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Social Influence Effects in Online Product Ratings

Websites prominently display consumers' product ratings, which influence consumers' buying decisions and willingness to pay. Few insights exist regarding whether a consumer's online product rating is prone to social influence from others' online ratings. Examining this issue, the authors hypothesize that other consumers' online ratings moderate the effects of positive and regular negative features of product experience, product failure, and product recovery (to address product failure) on the reviewer's online product rating. The results from a model using 7499 consumers' online ratings of 114 hotels support the hypotheses. Other consumers' online ratings weaken the effects of positive and regular negative features of product experience but can either exacerbate or overturn the negative effect of product failure, depending on the quality of product recovery. For marketing theory, the findings indicate that consumers who influence others are themselves influenced by other consumers and that this influence is contingent on their product experience. For managerial practice, the authors offer a method to estimate the effects of product experience characteristics on online product ratings and show that social influence effects make high online product ratings a double-edged sword, exacerbating the negative effect of product failure and strengthening the benefit of product recovery.

Keywords: online ratings, social influence, product failure, product recovery, word of mouth

O nline consumer reviews and ratings, a key form of online user-generated content, are now widely available for many products. An online reviewer provides a qualitative assessment (online review) of his or her product experience, which informs and influences his or her quantitative evaluation (online product rating). The online reviewer is usually preceded by reviewers who have already rated the product. The average online product rating is prominently displayed (e.g., www.epinions.com; www.tripadvisor.com) to convey consensus information about the online reviewer community's product evaluations. Here, we address whether and how other consumers' online ratings,[1] measured by their average ratings, moderate the effects of product experience characteristics on a reviewer's online product rating. We first provide the motivation.

From a theoretical perspective, 40 years ago, Myers and Robertson (1972, p. 41) proposed that "opinion leadership is two-way: people who influence others are themselves influenced by others in the same topic area" and found preliminary

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[1]Hereinafter, we use "other consumers' online ratings" to refer to other consumers' online product ratings.

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support for this idea. Myers and Robertson (p. 46) issued a call for research, noting that "the model of opinion leadership should be revised to include the concept of two-way influence." The online context, in which online product reviewers (who seek to influence future consumers) provide ratings after observing other consumers' online ratings, enables us to investigate this issue, which, to the best of our knowledge, has not been addressed in the marketing literature.

Given the growth of online review websites, marketing scholars have examined demand consequences of online product ratings (Bickart and Schindler 2001). High online product ratings increase the online market shares of books (Chevalier and Mayzlin 2006), offline sales of television shows (Godes and Mayzlin 2004), sales of toiletry products (Moe and Trusov 2011), and sales of video games (Zhu and Zhang 2010). There is limited and mixed empirical evidence on social influence in online ratings. Schlosser (2005) reports that reviewers, motivated by a need to be perceived as discriminating, *decrease* their online product ratings after reading others' online reviews. Other research reports that when others' online ratings are at the lower end of the rating scale, reviewers tend to *increase* their online product rating (Moe and Trusov 2011). A possible reason for the mixed evidence is that past research has overlooked the contingent nature of social influence effects in the online ratings context.

Insights into social influence effects in online product ratings have high managerial relevance. A comScore Inc. survey (2007) reports that 24% of consumers use online consumer reviews before purchasing a product. With respect to hotels, the empirical context for this article, online consumer reviews influenced choices for most consumers (87%). High online product ratings also translate into price

premiums. In the comScore study, consumers were willing to pay more for a product with an "excellent" rating (5) than for one with a "good" rating (4); the premiums were 99% for legal services, 38% for hotels, and 20% for real estate agents. Managers find it useful to decompose online reviews to learn how their products' characteristics affect their online product ratings. In particular, insights into social influence effects in online product ratings provide actionable insights to managers, including how to use online product ratings as a marketing communications element.

We extend developments in social psychology on how influence from groups, in conjunction with situational characteristics, affects the consumer's uniqueness and conformity needs or induces normative conflict, which in turn affects the consumer's behaviors (for a review, see Cialdini and Goldstein 2004). By describing his or her product experience and providing an online product rating, the reviewer is a de facto member of the online reviewer community (social group) (Hennig-Thurau et al. 2004). Furthermore, the average of other consumers' online product ratings provides consensus information about their product evaluations. Thus, we propose that, contingent on an online reviewer's product experience, other consumers' online ratings will change the relative salience of the online reviewer's conformity needs, uniqueness needs, and normative conflict, which in turn will differentially moderate the effects of various product experience characteristics on that reviewer's online product rating.

While evaluating product experiences, consumers find some variability in product quality acceptable and extreme variability unacceptable (Gürhan-Canli 2003; Kardes and Allen 1991). Therefore, we categorize an online reviewer's product experience into positive features, regular negative features acceptable to him or her, and product failure (negative and generally unacceptable). In addition, when a product failure occurs, a firm may sometimes undertake a product recovery to rectify it. Thus, we hypothesize moderating effects from other consumers' online ratings on the effects of a reviewer's (1) positive and regular negative features of product experience (H_1 and H_2), (2) product failure (H_3), and (3) product recovery to address product failure (H_4) on the reviewer's online product rating.

We use data from 7499 consumers' online ratings and reviews of 114 hotels in Boston and Honolulu, posted on a third-party travel website between 2006 and 2010, to test the hypotheses. We use both automated text analysis and human coders to obtain measures of product experience characteristics from the online review text. We estimate a nested ordered logit model to test the hypotheses, accounting for the endogeneity of product experience characteristics and controlling for hotel and online reviewer characteristics.

The results support the hypotheses. The positive (negative) effects of positive (regular negative) features of product experience on a reviewer's online product rating become weaker as other consumers' online ratings increase. In contrast, the negative effect of product failure on a reviewer's online product rating becomes stronger as other consumers' online ratings increase. Finally, as the quality of product recovery increases, the negative interaction effect between other consumers' online ratings and product failure on a reviewer's online product rating becomes weaker.

The results are robust to alternative measures, model specifications, text analysis methods, and samples. The size of the social influence effects are nontrivial; they weaken the effect of regular positive and negative features of product experience on a reviewer's online product rating by 84% and 81%, respectively, and strengthen the negative effects of product failure by 63%. Furthermore, social influence along with superior product recovery overturns the negative effect of product failure on a reviewer's online product rating.

We generate three theoretical contributions. First, we document the adaptive and bidirectional nature of social influence in word-of-mouth provision. Specifically, online product reviewers, who are opinion leaders for future consumers, are influenced by information provided by other opinion leaders. Furthermore, online social influence on word of mouth is adaptive rather than passive (i.e., blindly following the crowd), as noted in the literature (Iyengar, Van den Bulte and Valente 2011). Second, we find that social influence from other consumers' online ratings can either strengthen (e.g., product failure without product recovery) or weaken a reviewer's online product rating (e.g., product failure followed by a superior product recovery), and in doing so, we clarify the mixed empirical evidence in the literature (Moe and Trusov 2011; Schlosser 2005). Third, our findings indicate that online social influence substantively alters marketing phenomena. For example, the marginal impact of product failure would be expected to be negative, but together with a superior product recovery and social influence effects, this negative marginal effect may be overturned.

We also generate three key implications that managers can use. First, they can implement the proposed text analysis approach to estimate the marginal effects of product experience characteristics on their customers' online product ratings. Second, because online product ratings may be viewed as proxies for demand, managers can estimate elasticities of product experience characteristics, a cost-effective alternative to conjoint analysis. Third, because other consumers' online ratings can either strengthen (i.e., product failure, superior product recovery) or weaken (i.e., product failure, no recovery) the effects of product failure on a reviewer's online product rating, managers should be cognizant of the double-edged effects of high online ratings of their products.

We organize the remainder of the article as follows: We first develop theory and hypotheses about social influence effects in the online ratings context, following which we present the empirical analysis and hypotheses tests. Next, we document the sizes of the social influence effects for the four product experience characteristics. We conclude with a discussion of the study's contributions to marketing theory and managerial practice and its limitations, which present opportunities for further research.

Theory and Hypotheses

Online Product Ratings Context

Effects of product experience characteristics. Our dependent variable is the reviewer's online product rating,

the summary online evaluation of the product and a parsimonious word-of-mouth metric that influences other consumers' purchase behaviors and willingness to pay (Anderson 1998). Extensive evidence indicates that positive and negative features of products affect consumers' overall product evaluations (e.g., Mano and Oliver 1993). Furthermore, consumers appear to find some variability in the quality of their product experiences acceptable (Gürhan-Canli 2003; Kardes and Allen 1991). Sometimes, consumers experience product failures; that is, the product's performance is simply not acceptable. Thus, negative product experiences include both acceptable experiences (regular negative features) and unacceptable experiences (product failures). This distinction is important because product failures evoke different negative emotions and also induce different behaviors from regular negative experiences (Anderson 1998; Zeelenberg and Pieters 1999), including on online review websites (Hennig-Thurau et al. 2004). Moreover, when product failure occurs, firms may undertake product recovery to address it, which may or may not overcome the negative effect of product failure on product evaluations. In summary, a consumer's product experience will consist of positive features, regular negative features, product failure, and product recovery, which in turn will influence the reviewer's online product rating. These factors are represented by the solid line arrows in Figure 1.

Note that a consumer's product experience may not always include product failure.

Source of social influence. An online product reviewer is an opinion leader for others who are considering the purchase of the product. However, an online product reviewer also observes other consumers' online ratings when submitting his or her rating on an online review website. Thus, the online reviewer (an opinion leader) is a member of the social group of online product reviewers (other opinion leaders) and will likely be influenced by their ratings. As evidence that an online reviewer is a member of the social group of online product reviewers, in a survey of more than 2000 online reviewers, Hennig-Thurau et al. (2004, p. 46) report that by posting online reviews and ratings, reviewers report seeking social benefits of affiliating with the online reviewer community.

