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# Magnify Cascades of Electronic Word-of-Mouth (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**
Electronic word-of-mouth (eWOM), behavioral cascading, social media operations, competitive altruism

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## 1 Introduction

A 2022 report by Kepios reveals that approximately 4.74 billion individuals globally are active social media users, representing 59.3% 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

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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 the 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 Van 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 8,289 restaurants in the state of Washington (WA) 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 followee'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 (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., 2010a, 2010b; 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 closest 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 are 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 the 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 and Ghoshal, 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 et al., 2010b; 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," that is, 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.

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 WA, which we chose as a representative metropolitan area in the United States based on the number of restaurants and new reviews

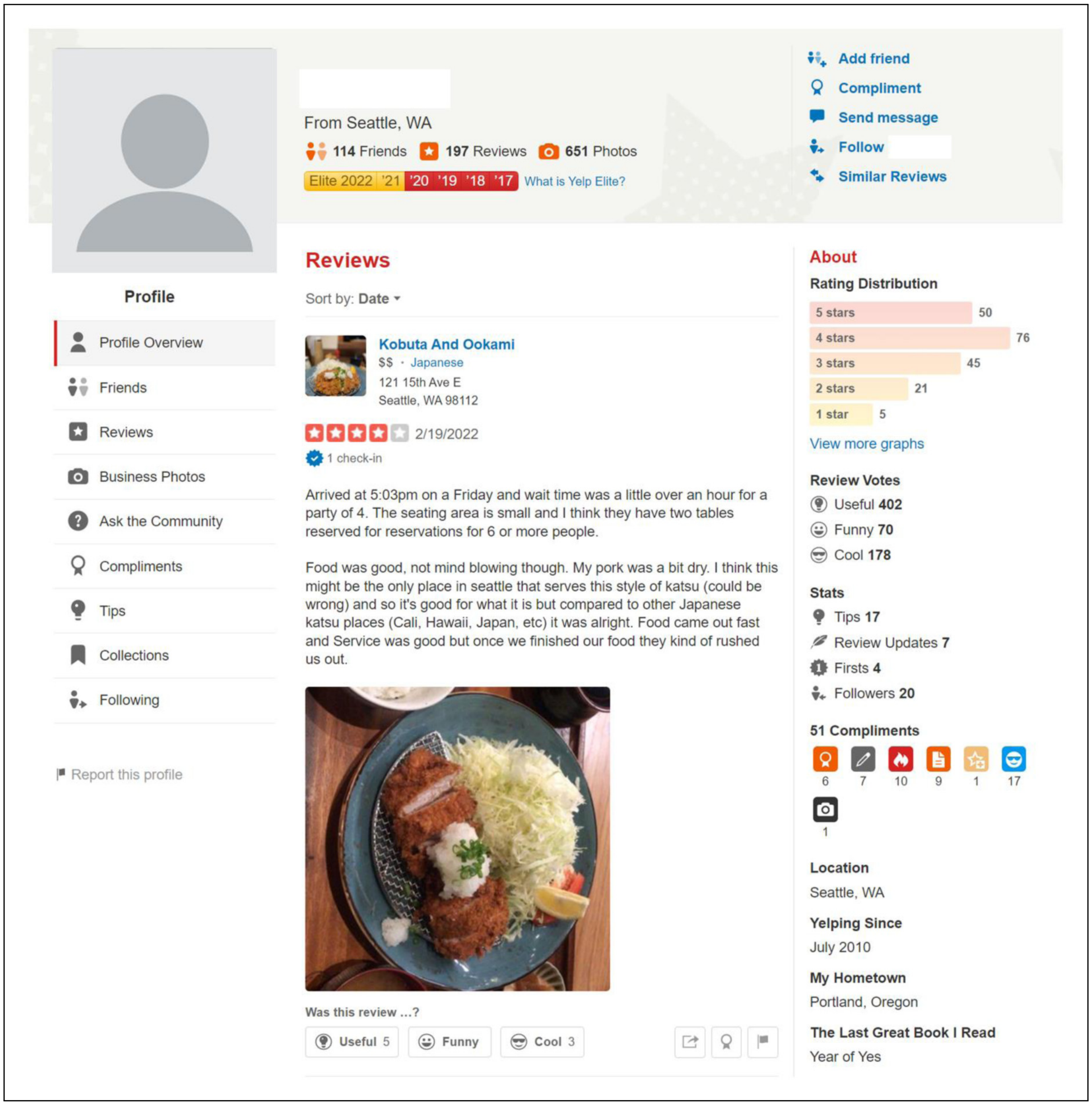


**Figure 1.** An example of a Yelp user's public profile page.

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 (a) were in WA and (b) 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, that is, 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, that is, 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* (nonelite). We inferred users' gender using a 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, that is, 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:

$$\begin{aligned} logit(Review_{ijt}) = \beta_0 &+ \beta_1 EliteCurFrndReviews_{i,j,t-1} \\ &+ \beta_2 EliteFutFrndReviews_{i,j,t-1} \\ &+ \beta_3 CurFrndReviews_{i,j,t-1} \\ &+ \beta_4 FutFrndReviews_{i,j,t-1} \\ &+ \beta_5 NewReviews_{j,t-1} + \gamma Controls_{i,j,t-1} + \varepsilon_{ijt} \end{aligned} \quad (1)$$

