performance in Competitive Environments: Gender Differences," *Quarterly Journal of Economics* (118:3), pp. 1049–1074.

- Gunarathne, P., Rui, H., and Seidmann, A. 2017. "Whose and What Social Media Complaints Have Happier Resolutions? Evidence from Twitter," *Journal of Management Information Systems* (34:2), pp. 314–340.
- Hardy, C. L., and Vugt, M. Van. 2006. "Giving for Glory in Social Dilemmas: The Competitive Altruism Hypothesis," *Personality and Social Psychology Bulletin* (32), pp. 1402–1413.
- Henrich, J., and Gil-White, F. J. 2001. "The Evolution of Prestige: Freely Conferred Deference as a Mechanism for Enhancing the Benefits of Cultural Transmission," *Evolution and Human Behavior* (22:3), pp. 165–196.
- Herring, S. C. 1992. "Gender and participation in computer-mediated linguistic discourse," *Education Resources Information Center*.
- Herring, S. C. 2003. "Gender and Power in On-Line Communication," in *The Handbook of Language and Gender*, J. Holmes and M. Meyerhoff (eds.), Oxford, UK: Blackwell Publishing Ltd, pp. 1–759.
- Herring, S. C. 2008. "Gender and Power in Online Communication," in *The Handbook of Language and Gender*, John Wiley and Sons.
- Herring, S., Johnson, D., and DiBenedetto, T. 1995. "This Discussion Is Going Too Far!' Male Resistance to Female Participation on the Internet," in *Gender Articulated: Language and the Socially Constructed Self*, M. Bucholtz and K. Hall (eds.), New York: Routledge, pp. 67–96.
- Ho, J., and Dempsey, M. 2010. "Viral Marketing: Motivations to Forward Online Content," *Journal of Business Research* (63:9), pp. 1000–1006.
- Hofstetter, C. R., Schultze, W. A., and Mulvihill, M. M. 1992. "Communications Media, Public Health, and Public Affairs: Exposure in a Multimedia Community," *Health Communication* (4:4), pp. 259–271.
- Hong, Y., Huang, N., Burtch, G., and Li, C. 2016. "Culture, Conformity and Emotional Suppression in Online Reviews," *Journal of the Association for Information Systems* (17:11), pp. 737–758.
- Ke, Z., Liu, D., and Brass, D. J. 2020. "Do Online Friends Bring out the Best in Us? The Effect of Friend Contributions on Online Review Provision," *Information Systems Research* (31:4), pp. 1322–1336.
- Keltner, D., Gruenfeld, D. H., and Anderson, C. 2003. "Power, Approach, and Inhibition," *Psychological Review* (110), pp. 265–284.
- Kim, H. Y., and Chung, J. E. 2011. "Consumer Purchase Intention for Organic Personal Care Products," *Journal of Consumer Marketing* (28:1), pp. 40–47.
- Kim, Y., and Krishnan, R. 2015. "On Product-Level Uncertainty and Online Purchase Behavior: An Empirical Analysis," *Management Science* (61:10), pp. 2449–2467.
- Kite, M. E. 2001. "Gender Stereotypes," in *Encyclopedia of Women and Gender* (Vol. 1), J. Worell (ed.), Academic Press, p. 563.
- Kwok, L., and Xie, K. L. 2016. "Factors Contributing to the Helpfulness of Online Hotel Reviews: Does Manager Response Play a Role?" *International Journal of Contemporary Hospitality Management* (28:10), pp. 2156–2177.
- Le Bon, G. 2002. "The Crowd: A Study of the Popular Mind.," *Courier Corporation*, New York: The Macmillan Company.
- Lee, E. J., and Shin, S. Y. 2014. "When Do Consumers Buy Online Product Reviews? Effects of Review Quality, Product Type, and Reviewer's Photo," *Computers in Human Behavior* (31:1), pp. 356–366.