The structural view of the social influence process (Rashotte 2009) suggests that people combine their ideas and the opinions of others in their decision making. Building on this idea, we propose that the average online product rating,[2] which is prominently displayed (e.g., http://www.

[2]Because other consumers' online ratings are the arithmetic mean (range between 1 and 5) of other consumers' online product ratings preceding the focal reviewer, negative values of other consumers' online ratings do not exist.

FIGURE 1
Social Influence Effects on the Relationships Between Product Experience Characteristics and Online Product Ratings
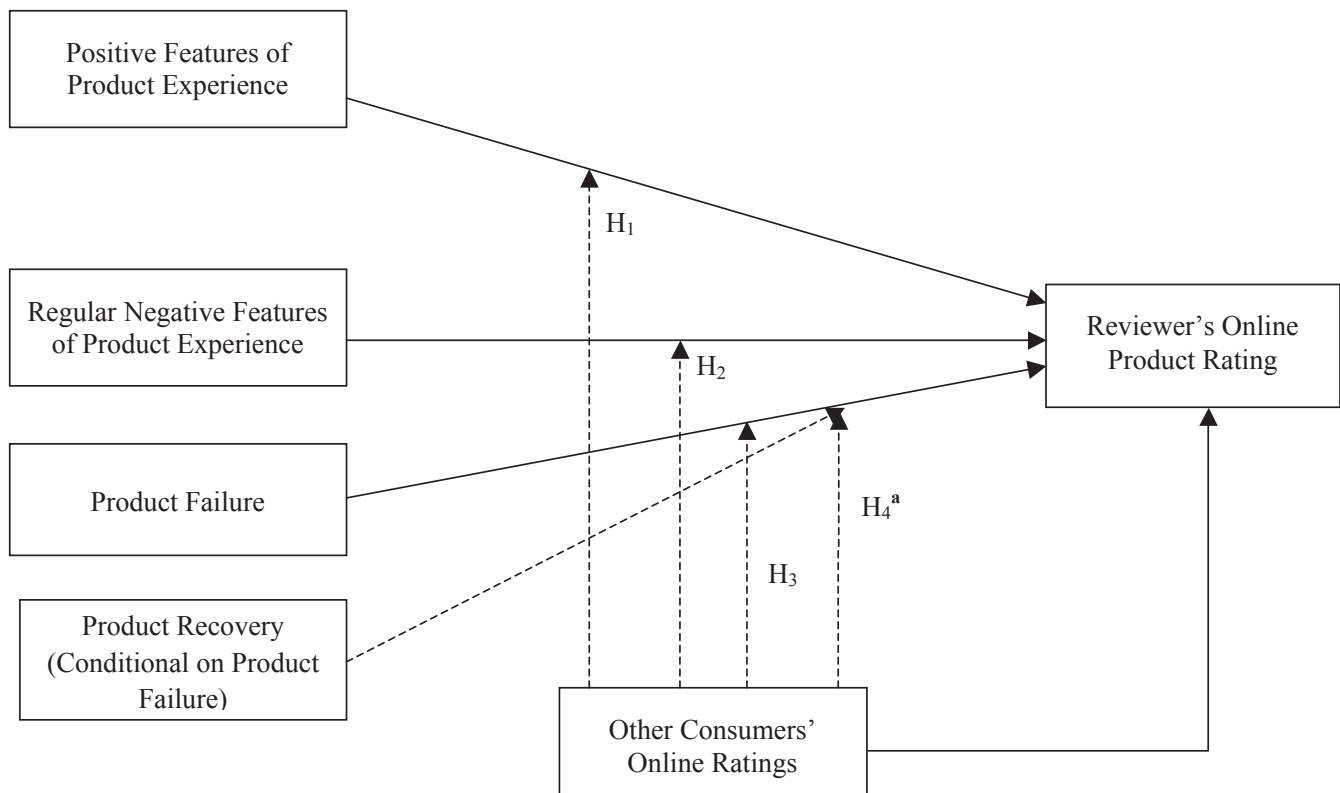
[a]H_4 is a three-way interaction effect among other consumers' online ratings, product failure, and product recovery.

epinions.com; http://www.tripadvisor.com) and conveys the online reviewer community's consensus product evaluation, is a source of social influence on that reviewer's online product rating.

We expect social influence from other consumers' online ratings to manifest in two ways. First, other consumers' online ratings have a main effect on the reviewer's online product rating (the solid line arrow in Figure 1). We expect other consumers' online ratings to have a positive main effect on the reviewer's online rating. Support for the main effect of other consumers' online ratings stems from social influence theory (e.g., Fromkin 1970), which states that people build their own opinion on the basis of the group's consensus. We do not formally hypothesize this positive main effect but include it, for completeness, in the model that we estimate.

Second, we focus on how other consumers' online ratings moderate the effects of the four product experience characteristics (described previously) on the reviewer's online product rating. In other words, we examine the process by which other consumers' online ratings and the reviewer's product experience characteristics are combined to generate the online reviewer's online product rating. These are shown by the dotted line arrows in Figure 1 and represent the four hypotheses. We next discuss the four key ideas from social influence theory that we extend to develop the hypotheses.

Social Influence Theory: Related Developments

First, people experience conformity pressures from other members in a social group. The actions of others have a powerful effect on a given member's behavior (for a review, see Cialdini and Goldstein 2004). Indeed, direct observation of the group members' behaviors is not even required for social influence to occur. Simply communicating a norm in writing (e.g., how other people behave in a given situation) induces conformity (Parks, Sanna, and Berel 2001; Von Borgstede, Dahlstrand, and Biel 1999). People conform to social influence from various sources, including peers they do not know (Darley and Latane 1967) and even abstract reference groups (Cohen 2003).

Second, people in a social group simultaneously experience competing needs to conform and be unique. Whereas the early literature (e.g., Asch 1956, Deutsch and Gerard 1955; Sherif 1936) stresses conformity pressures, there is now robust evidence that people also experience uniqueness needs (e.g., Fromkin 1970). When people feel overly undifferentiated from others in a social group, because of situational pressures or stable individual differences, they experience a negative state, which they alleviate by being unique from the group (Snyder and Fromkin 1980). For example, people diverge from other consumers' product choices to ensure that the group makes desirable inferences about their identities, which are signaled by their choices (Berger and Heath 2007).

Third, people may experience normative conflict and deviate from social group opinions if they believe that doing so is better for the group. Normative conflict can arise when people perceive a large discrepancy between a group norm and their experiences (Ashforth, Kreiner, and Fugate 2000). In such a situation, people may overlook their conformity needs and behave altruistically for the group, even if it requires them to deviate from the group's opinion (Hornsey 2006; Hornsey, Oppes, and Svensson 2002).

Fourth, situational factors make one social need (conformity or uniqueness) or normative conflict more salient than others. In a social group, individuals simultaneously experience conformity needs, uniqueness needs, and normative conflict. Thus, which of these dominate in influencing behaviors is contingent on situational characteristics (Packer 2008). For example, normative conflict resulting in dissent from the group's opinion occurs when the individual believes that the group's opinion is harmful to the group's well-being. In the individual's viewpoint, in such a situation, conformity is suboptimal, and the expression of dissent from the group is beneficial for the group (De Dreu 2002).

Hypotheses

With this theoretical background, we develop hypotheses in the following subsections. They include moderating effects of other consumers' online ratings on the effects of positive features of product experience (H_1), regular negative features of product experience (H_2), product failure (H_3), and a firm's product recovery effort to address the product failure (H_4) on the reviewer's online product rating.

Positive features. We expect a positive main effect of positive features of product experience on the reviewer's online product rating. Our interest here is in the moderating role of other consumers' online ratings. If other consumers' online ratings increase (signifying a superior product) and a reviewer's product experience has many positive features, the online reviewer may feel very similar to other group members. As people perceive more similarity between themselves and others in the group, they become increasingly motivated to reaffirm their distinctiveness, creating a need for uniqueness (Lynn and Snyder 2002; Snyder and Fromkin 1980). Need for uniqueness is a psychological state in which individuals feel indistinguishable from others, which motivates compensatory acts by them (distinct from those of the group) to reestablish their uniqueness. A way people can address their uniqueness needs is by increasing the distinctiveness of their attitudes from those in the group (Imhoff and Erb 2009). For example, people who believed that they were similar to others (control subjects) conformed less in a judgment task (Duval 1976) and expressed less popular attitudes (Weir 1971).

Applying this logic, we propose that when a reviewer's product experience has many positive features, as other consumers' online ratings increase, the reviewer's product experience will be consistent with other consumers' high online ratings. As this consistency increases, the online reviewer may begin to perceive that he or she is indistinguishable from other online reviewers. This will activate the reviewer's need for uniqueness, which the reviewer can satisfy by projecting him- or herself as a more discerning

consumer than the other online reviewers. The reviewer can achieve some uniqueness in the online reviewer community by providing an online product rating that is lower than commensurate for the level of positive features of his or her product experience. Thus, other consumers' online ratings will decrease the positive effect of positive features of the product experience on the online product rating. Therefore, we propose the following:

H[1]: The higher other consumers' online ratings, the weaker is the positive effect of the positive features of product experience on a reviewer's online product rating.[3]

Regular negative features. Again, we expect a negative main effect of regular negative features of product experience on the reviewer's online product rating. We focus on the moderation effect of other consumers' online ratings. As other consumers' online ratings increase and a reviewer's product experience has more regular negative features (which are acceptable to him or her) and therefore appear to be only marginally discrepant from other consumers' high online ratings, the reviewer's need for uniqueness in the online reviewer community is satisfied. When confronted with a minor discrepancy from the majority opinion, the group member may infer that the group's opinion is valid ("high consensus implies correctness") and "is accepted as reflecting objective reality" (Mackie 1987, p. 42).