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 and an elite future friend, respectively, relative to a review written by a nonelite 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 nonelite 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 $\varepsilon_{ijt}$ 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:

$$\begin{aligned} & logit(Review_{ijt}) \\ & = \beta_0 + \beta_1 Promoted_{j,t-1} * CurFrndReviews_{i,j,t-1} \\ & \quad + \beta_2 Promoted_{j,t-1} * FutFrndReviews_{i,j,t-1} \\ & \quad + \beta_3 CurFrndReviews_{i,j,t-1} + \beta_4 FutFrndReviews_{i,j,t-1} \\ & \quad + \beta_5 NewReviews_{j,t-1} + \beta_6 Promoted_{j,t-1} \\ & \quad + \gamma Controls_{i,j,t-1} + \varepsilon_{ijt}. \end{aligned} \quad (2)$$

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).

*5.1.1 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 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 category[7] 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.

## 5.2 Results on the Effects of Status and Gender

Before estimating our models, we conducted collinearity tests and found no signs of collinearity (variance inflation factor $< 3$). 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 1 and significant ($\mathrm{OR} = 0.590$, $p < 0.01$), while that for *EliteFutFrndReviews* is greater than 1 and significant ($\mathrm{OR} = 2.534$, $p < 0.001$). 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 H1 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 do not have an effect, but *FemaleFutFrndReviews* do ($\mathrm{OR} = 2.502, p < 0.01$). 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 H2 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.

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.

**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 |
| $\#SelfReviews_{i,t-1}$ | # 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.

**Table 2.** Effects on behavioral cascading.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| Independent variables | OR (SE) | OR (SE) | OR (SE) | OR (SE) | OR (SE) | OR (SE) |
| $EliteCurFrndReviews_{i,j,t-1}$ | | 0.590** (0.108) | | | | |
| $EliteFutFrndReviews_{i,j,t-1}$ | | 2.534*** (0.681) | | | | |
| $FemaleCurFrndReviews_{i,j,t-1}$ | | | 1.032 (0.206) | | | |
| $FemaleFutFrndReviews_{i,j,t-1}$ | | | 2.502** (0.771) | | | |
| $Promoted_{j,t-1} \times CurFrndReviews_{i,j,t-1}$ | | | | 5.385** (3.230) | | |
| $Promoted_{j,t-1} \times FutFrndReviews_{i,j,t-1}$ | | | | – – | | |
| $Price_j \times CurFrndReviews_{i,j,t-1}$ | | | | | 0.777* (0.093) | |
| $Price_j \times FutFrndReviews_{i,j,t-1}$ | | | | | 1.358+ (0.228) | |
| $ComfrndCurFrndReviews_{i,j,t-1}$ | | | | | | 0.893 (0.251) |
| $ComfrndFutFrndReviews_{i,j,t-1}$ | | | | | | 2.952*** (0.785) |
| $CurFrndReviews_{i,j,t-1}$ | 2.853*** (0.232) | 4.410*** (0.708) | 2.786*** (0.472) | 2.834*** (0.231) | 4.608*** (1.170) | 3.146*** (0.837) |
| $FutFrndReviews_{i,j,t-1}$ | 1.674*** (0.256) | 0.827 (0.230) | 0.862 (0.267) | 1.677*** (0.256) | 0.941 (0.353) | 0.686 (0.193) |
| $NewReviews_{j,t-1}$ | 1.088*** (0.004) | 1.088*** (0.004) | 1.088*** (0.004) | 1.088*** (0.004) | 1.087*** (0.004) | 1.088*** (0.004) |
| $Promoted_{j,t-1}$ | 2.605*** (0.390) | 2.594*** (0.388) | 2.593*** (0.388) | 2.565*** (0.385) | 2.601*** (0.389) | 2.593*** (0.388) |
| $Price_j$ | 1.257*** (0.018) | 1.254*** (0.018) | 1.255*** (0.018) | 1.257*** (0.018) | 1.260*** (0.019) | 1.255*** (0.018) |
| $Elite_i$ | 1.723*** (0.037) | 1.723*** (0.037) | 1.723*** (0.037) | 1.723*** (0.037) | 1.723*** (0.037) | 1.722*** (0.037) |
| $Female_i$ | 0.921*** (0.014) | 0.922*** (0.014) | 0.922*** (0.014) | 0.921*** (0.014) | 0.921*** (0.014) | 0.922*** (0.014) |
| $Log\#Compliments_{i,t-1}$ | 1.222*** (0.016) | 1.221*** (0.016) | 1.222*** (0.016) | 1.222*** (0.016) | 1.223*** (0.016) | 1.220*** (0.016) |
| $\#SelfReviews_{i,t-1}$ | 1.122*** (0.004) | 1.122*** (0.004) | 1.122*** (0.004) | 1.122*** (0.004) | 1.122*** (0.004) | 1.122*** (0.004) |
| $Log\#CumSelfReview_{i,t-1}$ | 1.485*** (0.015) | 1.485*** (0.015) | 1.485*** (0.015) | 1.485*** (0.015) | 1.485*** (0.015) | 1.485*** (0.015) |
| $LogTenure_{i,t-1}$ | 0.782*** (0.012) | 0.782*** (0.012) | 0.782*** (0.012) | 0.782*** (0.012) | 0.782*** (0.012) | 0.782*** (0.012) |
| $Log\#Friends_{i,t-1}$ | 0.831*** (0.009) | 0.831*** (0.009) | 0.831*** (0.009) | 0.831*** (0.009) | 0.831*** (0.009) | 0.831*** (0.009) |
| $Log\#NewFriends_{i,t-1}$ | 1.198*** (0.011) | 1.198*** (0.011) | 1.198*** (0.011) | 1.198*** (0.011) | 1.198*** (0.011) | 1.198*** (0.011) |
| $Log\#Fans_{i,t-1}$ | 0.952*** (0.012) | 0.952*** (0.012) | 0.952*** (0.012) | 0.952*** (0.012) | 0.952*** (0.012) | 0.952*** (0.012) |
| $Urban_{i,t-1}$ | 0.713*** (0.020) | 0.713*** (0.020) | 0.713*** (0.020) | 0.713*** (0.020) | 0.713*** (0.020) | 0.713*** (0.020) |
| $CityIncome_i$ | 0.999 (0.001) | 0.999 (0.001) | 0.999 (0.001) | 0.999 (0.001) | 0.999 (0.001) | 0.999 (0.001) |