- Lee, Y., Hosanagar, K., and Tan, Y. 2015. "Do I Follow My Friends or the Crowd? Information Cascades in Online Movie Rating," *Management Science* (61:9), pp. 2241–2258.
- Levina, N., and Arriaga, M. 2014. "Distinction and Status Production on User-Generated Content Platforms: Using Bourdieu's Theory of Cultural Production to Understand Social Dynamics in Online Fields," *Information Systems Research* (25:3), pp. 468–488.
- Li, Z., Wang, G., and Wang, J. 2021. "Peer Effects in Competitive Environments: Field Experiments on Information Provision and Interventions," *MIS Quarterly* (45:1), pp. 163–191.
- Liao, S. L., Shen, Y. C., and Chu, C. H. 2009. "The effects of sales promotion strategy, product appeal and consumer traits on reminder impulse buying behaviour," *International Journal of Consumer Studies* (33:3), pp. 274–284.
- Lovett, M. J., Renana, P., and Shachar, R. O. N. 2013. "On Brands and Word of Mouth," *Journal of Marketing Research* (50:4), American Marketing Association, pp. 427–444.
- Lu, X., Lu, T., Wang, C., and Wu, R. 2021. "Can Social Notifications Help to Mitigate Payment Delinquency in Online Peer-to-Peer Lending?," *Production and Operations Management* (30:8), pp. 2564–2585.
- Ma, L., Sun, B., and Kekre, S. 2015. "The Squeaky Wheel Gets the Grease – An Empirical Analysis of Customer Voice and Firm Intervention on Twitter," *Marketing Science* (34:5), pp. 627–645.
- McAndrew, F. T. 2002. "New Evolutionary Perspectives on Altruism: Multilevel-Selection and Costly-Signaling Theories," *Current Directions in Psychological Science* (11:2), pp. 79–82.
- Moe, W., and Fader, P. 2004. "Dynamic Conversion Behavior at E-Commerce Sites," *Management Science* (50:3), pp. 326–335.
- Moe, W., and Schweidel, D. 2012. "Online Product Opinions: Incidence, Evaluation, and Evolution," *Marketing Science* (31:3), pp. 372–386.
- Moretti, E. 2011. "Social learning and peer effects in consumption: Evidence from movie sales," *The Review of Economic Studies* (78:1), pp. 356–393.
- Nahapiet, J. Ghoshal, S. 1998. "Social Capital, Intellectual Capital, and the Organizational Advantage," *The Academy of Management Review* (23:2), pp. 242–266.
- Otterbacher, J. 2013. "Gender, Writing and Ranking in Review Forums: A Case Study of the IMDb," *Knowledge and Information Systems* (35:3), pp. 645–664.
- Pu, J., Liu, Y., Chen, Y., Qiu, L., and Cheng, H. K. 2022. "What Questions Are You Inclined to Answer? Effects of Hierarchy in Corporate Q&A Communities," *Information Systems Research* (33:1), pp. 224–264.
- Qiu, L., and Whinston, A. B. 2017. "Pricing Strategies under Behavioral Observational Learning in Social Networks," *Production and Operations Management* (26:7), pp. 1249–1267.
- Ravichandran, T., and Deng, C. 2022. "Effects of Managerial Response to Negative Reviews on Future Review Valence and Complaints," *Information Systems Research* (Apr).
- Reagans, R., and McEvily, B. 2003. "Network Structure and Knowledge Transfer: The Effects of Cohesion and Range," *Administrative Science Quarterly* (48:2), Cornell University, pp. 240–267.
- Rehman, F. ur, Bin Md Yusoff, R., Bin Mohamed Zabri, S., and Binti Ismail, F. 2017. "Determinants of personal factors in influencing the buying behavior of consumers in sales promotion: a case of fashion industry," *Young Consumers* (18:4), pp. 408–424.

- Ren, Y., Harper, M. F., Drenner, S., Terveen, L., Kiesler, S., Riedl, J., and Kraut, R. E. 2012. "Building Member Attachment in Online Communities: Applying Theories of Group Identity and Interpersonal Bonds," *MIS Quarterly*, pp. 841–864.