Thus, we propose that when the online reviewer's product experience has many regular negative features and other consumers' product ratings are high, the online reviewer will experience conformity pressures to provide an online product rating consistent with the group's opinion (i.e., the high online product ratings). To satisfy his or her conformity need, the online reviewer will provide a higher online product rating than that warranted by the level of regular negative features of her product experience. Thus, we propose the following:

H[2]: The higher other consumers' online ratings, the weaker is the negative effect of the regular negative features of product experience on a reviewer's online product rating.

Product failure. We expect a negative main effect of product failure on the reviewer's online product rating. Our interest again is in the moderating role of other consumers' online ratings. To begin, the occurrence of a product failure is unacceptable, lowering product evaluations, increasing customer dissatisfaction (Anderson 1998), and evoking emotions different from those in regular negative experiences. Thus, we anticipate a different social influence effect for product failures from that for regular negative features (H[2]).

When there is a product failure, we propose that the online reviewer will primarily experience normative conflict and will not be as motivated by uniqueness and conformity needs (as in H[1] and H[2], respectively). Individuals

experience normative conflict if their personal experiences lead to conclusions that are in substantive conflict with those of the group (Hornsey, Oppes, and Svensson 2002). In such a situation, an individual may be motivated to deviate from the group's opinion, believing that doing so would be helpful to the group members and change the group for better (Louis, Taylor, and Neil 2004). Packer (2008) argues that such noncompliant dissenting behaviors arising from normative conflict are high when these behaviors have high visibility and when the individual has an opportunity to explain why he or she is challenging the group's opinion. This is the case when a reviewer describes his or her product failure experience in an online review (that others can read) and provides an online product rating.

When a product failure occurs, given the online reviewer's unacceptable product experience in the face of other consumers' high online product ratings, we propose that the online reviewer will experience high normative conflict. In such a situation, the online reviewer, already dissatisfied because of the product failure, may be motivated to provide an even lower online product rating to rectify the "incorrect" (according to personal experience) online product rating on the review website.

By providing a lower online rating than that warranted by the level of product failure, the online reviewer not only reduces normative conflict but also signals his or her helpfulness to the online reviewer community, albeit as a nonconforming group member (Hornsey and Jetten 2004). In support of this logic in the online ratings context, in response to consumers who rated a product highly, the online reviewer who experienced a product failure is motivated to warn subsequent users and disproportionately decreases his or her online product rating (Grégoire, Tripp, and Legoux 2009). Thus, we offer the following hypothesis:

H[3]: The higher other consumers' online ratings, the stronger is the negative effect of product failure on the reviewer's online product rating.

Product recovery. A common response of firms to product failures is to attempt actions to improve the consumer's product experience, in what is known as a product recovery effort (Smith, Bolton, and Wagner 1999; Tax, Brown, and Chandrashekaran 1998). Some studies report that post-recovery customer satisfaction levels are not high despite effective recovery efforts (Zeithaml, Berry, and Parasuraman 1996). However, other studies suggest that sometimes, product recovery efforts are effective and produce a "recovery paradox" in which customer satisfaction following the product failure and recovery effort is higher than the prefailure levels (McCollough, Berry, and Yadav 2000; Smith and Bolton 1998).

Here, we focus on the three-way interaction effect among other consumers' online ratings, product failure, and the firm's product recovery effort to address the product failure. In the online context, we note that product recovery itself has no main effect on the reviewer's online product rating because it is contingent on the occurrence of a product failure. In addition, we do not formally hypothesize the two-way interaction effect between product failure and

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[3]We did not include a separate hypothesis for extremely positively product experiences, because we did not have any a priori intuition on how this effect would be substantively different from H[1].

product recovery, but for completeness, we include it in the model that we estimate.

We interpret the three-way interaction effect as the moderating effect of product recovery on the two-way interaction effect between others consumers' online ratings and product failure on the reviewer's online product rating (H_3). As noted in H_3, when other consumers' ratings are high and an online reviewer experiences a product failure with no product recovery, the reviewer will experience normative conflict, resulting in the negative two-way interaction effect between product failure and other consumers' online rating on the reviewer's online product rating. As the quality of product recovery increases, we propose that the online reviewer will appreciate the firm's product recovery effort to address the product failure (McCollough, Berry, and Yadav 2000). Thus, we expect that the online reviewer will be more forgiving of the product failure in such a situation. This may, in turn, reduce the normative conflict the reviewer faces, which arises from the deviance between his or her product failure experience and other consumers' high online ratings. Thus, we propose that for a given level of product failure, as the quality of the product recovery increases, the negative two-way interaction effect between other consumers' online ratings and product failure (H_3) will be weakened. Thus, we propose the following:

H$_4$: The higher the quality of product recovery, the weaker is the negative (two-way) interaction effect between other consumers' online ratings and product failure on the reviewer's online product rating.

Data

Empirical Context

To test the hypotheses, we needed a context in which product experience characteristics are documented and available. One such class of products is services. Thus, we chose hotels as the product category. We use data on consumers' online ratings of hotels on an independent travel website. We test the hypotheses using data recorded between July 2006 and February 2010 for hotels in Boston and Honolulu. Boston is an important commercial center in the United States, and Honolulu is a popular holiday destination, which enabled us to test the robustness of the findings across two cities.

We collected data on consumers' online ratings of hotels (on a five-point scale) and the online review text. We also collected information about the hotel's class and amenities (e.g., business centers, swimming pools) and personal information (e.g., age, membership duration) that the reviewer voluntarily provided. Online reviews for which we had complete information on all the variables resulted in 7499 reviews of 114 hotels (Boston: 50 hotels and 3038 reviews; Honolulu: 64 hotels and 4461 reviews).

Dependent and Independent Variables

We define the dependent variable (RATING) as a reviewer's online rating of the hotel. We describe the independent variables in the following subsections.

Other customers' online rating. We use the average of other consumers' ratings of the hotel (OTHERS_AVG) before the focal reviewer provides the online rating as the measure that induces social influence.[4]

Product experience. We developed measures of the four product experience characteristics (i.e., positive features, regular negative features, product failure, and product recovery) using computer-aided text analysis (CATA) and manual coding of the online review text.[5] Measures obtained from text analysis follow from the Whorf-Sapir hypothesis (Sapir 1944; Whorf 1956) that the cognitive categories to which individuals attend are embedded in the words that they use. Accordingly, we assume that online reviewers mainly choose words in the online review text that reflect their product experiences.

Product failure and product recovery. Because the empirical context for this study, hotels, is a service, we adapted the schema developed by Bitner, Booms, and Tetreault (1990) and also used by Kelley, Hoffman, and Davis (1993) to code product failures. We defined a product failure as having occurred if there was (1) a core facility failure (e.g., bed bugs in the room, unwashed linen), (2) employee negligence to consumers' explicit requests (e.g., the consumer requests vegan food but is served chicken), or (3) extreme negative employee behaviors (e.g., insults).

Off-the-shelf CATA software (e.g., General Inquirer [Stone et al. 1966], Linguistic Inquiry and Word Count [Pennebaker, Francis, and Booth 2001]) typically provides a count of preselected positive (negative) words occurring in a textual description (a proxy measure for positivity or negativity). Because there are no preselected words to measure product failure and product recovery, automated coding is not feasible for them. Thus, we used human coders (two graduate students in marketing) to code product failure and product recovery.

To train the coders, we and the coders independently coded 50 online product reviews (not included in the final sample). If a product failure was not observed, a 0 was recorded for both product failure and product recovery (no product failure case). If a product failure was observed, we and coders rated the severity of product failure on a scale from 1 ("least severe") to 9 ("most severe") and the quality of product recovery to address product failure (if it occurred) on a scale from 1 ("very poor product recovery") to 9 ("excellent product recovery"). Following the development of consistent guidelines based on the test sample, the two coders independently read the 7499 online reviews to assess whether a product failure (PROD_FAILURE) occurred and whether the firm attempted a product recovery (PROD_RECOVERY) to address the product failure.

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[4]We interact OTHERS_AVG with each of the four product experience characteristics. Thus, the main effect of a product experience characteristic implies that OTHERS_ AVG is 0, which does not occur. To aid in the interpretation of the main effects, we subtract 1 (i.e., the minimum) from OTHERS_AVG. We thank an anonymous reviewer for this suggestion.

[5]We thank the three anonymous reviewers for their many suggestions on the text analysis.

When the coders found any instance of product failure (PROD_FAILURE > 0) or product recovery (PROD_RECOVERY > 0), they manually parsed the relevant portion of the online review text so that we could verify their coding. The two coders agreed on the occurrence of product failure in 97% of the cases, and their ratings of product failure and quality of product recovery were within two points of each other in 98% of the cases. A third coder (also a graduate student in marketing trained in coding) resolved the inconsistencies.

Positive and regular negative features of product experience. We developed a custom computerized algorithm to extract positive and regular negative features of product experience from the portion of the online review text after excluding the portion pertaining to product failure and product recovery (if any). We describe the algorithm next.

> Step 1: Extract count of positive and negative features of the reviewer's product experience.

Online reviews mainly contain positive and/or negative information about product attributes. In addition, a perusal of the reviews suggested that online reviewers also used "not-positive" words (e.g., "not so good") and "not-negative" words (e.g., "not so bad"), which we categorized separately. Because reviews may sometimes contain positive or negative words not pertinent to the product (e.g., "the weather was beautiful"), we focus only on the portion of the online review pertaining to the hotel (e.g., room service, lobby). Toward this end, the algorithm decomposed each online review into a bag of words (removing duplicate words). We went through the list of words and developed five dictionaries of product attributes (e.g., "room service"), positive words (e.g., "polite"), negative words (e.g., "dirty"), not-positive words, and not-negative words. Using the custom dictionaries, the algorithm provided the counts of positive and negative words that co-occurred in a sentence with a product attribute for each online review.

> Step 2: Weight count measure by intensity of positivity/negativity.