(continued)

**Table 2.** Continued.

| Independent variables | Model 1 OR (SE) | Model 2 OR (SE) | Model 3 OR (SE) | Model 4 OR (SE) | Model 5 OR (SE) | Model 6 OR (SE) |
|---|---|---|---|---|---|---|
| $Dist_{i,j}$ | 0.981*** | 0.981*** | 0.981*** | 0.981*** | 0.981*** | 0.981*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $AvgRatingRestaurant_{j,t-1}$ | 1.308*** | 1.307*** | 1.307*** | 1.308*** | 1.308*** | 1.307*** |
| | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) | (0.025) |
| $DiffRatingRestaurant_{j,t-1}$ | 0.733*** | 0.734*** | 0.734*** | 0.733*** | 0.733*** | 0.733*** |
| | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) | (0.029) |
| $AvgVariRestaurant_{j,t-1}$ | 0.827*** | 0.827*** | 0.826*** | 0.827*** | 0.827*** | 0.827*** |
| | (0.036) | (0.036) | (0.036) | (0.036) | (0.036) | (0.036) |
| $Log\#CumReviews_{j,t-1}$ | 1.604*** | 1.603*** | 1.604*** | 1.604*** | 1.604*** | 1.604*** |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) |
| $Claimed_{j,t-1}$ | 1.105*** | 1.106*** | 1.106*** | 1.105*** | 1.105*** | 1.106*** |
| | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) | (0.021) |
| $Competition_{j,t-1}$ | 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 |

Note. OR = odds ratio; SE = standard error; DV = whether user *i* reviews restaurant *j* in period *t* ($Review_{ijt}$). The values in parentheses are SEs. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. — denotes the variables are removed due to collinearity.

## 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 OR for the interaction term $Promoted \times CurFrndReviews$ is significant and positive (OR = 5.385, $p < 0.01$), while $Promoted \times FutFrndReviews$ 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 H3 is inconclusive, and further investigations are needed.