- Ridgeway, C. L., and Walker, H. A. 1995. "Status Structures," *Sociological Perspectives on Social Psychology* (281), p. 310.
- Rishika, R., and Ramaprasad, J. 2019. "The Effects of Asymmetric Social Ties, Structural Embeddedness, and Tie Strength on Online Content Contribution Behavior," *Management Science* (65:7), pp. 3398–3422.
- Smith, E. A., and Bliege Bird, R. L. 2000. "Turtle Hunting and Tombstone Opening: Public Generosity as Costly Signaling," *Evolution and Human Behavior* (21:4), pp. 245–261.
- Song, T., Tang, Q., and Huang, J. 2019. "Triadic closure, homophily, and reciprocation: An empirical investigation of social ties between content providers," *Information Systems Research* (30:3), pp. 912–926.
- Stets, J. E., and Burke, P. J. 2000. "Femininity/Masculinity," in *Encyclopedia of Sociology* (Vol. 2), E. F. Borgatta and R. Montgomery (eds.), Macmillan Reference USA, pp. 997–1005.
- Strömbäck, J., and Shehata, A. 2010. "Media Malaise or a Virtuous Circle? Exploring the Causal Relationships between News Media Exposure, Political News Attention and Political Interest," *European Journal of Political Research* (49:5), pp. 575–597.
- Tanner, J., and Raymond, MA. 2010. "Consumer Behavior: How People Make Buying Decisions," in *Marketing Principles*.
- Taxidou, I., and Fischer, P. M. 2014. "Online analysis of information diffusion in twitter," in *WWW 2014 Companion - Proceedings of the 23rd International Conference on World Wide Web*, April 7, pp. 1313–1318.
- Thomas, M. R. 2001. "Feminist Perspectives," in *Recent Theories of Human Development*, M. R. Thomas (ed.), Thousand Oaks, California: Sage, p. 248.
- Wang, A., Zhang, M., and Hann, I. 2018. "Socially Nudged: A Quasi-Experimental Study of Friends' Social Influence in Online Product Ratings," *Information Systems Research* (29:3), pp. 641–655.
- Wang, Z. 2010. "Anonymity, Social Image, and the Competition for Volunteers: A Case Study of the Online Market for Reviews," *The B.E. Journal of Economic Analysis & Policy* (10:1), pp. 1–34.
- Wei, Z., Xiao, M., and Rong, R. 2021. "Network Size and Content Generation on Social Media Platforms," *Production and Operations Management* (30:5), pp. 1406–1426.
- Willer, R. 2009. "Groups Reward Individual Sacrifice: The Status Solution to the Collective Action Problem," *American Sociological Review* (74:1), pp. 23–43.
- Yang, J., Adamic, L. A., and Ackerman, M. S. 2008. "Competing to Share Expertise: The Taskcn Knowledge Sharing Community," in *Proceedings of the 2nd International Conference on Weblogs and Social Media*, pp. 161–168.
- Yang, M., Ren, Y., and Adomavicius, G. 2019. "Understanding User-Generated Content and Customer Engagement on Facebook Business Pages," *Information Systems Research* (30:3), pp. 839–855.
- Yelp Inc. 2012. "What Makes a Yelp(er) Elite?" (<https://blog.yelp.com/community/what-makes-a-yelper-elite>, accessed April 4, 2022).
- Zeng, X., and Wei, L. 2013. "Social Ties and User Content Generation: Evidence from Flickr," *Information Systems Research* (24:1), pp. 71–87.

- Zhang, D., and Allon, G. 2015. "Does Social Interaction Improve Service Quality? Field Evidence from Massive Open Online Education." *Kellogg School of Management, Northwestern University, Evanston, IL*.
- Zhang, B., Pavlou, P. A., and Krishnan, R. 2018. "On direct vs. indirect peer influence in large social networks," *Information Systems Research* (29:2), pp. 292–314.