A sum of the occurrence count of all positive and not-negative words and negative and not-positive words in an online review would capture positive and regular negative features, respectively, of product experience. However, positive (negative) words vary in their intensity (e.g., "good," "fantastic"), and merely summing the counts of their occurrence (when they co-occur with a product attribute) does not account for this intensity variation. Thus, we asked two graduate students to rate every positive (negative) word that occurred in the online reviews on a seven-point scale where 1 = "least positive (negative)" and 7 = "most positive (negative)." We obtained a weighted measure of positive (POS) and regular negative (REG_NEG) features of product experience by multiplying the count of each positive and negative word (co-occurring with a product attribute) by its intensity weight (e.g., Cho and Hambrick 2006). We describe the procedure in Appendix A.

Control Variables

We control for the volume of consumers' online ratings (OTHERS_VOL), a possible source of social influence. In addition, we include online reviewer characteristics as control variables in the model. First, because experts evaluate products differently from novices (Bendapudi and Berry 1997), we control for the reviewer's online rating experience, measured by the number of online reviews posted before the reviewer's focal product rating (R_RATE_EXPERIENCE). Second, because long reviews are likely to be more negative than short reviews (Poncheri et al. 2008), we control for review length (R_LENGTH_REV), measured by the number of characters in the online review text. Third, online reviewers' propensity to disclose personal information may also affect their ratings (Forman, Ghose, and Wiesenfeld 2008). Therefore, we control for information disclosed, measured by the count of the types of information the reviewer provided, scaled by the total number of types of information requested by the website (R_VOL_DISCLOS_REV).[6] Fourth, we control for the purpose of the reviewer's stay at the hotel (R_GOAL: 1 for leisure and 0 for business). Finally, we control for the reviewer's membership duration on the review website (R_MEMBERSHIP) as the number of months between the reviewer's registration on the website and provision of the online product rating.

We also control for the hotel's class (PROD_CLASS: one star to five stars)[7] and the breadth of the hotel's product offerings (PROD_OFFERING), which we measure using the average of six dummy variables: whether the hotel had parking, a business center, a fitness center, a restaurant, room service, and a swimming pool (1 if the amenity was offered and 0 if not). We also include a dummy variable for the two cities (PROD_CITY: 1 for Boston and 0 for Honolulu). Table 1 describes the measures, and Table 2 provides the descriptive statistics and correlations. The distribution of online ratings in our sample is consistent with previous work that reports that online ratings are at the high end of the rating scale (e.g., Li and Hitt 2008).

Method

Model Specification

Because online ratings are ordered variables that are not distributed normally and we have a nested data structure (each hotel receives ratings from multiple reviewers), we employ the nested ordered logit model. Consider the rating $y_{ij} = \{1, 2, 3, 4, 5\}$ that reviewer i provided for hotel j. Let

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[6]The registration profile requests information about age, sex, location, and travel behavior (i.e., work or leisure, the amount of money the reviewer usually spends on a trip, and whether the reviewer usually travels alone or with someone else) and also provides three open-ended questions that ask reviewers to describe themselves and their ideal vacation.

[7]Most of the hotels in the sample are three-star hotels (22 in Boston, 29 in Honolulu), followed by four-star hotels (19 in Boston, 15 in Honolulu) and two-star hotels (6 in Boston, 12 in Honolulu), with few one- and five-star hotels (3 in Boston, 8 in Honolulu).

TABLE 1
Variables and Measures

Variable	Name	Measure
Reviewer's online product rating	RATING	Online rating posted for a hotel by a reviewer.
Other consumers' online ratings (average)	OTHERS_AVG	The average of all online ratings received by the hotel before the online rating is provided by reviewer.
Product failure	PROD_FAILURE	Coded on a nine-point scale, where 0 represents "no failure" and 9 represents "severe failure," obtained through human coding.
Product recovery	PROD_RECOVERY	Coded on a nine-point scale, where 0 represents "no product recovery" and 9 represents an "excellent product recovery," obtained through human coding.
Positive features of product experience	POS	Weighted measure of the count of positive words about product attributes in the review text, with the count of each positive word multiplied by its respective intensity of positivity (for details, see Appendix A). The measure is obtained through computerized content analysis on the review text, after the portion of the text pertaining to product failure and product recovery is manually parsed out.
Regular negative features of product experience	REG_NEG	Weighted measure of the count of negative words about product attributes in the review text, with the count of each negative word multiplied by its respective intensity of positivity (for details, see Appendix A). The measure is obtained through computerized content analysis on the review text, after the portion of the text pertaining to product failure and product recovery is manually parsed out.
Volume of other consumers' online ratings	OTHERS_VOL	Number of online ratings received by the hotel before the current rating was provided by the reviewer.
Online rating experience (of reviewer)	R_RATE_EXP	Number of online ratings of other hotels provided by the reviewer before the current rating was provided.
Length of review	R_LENGTH_REV	Count of characters in the online review text.
Reviewer's information disclosure	R_VOL_DISCLOS_REV	Percentage of voluntary registration information (e.g., sex) provided by the reviewer.
Reviewer's consumption goal	R_GOAL	Dummy variable coded as 1 if the visit at the hotel was for leisure and 0 for business.
Reviewer's membership duration	R_MEMBERSHIP	Duration in months between date of membership on online review website and date of post.
Product class	PROD_CLASS	An ordinal variable capturing the hotel's one-, two-, three-, four-, or five-star hospitality rating.
Product offering	PROD_OFFERING	We used the average of six dummy variables to represent the breadth of the hotel's product offerings: whether the hotel provided parking, a business center, fitness center, restaurant, room service, and a swimming pool (the code was 1 if the amenity was offered and 0 if not).
City	PROD_CITY	A dummy variable coded as 1 if the hotel is situated in Boston and 0 if situated in Honolulu.

be the underlying latent variable that captures the reviewer's product evaluation. The nested ordered logit model is as follows:

$$(1) \quad y_{ij}^* = \gamma_0 \text{OTHERS\_AVG}_{ij} + \beta_1 \text{POS}_{ij} + \beta_2 \text{REG\_NEG}_{ij}$$
$$+ \beta_3 \text{PROD\_FAILURE}_{ij} + \beta_4 \text{PROD\_FAILURE}_{ij}$$
$$\times \text{PROD\_RECOVERY}_{ij} + \kappa_1 \text{POS}_{ij} \times \text{OTHERS\_AVG}_{ij}$$
$$+ \kappa_2 \text{REG\_NEG}_{ij} \times \text{OTHERS\_AVG}_{ij}$$
$$+ \kappa_3 \text{PROD\_FAILURE}_{ij} \times \text{OTHERS\_AVG}_{ij}$$
$$+ \kappa_4 \text{PROD\_FAILURE}_{ij} \times \text{PROD\_RECOVERY}_{ij}$$
$$\times \text{OTHERS\_AVG}_{ij} + \theta' \mathbf{Z_{ij}} + \varepsilon_{ij}.$$

In Equation 1, γ_0 is the main effect of OTHERS_AVG_{ij} on reviewer i's online rating of hotel j. In addition, β_1 and

β_2 capture the main effects of positive (POS_{ij}) and regular negative features (REG_NEG_{ij}) of the product on y_{ij}. The term β_3 captures the main effect of product failure, and β_4 captures the two-way interaction effect of product failure (PROD_FAILURE_{ij}) and product recovery ($\text{PROD\_RECOVERY}_{ij}$) on y_{ij} because product recovery is conditional on product failure. The hypothesized moderation effects of OTHERS_AVG_{ij} on the effects of product experience characteristics and (pertaining to H_1–H_4) are given by the coefficients κ_1, κ_2, κ_3, and κ_4, respectively. Because product recovery is conditional on product failure, κ_4 pertaining to H_4 is a three-way interaction effect among product failure, product recovery, and other consumers' online ratings. The term $\mathbf{Z_{ij}}$ refers to the vector of control variables, and their effects on the reviewer's online rating are captured through the vector $\mathbf{\theta}$.

TABLE 2
Descriptive Statistics

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Reviewer's online rating	4.0	1.2	1.00														
2. Other consumers' online ratings	3.9	.5	.40	1.00													
3. Positive features of product experience (average)	21.7	18.9	.34	.18	1.00												
4. Regular negative features of product experience	3.7	5.7	−.02	−.03	.36	1.00											
5. Product failure	.8	2.1	−.55	−.20	−.29	−.19	1.00										
6. Product recovery	.2	1.0	−.08	−.03	−.02	−.03	.33	1.00									
7. Volume of other consumers' online ratings	67.8	67.7	.09	.24	.07	−.05	−.05	−.02	1.00								
8. Online rating experience (of reviewer)	1.9	3.8	−.05	−.02	.00	.05	−.03	.00	−.15	1.00							
9. Length of review	869.7	676.0	−.05	−.01	.57	.46	.19	.13	−.02	.02	1.00						
10. Reviewer's information disclosure	.4	.5	.04	.01	.03	.03	−.07	.01	.04	.24	.03	1.00					
11. Reviewer's consumption goal	.4	.5	.11	.09	.00	−.04	−.07	−.02	.25	−.17	−.06	.27	1.00				
12. Reviewer's membership duration	22.5	115.8	.01	.00	−.03	−.02	−.01	.03	−.14	.01	−.03	.00	.04	1.00			
13. Product class	3.4	.8	.01	.30	.10	−.01	−.04	−.01	.01	.05	.04	.07	.07	.01	1.00		
14. Product offering	.5	.2	−.06	−.13	−.08	.02	.06	.01	−.20	.12	.01	.09	−.03	.05	.40	1.00	
15. City	.4	.5	−.09	.07	−.09	−.07	.03	.01	−.15	.13	−.13	.06	−.03	.03	.19	.27	1.00

Notes: Correlations above .05 are significant at $p < .05$ and above.