We also find that the OR for the interaction term $Price \times CurFrndReviews$ (Model 5 in Table 2) is less than 1 and significant (OR = 0.777, $p < 0.05$), while that for $Price \times FutFrndReviews$ 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, H4 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 H5 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.* Althoughour 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-effect models: a user-fixed-effect model and a restaurant-fixed-effect model. User- and restaurant-fixed-effect models control for the unobserved, time-invariant

**Table 3.** Fixed effects of status and gender.

| | Model 2a (restaurant-fixed effect) | Model 2b (user-fixed effect) | Model 2c (first difference) | Model 3a (restaurant-fixed effect) | Model 3b (user-fixed effect) | Model 3c (first difference) |
|---|---|---|---|---|---|---|
| Independent variables | OR (SE) | OR (SE) | OR (SE) | OR (SE) | OR (SE) | OR (SE) |
| $EliteCurFrndReviews_{i,j,t-1}$ | 0.625** | 0.678* | 0.650* | | | |
| | (0.111) | (0.121) | (0.294) | | | |
| $EliteFutFrndReviews_{i,j,t-1}$ | 1.687** | 2.357*** | 4.368* | | | |
| | (0.309) | (0.444) | (3.347) | | | |
| $FemaleCurFrndReviews_{i,j,t-1}$ | | | | 0.868 | 0.947 | 1.430 |
| | | | | (0.129) | (0.141) | (0.806) |
| $FemaleFutFrndReviews_{i,j,t-1}$ | | | | 1.606* | 2.077*** | 6.190*** |
| | | | | (0.308) | (0.421) | (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 |

Note. OR = odds ratio; SE = standard error; DV = whether user $i$ reviews restaurant $j$ in period $t$ ($Review_{ijt}$). The values in parentheses are SEs. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. 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 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.

| | Model 4a (restaurant-fixed effect) | Model 4b (user-fixed effect) | Model 4c (first difference) | Model 5a (restaurant-fixed effect) | Model 5b (user-fixed effect) | Model 5c (first difference) |
|---|---|---|---|---|---|---|
| Independent variables | OR (SE) | OR (SE) | OR (SE) | OR (SE) | OR (SE) | OR (SE) |
| $Promoted_{j,t-1} \times CurFrndReviews_{i,j,t-1}$ | 5.027** | 4.832** | 3.238* | | | |
| | (2.102) | (1.820) | (2.134) | | | |
| $Promoted_{j,t-1} \times FutFrndReviews_{i,j,t-1}$ | – | – | 0.047$^{+}$ | | | |
| | – | | (0.087) | | | |
| $Price_j \times CurFrndReviews_{i,j,t-1}$ | | | | 0.703** | 0.656*** | 0.533* |
| | | | | (0.083) | (0.074) | (0.172) |
| $Price_j \times FutFrndReviews_{i,j,t-1}$ | | | | 1.122 | 1.129 | 2.148 |
| | | | | (0.276) | (0.252) | (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 |

Note. OR = odds ratio; SE = standard error; DV = whether user $i$ reviews restaurant $j$ in period $t$ ($Review_{ijt}$). The values in parentheses are SEs. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. — denotes the variables are removed due to collinearity.

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 a 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 Table 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.

*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

**Table 5.** Fixed effects of relationship strength and matching.

| | Model 6a (restaurant-fixed effect) | Model 6b (user-fixed effect) | Model 6c (first difference) | Model 4d (matched samples) |
|---|---|---|---|---|
| Independent variables | OR (SE) | OR (SE) | OR (SE) | OR (SE) |
| $Promoted_{j,t-1} \times CurFrndReviews_{i,j,t-1}$ | | | | 10.700* |
| | | | | (10.792) |
| $Promoted_{j,t-1} \times FutFrndReviews_{i,j,t-1}$ | | | | – |
| $ComfrndCurFrndReviews_{i,j,t-1}$ | 0.694 | 0.881 | 2.273 | |
| | (0.180) | (0.231) | (3.677) | |
| $ComfrndFutFrndReviews_{i,j,t-1}$ | 1.728** | 2.442*** | 6.488*** | |
| | (0.323) | (0.464) | (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 |

Note. OR = odds ratio; SE = standard error; DV = whether user $i$ reviews restaurant $j$ in period $t$ ($Review_{ijt}$). The values in parentheses are SEs. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. — denotes the variables are removed due to collinearity.

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: that is, 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 nonpromoted 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 constraints.

## 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 and Whinston, 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 section 6.2 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 (Herring, 2003; Broadhurst, 1993). 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 and Zozula, 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 "every day" 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, noncausal explanations; though we have taken many steps to alleviate endogeneity concerns (e.g., multiple fixed effect models, 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 the inclusion of product pictures in the reviews.

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## Notes

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.
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.
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.
6. We calculated this variable based on the categorization by United States Census Bureau (2010).
7. We categorized restaurants using latent Dirichlet allocation topic modeling, which reduced the number of restaurant categories from over 1,000 to 16 based on word co-occurrences.

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