Endogeneity of Product Experience Characteristics[8]

Whereas the online reviewer describes the product experience, which has already occurred, and then provides the online product rating, the researcher observes these events simultaneously. Thus, factors that are not included in Equation 1 as covariates but that are in the error term may also influence the four product experience characteristics (POS, REG_NEG, PROD_FAILURE, and PROD_RECOVERY). The endogeneity of the four product experience characteristics, because the error term ε_{ij} in Equation 1 may be correlated with the four product experience characteristics, may bias their effects on the reviewer's online product rating. Furthermore, reviewers' online reports of product experiences may themselves be influenced by other consumers' online ratings.

We address this endogeneity concern by using the control function approach (Petrin and Train 2010), whose basic intuition is as follows: Consider a dependent variable that is regressed on an independent variable. Assume that unobserved factors explaining the independent variable are correlated to the error term in the regression equation. Suppose that we add a new variable (the control variable) to the regression equation, such that, after accounting for the influence of the control variable on the dependent variable, the independent variable is no longer correlated with the error term in the regression equation. By construction, when the control variable is added to the regression equation, the independence assumption is established, and inference can proceed without bias. The challenge is to identify an appropriate control variable for the four independent variables—that is, product experience characteristics POS, REG_NEG, PROD_FAILURE, and PROD_RECOVERY.

Using Petrin and Train's (2010) approach, we obtain the control variable as follows. For each endogenous variable, we perform an auxiliary estimation with the endogenous variable as the dependent variable and at least one exogenous variable (the excluded variable) that affects the endogenous variable but is not related to the focal dependent variable (RATING) as a covariate. The predicted residuals from the auxiliary estimation serve as effective control variables to address the endogeneity concern. Thus, we estimate four auxiliary estimations for POS, REG_NEG, PROD_FAILURE, and PROD_RECOVERY and obtain the four predicted residuals, which we include as covariates in Equation 1.

We seek an excluded variable that directly affects the four product experience characteristics but only indirectly affects the reviewer's online product rating (i.e., through the effects of product experience characteristics). We use the Flesch-Kincaid readability index (FKI), a measure of the understandability of online review text (Ghose and Ipeirotis 2010), as an excluded variable in the four auxiliary equations. The FKI is appropriate as an excluded variable because (1) the understandability of the review text increases the accuracy of coding of product experience variables affecting them and (2) there is no reason to expect

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[8]We thank two anonymous reviewers for their many useful suggestions on the estimation approach.

that the grammatical quality in the reviewer's online review text will affect that reviewer's online product rating. Thus, we specify the auxiliary equations for POS, REG_NEG, PROD_FAILURE, and PROD_RECOVERY as follows:

$$(2a) \quad POS_{ij} = \alpha_0^1 + \alpha_1^1 FKI_{ij} + \alpha_2^1 OTHERS\_AVG_{ij} + m_{ij}^1,$$

$$(2b) \quad REG\_NEG_{ij} = \alpha_0^2 + \alpha_1^2 FKI_{ij} + \alpha_2^2 OTHERS\_AVG_{ij} + m_{ij}^2,$$

$$(2c) \quad PROD\_FAILURE_{ij} = \alpha_0^3 + \alpha_1^3 FKI_{ij} + \alpha_2^3 OTHERS\_AVG_{ij} + m_{ij}^3, \text{ and}$$

$$(2d) \quad PROD\_RECOVERY_{ij} = \alpha_0^4 + \alpha_1^4 FKI_{ij} + \alpha_2^4 OTHERS\_AVG_{ij} + \alpha_3^4 PROD\_FAILURE + m_{ij}^4,$$

where α_0^m, $m = \{1, 2, 3, 4\}$, represent the intercept in each equation α_1^m and α_2^m, $m = \{1, 2, 3, 4\}$, represent the effect of FKI and OTHERS_AVG on POS, REG_NEG, PROD_FAILURE, and PROD_RECOVERY, respectively.

As we noted previously, reviewers' reports of product experience may themselves be influenced by other consumers' online ratings (OTHERS_AVG). Thus, we control for this factor by including OTHERS_AVG in the auxiliary equations. In addition, because product recovery is conditional on product failure, we capture the effects of PROD_FAILURE on PROD_RECOVERY in Equation 2d; α_3^4 is the pertinent coefficient. We built an automated algorithm to obtain FKI for each of the 7499 reviews using the web application at http://www.read-able.com.

Note that m_{ij}^m, $m = \{1, 2, 3, 4\}$ represent the error terms in Equations 2a–2d whose predicted values we insert into Equation 1, to yield the augmented specification for hypotheses testing:

$$
\begin{aligned}
(3) \quad y_{ij}^* = {} & \gamma_0 OTHERS\_AVG_{ij} + \beta_1 POS_{ij} + \beta_2 REG\_NEG_{ij} \\
& + \beta_3 PROD\_FAILURE_{ij} + \beta_4 PROD\_FAILURE_{ij} \\
& \times PROD\_RECOVERY_{ij} + \kappa_1 POS_{ij} \times OTHERS\_AVG_{ij} \\
& + \kappa_2 REG\_NEG_{ij} \times OTHERS\_AVG_{ij} \\
& + \kappa_3 PROD\_FAILURE_{ij} \times OTHERS\_AVG_{ij} \\
& + \kappa_4 PROD\_FAILURE_{ij} \times PROD\_RECOVERY_{ij} \\
& \times OTHERS\_AVG_{ij} + \boldsymbol{\theta}' \mathbf{Z_{ij}} + \delta^1 \hat{\mu}_{ij}^1 + \delta^2 \hat{\mu}_{ij}^2 + \delta^3 \hat{\mu}_{ij}^3 \\
& + \delta^4 \hat{\mu}_{ij}^4 + \varepsilon_{ij},
\end{aligned}
$$

where all terms are as described previously and δ^m, $m = \{1, 2, 3, 4\}$ capture the effect of the predicted residuals from Equations 2a–2d on the dependent variable. Given the specification for y_{ij}^* and denoting the cumulative distribution of y_{ij}^* as $\Phi(\cdot)$, the probability of $y_{ij}^* = \{1, 2, 3, 4, 5\}$ is as follows:

$$
(4) \quad p\left(y = y_{ij}\right) = \begin{cases}
-\Phi\left(\lambda_4 - y_{ij}^*\right), & y = 5 \\
\Phi\left(\lambda_4 - y_{ij}^*\right) - \Phi\left(\lambda_3 - y_{ij}^*\right), & y = 4 \\
\Phi\left(\lambda_3 - y_{ij}^*\right) - \Phi\left(\lambda_2 - y_{ij}^*\right), & y = 3 \\
\Phi\left(\lambda_2 - y_{ij}^*\right) - \Phi\left(\lambda_1 - y_{ij}^*\right), & y = 2 \\
1 - \Phi\left(\lambda_1 - y_{ij}^*\right), & y = 1
\end{cases}
$$

We also estimate λ_k (k = 1–4), which captures the range of the distribution associated with y_{ij}. The model accommodates nonlinear effects of the independent variables on y^*_{ij}. To incorporate unobserved heterogeneity, we employ a random-intercept model; to accommodate the nested data structure of ratings within hotels, we use a hierarchical linear modeling approach to estimate the model (Raudenbush and Bryk 2002).

Results

Model Selection

In addition to the social influence effects manifest through the average of other consumers' online ratings (OTHERS_ AVG) and the four product experience characteristics, following the suggestion of an anonymous reviewer, we included the interaction effects between the average of other consumers' online ratings and the reviewer's online rating experience (R_RATE_EXPERIENCE) in the model that we estimated. In Table 3, we present Model 1, with

only the main effects of the product experience characteristics, and Model 2, with the addition of interaction effects between the product experience characteristics and the average of other consumers' online ratings (OTHERS_ AVG). Model 2's inclusion of the four interaction effects between product experience characteristics and other consumers' online ratings (OTHERS_ AVG) significantly improves its fit over Model 1 ($\Delta_{deviance}$ = 53.230, d.f. = 4, $p < .01$). Thus, we use the results in Model 2 for hypotheses testing.

Estimation Results

Hypotheses tests. We find a positive main effect of other consumers' online ratings on the reviewer's online product rating (γ_0 = .964, $p < .01$). As we expected, positive features of product experience has a positive main effect (β_1 = .105, $p < .01$), and regular negative features has a negative main effect on the reviewer's online product rating ($\beta_2 = -.148, p < .01$). In support of H_1, the higher other consumers' online ratings, the weaker is the positive effect of positive features of product experience on the reviewer's online product rat-

TABLE 3
Estimation Results

	Hypotheses	Model 1 Parameter Estimate (SE)	Model 2 Parameter Estimate (SE)
Other consumers' online ratings (average)		.587*** (.078)	.964*** (.105)
Other consumers' online ratings (average) × positive features of product experience	H_1 (−)		−.022*** (.003)
Other consumers' online ratings (average) × regular negative features of product experience	H_2 (+)		.030*** (.008)
Other consumers' online ratings (average) × product failure	H_3 (−)		−.055** (.022)
Other consumers' online ratings (average) × product failure × product recovery	H_4 (+)		.017** (.008)
Positive features of product experience		.038*** (.003)	.105*** (.010)
Regular negative features of product experience		−.064*** (.010)	−.148*** (.026)
Product failure		−.505*** (.028)	−.351*** (.066)
Product recovery × product failure		−.001 (.014)	−.044* (.025)
Other consumers' online ratings (volume)[a]		.000 (.000)	.000 (.000)
Online rating experience (of reviewer)		.008 (.031)	.015 (.031)
Online rating experience × other consumers' online ratings (average)		−.011 (.011)	−.013 (.011)
Length of review[a]		.000 (.000)	.000 (.000)
Reviewer's information disclosure		−.016 (.054)	−.021 (.054)
Reviewer's consumption goal		.279*** (.053)	.278*** (.053)
Reviewer's membership duration[a]		.000 (.000)	−.002 (.019)
Product class		−.150*** (.053)	−.153*** (.053)
Product offering		−.778*** (.185)	−.831*** (.184)
City		−.211*** (.078)	−.199** (.078)
Residual for positive features of product experience		−.096* (.057)	−.102* (.057)
Residual for regular negative features of product experience		−.103** (.049)	−.107** (.048)
Residual for product failure		.126** (.028)	.128** (.028)
Residual for product recovery		.166 ** (.076)	.154** (.076)
Intercept −5		−1.404*** (.229)	−2.479*** (.030)
Intercept −4		.385* (.229)	−.678** (.030)
Intercept −3		1.621*** (.230)	.575* (.030)
Intercept −2		2.885*** (.234)	1.856*** (.030)
AIC		16,922.260	16,869.030
Deviance difference			53.230

*$p < .10$.
**$p < .05$.
***$p < .01$.
[a]Coefficients and standard errors for these variables are multiplied by 100 for readability.

ing ($\kappa_1 = -.022$, $p < .01$). In support of H_2, the higher other consumers' online ratings, the weaker is the negative effect of regular negative features of product experience on the reviewer's online product rating ($\kappa_2 = .030$, $p < .01$).[9]

As we expected, product failure has a negative main effect on the reviewer's online product rating ($\beta_3 = -.351$, $p < .01$). In support of H_3, the higher other consumers' online ratings, the stronger is the negative effect of product failure on the reviewer's online product rating ($\kappa_3 = -.055$, $p < .05$). The two-way interaction effect between product failure and product recovery (included for completeness) is negative and weakly significant ($\beta_4 = -.044$, $p < .10$). In support of H_4, the higher the quality of product recovery, the weaker is the negative two-way interaction effect between other consumers' online ratings and product failure on the reviewer's online product rating ($\kappa_4 = .017$, $p < .05$).

Control variables. The volume of other consumers' ratings does not affect the reviewer's online product rating ($\theta = .000$, not significant [n.s.]).[10] With respect to reviewer characteristics, the reviewer's online rating experience does not affect online product rating either independently ($\theta = .015$, n.s.) or jointly with other consumers' online ratings ($\theta = -.013$, n.s.). Online product rating is also not affected by the reviewer's membership duration ($\theta = -.002 \times 10^{-2}$, n.s.), disclosure of reviewer's personal information on the review website ($\theta = -.021$, n.s.), or the length of the online review ($\theta = .000$, n.s.). However, the reviewer's online product rating is higher when the hotel stay is for leisure than for work ($\theta = .278$, $p < .01$), and hotels with more breadth in product offerings have lower online product ratings ($\theta = -.831$, $p < .01$), a result we attribute to differences in the profiles of the hotel's consumers.

Finally, the effects of predicted residuals of positive and regular negative features of product experience, product failure, and product recovery on online product ratings are significant ($\delta^1 = -.102$, $p < .10$; $\delta^2 = -.107$, $p < .05$; $\delta^3 = .128$, $p < .05$; $\delta^4 = .154$, $p < .05$). In summary, the results strongly support the four hypotheses. We next report analysis that examines the robustness of the findings.

Additional Analysis

Results without endogeneity correction. We first examine the sensitivity of the results to the control function approach by estimating an alternative model without the endogeneity correction for the four product experience characteristics. The results, reported in Column 2 of Table 4, are similar to those for the estimated model with endogeneity correction (presented in Column 1 of Table 4), testifying to their robustness.

Continuous specification of dependent variable. To examine the robustness of the results to the ordered dependent variable specification, we estimated an alternative model, treating the online product rating as a continuous variable. The results, reported in Column 3 of Table 4, are similar to those for the estimated model using the ordered dependent variable (Column 1 of Table 4). Thus, even a simple model supports the phenomenon, testifying to its robustness.

Choice of excluded variable. To examine the robustness of the results to the choice of excluded variable used in the endogeneity correction, we estimated an alternative model using the Gunning Fog (readability) index (Ghose and Ipeirotis 2010) instead of the FKI as the excluded variable in Equations 2a–2d. The results, reported in Column 4 of Table 4, are similar to those for the estimated model using the FKI as the excluded variable (Column 1 of Table 4). Thus, our results are robust to the choice of the excluded variable.

Unweighted measure of positive and regular negative features of product experience. We estimated an alternative model using just the sum of the raw count of positive and negative words in the text that co-occur with a product attribute as measures of POS and REG_NEG, respectively—that is, without weighting them by their related intensity. The results, reported in Column 5 of Table 4, are similar to those using the weighted measures (Column 1 of Table 4).

Different text analysis software. We used Linguistic Inquiry and Word Count (Pennebaker, Francis, and Booth 2001), an off-the-shelf CATA software used in social science research, to obtain the measures of positive and regular negative features of the product experience. We obtained count measures of all positive and negative words in the online review text (after parsing out the text pertaining to product failure and product recovery, as in our custom algorithm approach) from the software, which we used as a measure of positive and regular negative features of the product experience, respectively. The results, reported in Column 6 of Table 4, are similar to those for the estimated model using our custom algorithm (Column 1 of Table 4), demonstrating the robustness of the results to the text analysis method.

Hotel classes and cities. We examined the robustness of the results to hotel class by estimating the final model excluding (1) one-star and two-star hotels and (2) five-star hotels. The estimates in these models (we do not report these results here for the sake of brevity) are similar to those using data from all hotels. We also examined the robustness of the results by city. The results (again, not reported here) indicate that the separate results in Boston and Honolulu are similar to those with the full sample from both cities.

Auxiliary survey: Social influence in the online ratings context. To provide face validity for the theoretical mecha-

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[9]Following the suggestion of an anonymous reviewer that the effects hypothesized in H_1 and H_2 may be arising from ceiling and floor effects, respectively, we reestimated the regression model in two samples excluding observations in which (1) other consumers' online ratings are greater than 4.75 and (2) other consumers' online ratings are less than 1.5. In both these samples, the results of the four hypotheses tests remain unchanged, ruling out ceiling and floor effects.

[10]Following the suggestion of an anonymous reviewer, we examined and did not find support for the effect of variance in other consumers' online ratings on a given reviewer's online product rating. We conjecture that this may be because the variance of online product ratings is not prominently displayed on online product ratings websites.

TABLE 4
Robustness Checks

	Hypotheses	Model 2: Estimated Model (Column 1) Parameter Estimate (SE)	Model R1: No Endogeneity Correction (Column 2) Parameter Estimate (SE)	Model R2: Continuous Measure of Rating (Column 3) Parameter Estimate (SE)	Model R3: GFI as Excluded Variable (Column 4) Parameter Estimate (SE)	Model R4: Unweighted Measures (Column 5) Parameter Estimate (SE)	Model R5: LIWC Content Analysis (Column 6) Parameter Estimate (SE)
Other consumers' online ratings (average)	H_1 (−)	.964*** (.105)	1.025*** (.101)	.507*** (.047)	.968*** (.105)	.945*** (.104)	1.125*** (.121)
Other consumers' online ratings (average) × positive features of product experience		−.022*** (.003)	−.022*** (.003)	−.013*** (.001)	−.022*** (.003)	−.087*** (.012)	−.036*** (.011)
Other consumers' online ratings (average) × regular negative features of product experience	H_2 (+)	.030*** (.008)	.030*** (.008)	.022*** (.004)	.030*** (.008)	.108*** (.030)	.074** (.033)
Other consumers' online ratings (average) × product failure	H_3 (−)	−.055** (.022)	−.056** (.022)	−.027*** (.010)	−.055** (.022)	−.058*** (.022)	−.070*** (.021)
Other consumers' online ratings (average) × product failure × product recovery	H_4 (+)	.017** (.008)	.020** (.008)	.012*** (.004)	.017** (.008)	.016* (.008)	.023*** (.008)
Positive features of product experience		.105*** (.010)	.100*** (.009)	.057*** (.004)	.105*** (.010)	.415*** (.038)	.298*** (.047)
Regular negative features of product experience		−.148*** (.026)	−.166*** (.025)	−.093*** (.012)	−.150*** (.026)	−.485*** (.092)	−1.154*** (.288)
Product failure		−.351*** (.066)	−.313*** (.062)	−.213*** (.030)	−.346*** (.066)	−.370*** (.066)	−.161 (.157)
Product recovery × product failure		−.044* (.025)	−.022 (.023)	−.031*** (.012)	−.044* (.025)	−.045* (.025)	−.010 (.024)
Other consumers' online ratings (volume)[a]		.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)
Online rating experience (of reviewer)		.015 (.031)	.015 (.031)	.007 (.015)	.015 (.031)	.015 (.031)	.022 (.030)
Online rating experience × other consumers' online ratings (average)		−.013 (.011)	−.013 (.011)	−.006 (.005)	−.013 (.011)	−.014 (.011)	−.017 (.010)
Length of review[a]		.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	.000 (.000)	.000*** (.000)
Reviewer's information disclosure		−.021 (.054)	−.017 (.054)	.008 (.025)	−.023 (.054)	−.027 (.054)	−.024 (.051)
Reviewer's consumption goal		.278*** (.053)	.271*** (.053)	.128*** (.024)	.275*** (.053)	.282*** (.053)	.175*** (.050)
Reviewer's membership duration[a]		−.002 (.019)	.000 (.019)	.008 (.009)	−.002 (.019)	.000 (.019)	.000 (.000)
Product class		−.153*** (.053)	−.147*** (.053)	−.083*** (.025)	−.151*** (.053)	−.125** (.052)	.088*** (.049)
Product offering		−.831*** (.184)	−.847*** (.185)	−.281*** (.087)	−.831*** (.184)	−.827*** (.179)	−.646*** (.168)
City		−.199** (.078)	−.235*** (.077)	−.100*** (.037)	−.204*** (.078)	−.184** (.076)	−.220*** (.073)
Residual for positive features of product experience		−.102* (.057)		−.051** (.025)	−.090 (.055)	−.159*** (.059)	−.398** (.109)
Residual for regular negative features of product experience		−.107** (.048)		−.055** (.022)	−.095** (.047)	−.159*** (.051)	.804** (.295)
Residual for product failure		.128** (.028)		.067** (.013)	.116** (.027)	.179** (.028)	−.619* (.337)
Residual for product recovery		.154** (.076)		.090** (.034)	.148* (.076)	.163** (.077)	−.056 (.128)
Intercept −5		−2.479*** (.304)	−2.533*** (.304)	2.929*** (.138)	−2.472*** (.305)	−2.599*** (.301)	−4.471*** (.338)
Intercept −4		−.678** (.303)	−.735** (.303)		−.672** (.304)	−.809*** (.300)	−2.261*** (.335)
Intercept −3		.575* (.304)	.516* (.303)		.581* (.305)	.441 (.300)	−.804** (.336)
Intercept −2		1.856*** (.307)	1.795*** (.306)		1.862*** (.307)	1.723*** (.303)	.750** (.339)

*$p < .10$.
**$p < .05$.
***$p < .01$.
[a]Coefficients and standard errors for these variables are multiplied by 100 for readability.

nism of social influence effects in online product ratings, we surveyed undergraduate business students (N = 58) to explore whether reviewers incorporate information from other consumers' online ratings when they provide online product ratings. Of the 58 students surveyed, 23 (40%) had provided online product ratings, and of these 23 students, 17 (74%) stated (in free responses) that other consumers' ratings influenced their online product ratings. Notably, 29 (83%) of the remaining 35 students who had not provided online product ratings agreed that a reviewer's online product rating would be influenced by other consumers' online ratings. Overall, these findings support, albeit indirectly, the proposed social influence effects in the online ratings context.

Marginal Effects

A pertinent question that arises is, What is the overall effect of a marginal increase in one product experience characteristic (e.g., product failure) on the reviewer's online product rating? In addition, what is the bias in marginal effects of product experience characteristics if managers omit social influence effects? To address these questions, we compute the marginal effects of the product experience characteristics on online product rating.

Marginal Effects Decomposition

We decompose the marginal effect of each product experience characteristic into the main effect and social influence effect (i.e., the hypothesized moderation effects). This decomposition is useful because (1) the main and social influence effects may have opposite signs, (2) it contrasts the relative sizes of the main and social influence effects, and (3) it allows comparisons of the relative sizes of social influence effects across the four product experience characteristics. In Appendix B, we provide details of the marginal

effect decomposition procedure. We present the marginal effects of the four product experience characteristics in Table 5, Panel A.

The main effect portion of the marginal effect of positive features of product experience is .050, and the negative social influence portion of the marginal effect is –.042. Thus, social influence decreases the marginal effect of regular positive features by 84%. The marginal effect of positive features of product experience on a reviewer's online product rating is still positive but much weaker (.008).

The main effect portion of the marginal effect of regular negative features is –.070, and the positive social influence portion of the marginal effect is .057. Thus, social influence decreases the marginal effect of regular negative features by 81%; that is, the marginal effect of regular negative features of product experience is still negative but substantially weaker (–.013).

The main effect portion of the marginal effect of product failure with no product recovery on the reviewer's online product rating is negative (–.166), as is the social influence effect portion of the marginal effect (–.105). Thus, the marginal effect of product failure is negative and weakened by social influence effects by 63% when product recovery is absent (–.270). We note that the marginal effect of product failure is 20 times that of regular negative features of product experience, testifying (indirectly) to the validity of the measures of regular negative features and product failure developed using content analysis of online review text.

Next, we set the level of quality of product recovery to 8 and obtained the marginal effect of superior product recovery effort to address product failure. The marginal effect of product failure on online product rating is positive (.010), with positive social influence (.031) from other consumers' online ratings overturning the negative effect of

TABLE 5
Effects of Product Experience Characteristics on Online Product Ratings

A: Marginal Effect Decomposition			
Source	Marginal Effect[a] (Column 1)	Main Effect (Column 2)	Social Influence Effect (Column 3)
Positive features of product experience	.008	.050	–.042
Regular negative features of product experience	–.013	–.070	.057
Product failure, no product recovery	–.270	–.166	–.105
Product failure, superior product recovery	.010	–.021	.031

B: Marginal Effect Bias			
Source	Marginal Effect with Social Influence (Column 1)	Marginal Effect Without Social Influence (Column 2)	Extent of Bias (Column 3)
Positive features of product experience	.008	.018	125%
Regular negative features of product experience	–.013	–.012	–8%
Product failure, no product recovery	–.270	–.224	–17%
Product failure, superior product recovery	.010	.001	–90%

[a]The marginal effect is the sum of the main effect and social influence effect, as we note in Appendix B. The marginal effect of positive features of the product experience ranges from .013 (OTHERS_AVG = minimum) to .005 (OTHERS_AVG = maximum). The marginal effect of regular negative features of the product experience ranges from –.018 (OTHERS_AVG = minimum) to –.009 (OTHERS_AVG = maximum). The marginal effect of product failure with no product recovery ranges from -.1 (OTHERS_AVG = minimum) to –.32 (OTHERS_AVG = maximum). The marginal effect of product failure with a superior product recovery ranges from –.002 (OTHERS_AVG = minimum)) to .016 (OTHERS_AVG = maximum). A poor product recovery refers to PROD_RECOVERY = 1, and superior product recovery refers to PROD_RECOVERY = 8.

product failure (−.021), resulting in a superior product recovery enabled by social influence in the online ratings context.

Omission of Social Influence Effects Creates Bias

To examine the bias in the marginal effects when social influence effects are omitted, we estimated a model without other consumers' online ratings; that is, we include only the main effects of product experience characteristics and control variables and calculate the marginal effects. We present the bias in the marginal effects of the product experience characteristics in Column 2 of Table 5, Panel B.

First, the marginal effect of positive features (.008) is overstated by a substantial 125% when social influence effect is omitted (marginal effect without social influence = .018). Thus, if managers omit social influence effects, they overestimate the marginal effect of positive features on a reviewer's online product rating. When social influence effect is omitted (marginal effect without social influence = −.012), the negative marginal effect of regular negative features (−.013) is again overstated, but only by approximately 8%.

Turning to product failure with no product recovery, the marginal effect of product failure (−.270) is 17% higher when the social influence effect is omitted (marginal effect without social influence = −.224), which implies that if managers overlook the social influence effect, they risk underestimating the negative impact of product failure. Finally, the marginal effect of a product failure with a superior product recovery (.010) is lower by 90% when social influence effects are omitted (marginal effect without social influence = .001), implying that managers significantly underestimate the ability of a superior product recovery effort to mitigate the impact of a product failure on a reviewer's online product rating.

Discussion

Among consumers, online ratings and reviews are a growing form of interpersonal communication that is not only outside a firm's control but also exerts a strong influence on consumers' purchase decisions. In this article, we develop theory and report evidence on how social influence from the average of other consumers' online ratings moderates the effect of a reviewer's product experience characteristics on the reviewer's online product rating. We conclude with a discussion of the article's contributions to marketing theory and managerial practice and its limitations and opportunities for further research.

Theoretical Implications

First, we document evidence of the adaptive and bidirectional nature of social influence among opinion leaders. We report robust evidence on the important role of the crowd on a given consumer's opinion (i.e., online product rating). By doing so, we address a call issued four decades ago by Myers and Robertson (1972) to examine bidirectional social influence in consumers' opinions. We find that online reviewers (i.e., online opinion leaders for products for potential consumers) are influenced by the ratings of other online opinion leaders. The finding that social influence is

also exerted *on* the opinion leader supplements the dominant focus in the marketing literature on how social influence effect is exerted *by* the opinion leader on the opinion seeker (e.g., Flynn, Goldsmith, and Eastman 1996). This suggests that social influence effects exerted on and by an opinion leader should be studied in tandem in the future.

Notably, the results indicate that the bidirectional effect of social influence on a given consumer's online word of mouth (i.e., product evaluation) is contingent rather than passive (merely following the crowd). In some cases (e.g., positive features of product experience and product failure), the social influence effect is negative, while in others (e.g., regular negative features of product experience, product recovery), it is positive. This is in contrast to extant research (Iyengar, Van den Bulte, and Valente 2011) that has focused only on positive social influence effects.

Second, we clarify the mixed evidence in the literature on the effect of other consumers' online ratings. As we noted at the beginning of the article, Schlosser (2005) reports that reviewers decrease their online product ratings after seeing other consumers' online ratings, whereas Moe and Trusov (2011) report evidence of both increases and decreases. We find empirical evidence for a contingent framework that indicates that, depending on the reviewer's idiosyncratic product experience, social influence from other consumers' online ratings can either strengthen (e.g., product failure without product recovery) or weaken (e.g., product failure, followed by a superior product recovery) a reviewer's online product rating. In doing so, we clarify the mixed evidence on how others consumers' online ratings affect a given reviewer's online product rating, generating insights into the evolution of online product ratings over time in online reviewer communities.

Third, we find that social influence effects can alter underlying marketing phenomena. The marginal effects analysis indicates that social influence effects on online product ratings are substantially large; for example, social influence decreases the marginal effect of regular positive features by 84%. In addition, social influence effects can be large enough to substantially alter real marketing phenomena; for example, the social influence effect for superior product recovery overcomes the negative effect of product failure, creating a "socially enhanced online product recovery." Additional research on when the prevalence of such adaptive social influence effects in other online contexts (e.g., blogs, Twitter feeds) can overturn the sign of marketing phenomena (e.g., customer repurchase) would represent useful extensions to this work.

Managerial Implications

With regard to managerial implications, first, managers can use our approach to estimate the marginal effects of product experience characteristics on their online product rating, isolating the role of social influence. Consumer-created online reviews are, by definition, user-generated content. They describe product experience attributes in terms of usage situations and therefore are actionable from the firm's standpoint (Bickart and Schindler 2001). However, making sense of thousands of online product ratings can be a chal-

lenging task. In this regard, our study provides some action-able results for managers.

The first result is that we separate the online review text into four product experience characteristics that include both acceptable product experience characteristics and product failure. In addition, our custom algorithm, which uses computerized coding and human coders, provides good measures of product characteristics. Our text analysis approach has face validity. The negative marginal impact of product failure is 20 times worse than the negative marginal effect of regular negative features of product experience, and the (negative) marginal effect of regular negative features of product experience is 1.5 times the (positive) marginal effect of positive features of product experience. Managers can use the steps outlined in Appendix A to generate measures of their customers' product experience characteristics. Using the outputs of text analysis of online product reviews, managers can use a regression modeling approach (which can be easily implemented in Microsoft Excel) to estimate the marginal effects of product experience characteristics and social influence on their customers' online product ratings.

The second result pertains to our examination of how social influence effects change the marginal effects of the product experience characteristics. We find that omitting social influence effects can misstate the effect of product experience characteristics, which in turn has implications for resource allocations for designing products.

Our second managerial implication is that managers can use our approach to assess how consumers trade off product experience characteristics and how these trade-offs are subject to social influence. Managers can estimate the product experience elasticity of the online product rating using our approach—that is, the percentage change in the online product rating for a 1% change in a product experience characteristic. Given that online product ratings are demand proxies, managers can estimate demand elasticities of product experience characteristics. This offers a cost-effective alternative to conjoint analysis, which is often used to assess how buyers trade off among product features. In addition, managers can isolate the individual customer as well as the social influence component of the demand elasticity of various product experience characteristics. For example, not considering social influence effects, the marginal impact of product failures on demand could be substantially biased.

Our third managerial implication is that, managers should be cognizant that their product's online ratings can be a double-edged sword when used as a marketing communications element. The pattern of moderation effects reveals insight into when and how firms can effectively use products' online ratings as a marketing-mix element for customer relationship management. For example, social influence effects weaken the negative effects of regular negative features of product experience on online product ratings by 81%. Thus, managers of firms with high online product ratings can use information on their online product ratings while following up with consumers with regular negative product experience, which should, ceteris paribus, strengthen these consumers' product ratings. In contrast, high online product ratings generate severe negative social influence when reviewers experience product failures with no product recovery. In such a situation, firms can proactively contact such consumers requesting direct, actionable feedback, instead of letting them vent online.

Finally, when product failure is followed by a superior product recovery, the marginal effect of product failure on online product rating is, on net, positive (.010), with the positive (.031) social influence effect from other consumers' online ratings overcoming the negative (–.021) main effect of product failure. Here, social influence effect in online product forums enables a positive effect from the superior product recovery. For customer relationship management, this insight suggests that when a firm with high online product ratings has customers who have experienced a product failure, followed by a superior product recovery, managers can leverage their product recovery effort with their customers by developing targeted marketing communications highlighting their high online ratings.

Limitations and Opportunities for Further Research

In this first study of social influence effects on online product ratings, we focus on the effects of various product experience characteristics and use secondary data for the empirical test. Further research on social influence effects in experimental and field settings, using other outcomes (e.g., satisfaction, willingness to recommend, repeat purchase) would be useful to generate additional insights. In addition, we focused on online product ratings and reviews posted on third-party websites because users consider them more credible than firm-sponsored review websites. As a result, we have data only on consumers who posted ratings and are unable to model why some consumers post ratings while others do not. Thus, further research on social influence effects on online ratings on firm-sponsored product review websites would be useful.

Finally, for the empirical testing, we focused on consumers' online ratings of hotels in two cities in the United States. Further research on online ratings in other contexts, including durable and fast-moving consumer goods and other services, such as restaurants, health care, and financial services, would increase the generalizability of this study's findings. Given the widespread proliferation of online review websites around the world, a useful extension to this study would be to investigate cross-country differences in the evolution of online product ratings.

In summary, this research extends the marketing literature by identifying a moderating role for social influence from the online reviewer community on the effects of a reviewer's product experience on his or her online product rating. As the influence of online review websites continues to grow, we hope that this study stimulates additional work in the area.

Appendix A
Algorithm for Text Analysis of Online Product Reviews

Because online reviews sometimes contain information not pertinent to the product in question (e.g., "the weather was

beautiful"), we needed an approach that allowed us to focus on only the portion of the online review related to the product (i.e., that contains product attributes). Next, we describe the implementation of the algorithm for text analyses of online product reviews.

Step 1: Creating a Dictionary of Product Attributes and Positive and Negative Words

Step 1a: We first identified product attributes (in the case of hotels, e.g., "room," "view"); positive (e.g., "clean," "prompt") and negative (e.g., "dirty," "noisy") words; not-positive words, which denote negative words (e.g., "not clean"); and not-negative words, which denote positive words (e.g., "not noisy") for each review. To do this, using a web scripting software, we first decomposed the 7499 online reviews into individual words. We removed duplicate words, which resulted in a list of 19,801 words.

Step 1b: Then, we independently classified each word in this list as an attribute, a positive word, a negative word, a not-positive word, a not-negative word, or not relevant (i.e., not an attribute or positive or negative word). Across the five categories, the interrater agreement on this classification was 99.75%; the .25% discrepancies were resolved through discussion. With this, we created a dictionary of product attributes (n = 2131), positive words (n = 1341), negative words (n = 1745), not-positive words (n = 370), and not-negative words (n = 136).

Step 2: Classifying Online Review Text into Positive and Regular Negative Features of Product Experience

Step 2a: We created five tables of this dictionary of product attributes, positive words, negative words, not-positive words, and not-negative words in a database.

Step 2b: We decomposed each of the 7499 online reviews into individual words and checked each word with the five tables to examine if at least one product attribute was present in a sentence. If at least one product attribute was present in the sentence, we then compared the words in a sentence by comparing each word with the positive words and negative words in the dictionary tables.

Step 2c: We extracted the not-positive word(s) if present, from the sentence in the online review using a regular expression matching algorithm and compared it with the not-positive dictionary. Note that because the not-positive word will be counted once for the not-positive word category and once for the positive word category, when a positive word occurs, we compared the word with the second part of the not-positive words' occurrences in the same sentence. If the words matched, then we did not include it in the positive word count for that sentence. We followed a similar procedure for counting the not-negative words in a sentence.

Step 2d: We counted the positive, negative, not-positive, and not-negative words for all sentences in an online review in which there was at least one product attribute in the sentence and populated a database with them.

Step 2e: We asked two graduate students to code every positive (negative) word on a seven-point scale, where 1 = "least positive (negative)" and 7 = "most positive (negative)."

Step 2f: After we obtained the counts of the positive and negative words in a review relevant to a product attribute, we multiplied the occurrence count of each positive and negative word by its weight. We then summed the weighted count of positive and not negative words and the negative and not positive words in a review to obtain POS and REG_NEG, respectively. We automated the procedure for all 7499 reviews.

Appendix B
Marginal Effects Decomposition

As provided in Equation 3, rearranging the terms, we obtain the following:

(A1) $y_{ij}^* = \gamma_0 OTHERS\_AVG_{ij} + (\beta_1 + \kappa_1 OTHERS\_AVG_{ij})$
$\times POS_{ij} + (\beta_2 + \kappa_2 OTHERS\_AVG_{ij}) \times REG\_NEG_{ij}$
$+ (\beta_3 + \kappa_3 OTHERS\_AVG_{ij}) \times PROD\_FAILURE_{ij}$
$+ (\beta_4 + \kappa_4 OTHERS\_AVG_{ij}) \times PROD\_FAILURE_{ij}$
$\times PROD\_RECOVERY_{ij} + \delta^1 \hat{\mu}_{ij}^1 + \delta^2 \hat{\mu}_{ij}^2 + \delta^3 \hat{\mu}_{ij}^3$
$+ \delta^4 \hat{\mu}_{ij}^4 + \varepsilon_{ij}.$

In addition, if we denote the cumulative distribution of y_{ij}^* as $\Phi(\cdot)$, the probability of observing a given rating $y = y_{ij} = \{1, 2, 3, 4, 5\}$ is as follows:

(B2) $p(y = y_{ij}) = \begin{cases} -\Phi(\lambda_4 - y_{ij}^*), \ y = 5 \\ \Phi(\lambda_4 - y_{ij}^*) - \Phi(\lambda_3 - y_{ij}^*), \ y = 4 \\ \Phi(\lambda_3 - y_{ij}^*) - \Phi(\lambda_2 - y_{ij}^*), \ y = 3 \\ \Phi(\lambda_2 - y_{ij}^*) - \Phi(\lambda_1 - y_{ij}^*), \ y = 2 \\ 1 - \Phi(\lambda_1 - y_{ij}^*), \ y = 1 \end{cases}$

Next, the marginal impact of a focal independent variable (e.g., POS) on the underlying propensity of observing a rating n can be given as follows:

(B3) $\dfrac{\partial p(y = n)}{\partial (POS)} =$

$\left[\Phi(\lambda_n - y_{ij}^*) - \Phi(y_{ij}^* - n) \right] (\beta + \kappa_1 OTHERS\_AVG_{ij}).$

We can decompose the marginal effect further into its main and social influence effect components:

(B4) $\dfrac{\partial p(y = n)}{\partial (POS)} = \left[\Phi(\lambda_n - y_{ij}^*) - \Phi(y_{ij}^* - n) \right] \beta_1$

$+ \left[\Phi(\lambda_n - y_{ij}^*) - \Phi(y_{ij}^* - n) \right] (\kappa_1 OTHERS\_AVG_{ij}).$

Equation B4 captures how a small change in POS affects the probability of a rating ($y_{ij} = n$) and decomposes this effect into the main effect factor (β_1), which should increase the rating, and the social influence effect (κ_1 of $OTHERS\_AVG_{ij}$), which should reduce the rating. We obtained the marginal effect, as well as the related main and social influence effect for the four product experience characteristics at the sample mean rating values of n (i.e., 4) and $OTHERS\_AVG_{ij}$ (3.93), respectively.

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