MANAGING THE ONLINE CONVERSATION: THE ROLES OF EXPRESSED BEHAVIORAL COMMITMENT AND DECREASED CUSTOMER EFFORT IN ONLINE CUSTOMER REVIEWS

By

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ABSTRACT

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Word of mouth and online customer reviews are important factors that influence customer purchase behavior. However, firms face the challenge of motivating customers to share their experiences online and quantifying the value of this online engagement. My dissertation consists of two essays that address these challenges by showing how firms can motivate customers to engage online and measure their change in spending once they do so. Essay One examines the role of cognitive effort in the generation of word of mouth, and across six studies I show that when firms suggest positive pre-generated comments to their customers, effort is reduced and customers are more likely to share via social media. The first study establishes that offering one pre-generated comment is optimal and requires the least amount of cognitive effort. Study two shows that effort is the mediator between the pre-generated comments and customer posting intentions. Studies three and four are field experiments that show robustness of the main effect of a pre-generated comment increasing online engagement. Study five replicates these findings and highlights an added benefit of pre-generated comments: Firms can prime customers with desirable behavior (e.g., excitement) by using language cues, which can generate additional spending. Study six tests for potential backlash from customers when there is a mismatch between the positive pre-generated comment and the actual experience. Findings from study six show that the positive suggestions will not amplify customer negativity, which indicates that there are no significant downsides to these positive suggestions. Taken together, the study results

in Essay One show that firms can reduce cognitive effort for their customers by suggesting positive comments, and this will subsequently increase positive word of mouth and customer spending. Essay Two attempts to push forward the current understanding of how much online customer reviews are worth to firms. Much prior work has assessed the effect of reviews on potential customers, but little work has focused on changes in behavior of the reviewers themselves once they post a review. Drawing on the commitment-consistency principle, I conduct two studies that show how the act of posting a review changes customer spending. Study one uses a data set of over 60,000 loyalty program members of a large quick-serve restaurant, and results show that customers who are active reviewers spend differentially more and have more transactions than those customers who are not reviewers. I also find that relationship length affects this reviewer spending effect, where customers with a longer tenure exhibit even greater spending and transaction. Study two is an experiment that builds upon the results of study one by establishing causality and showing the value of a managerial response to an online customer review. When the review is acknowledged by management, interpersonal justice is increased, which partially explains the relationship between reviewer status and future spending. As a result, I conclude that when assessing the benefits of online customer reviews, managers must also account for changes in spending of the reviewers themselves. At the same time, firms should focus on converting customers into reviewers, since this could spur additional purchases from them in the future.

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KEY TO ABBREVIATIONS

OCR = Online Customer Review

WOM = Word of Mouth

DISSERTATION INTRODUCTION

Billions of conversations take place online every day, spread across blogs, social media, online reviews, and email (Berger 2014), and this chatter is the primary factor behind 20-50% of all purchase decisions (Bughin, Doogan, and Vetvik 2010). Similarly, customer referrals and positive word of mouth have a significant positive effect on firm sales (Floyd et al. 2014; Schmitt, Skiera, and Van den Bulte 2011). It is clear that for firms to remain competitive they must focus on increasing and maintaining positive online sentiment across all fronts. The goal of my dissertation is to examine how firms can make it easier for customers to post reviews online, as well as quantify the dollar value of online reviews once they are posted. Specifically, the first essay of my dissertation looks at the role of cognitive effort in the customer's decision to share comments online. By suggesting comments to customers directly, firms should be able to lower cognitive effort, subsequently increasing word of mouth generation. I explore the effectiveness of this strategy and potential moderating effects of satisfaction. The second essay of my dissertation examines changes in spending that occur following a customer posting an online review. Most word of mouth and online review research to date has focused on why reviewers choose to post and how customers respond once reading reviews. My work shifts the focus to assess changes in spending by the reviewers themselves following a post. Based on the commitment-consistency principle (Cialdini 2007), I expect that customers who post a review will be more committed, resulting in higher spending in the future relative to non-reviewers. Taken together, my dissertation essays show how managers can increase positive online word of mouth and how much additional revenue can be generated once customers are converted to reviewers.

ESSAY ONE

The Effects of Reduced Cognitive Effort on Electronic Word of Mouth Generation

Abstract

An emerging strategy leading firms are using to increase positive online engagement is to suggest pre-generated comments to customers. These comments require minimal effort, which enables the customer to make a quick decision rather than having to recall and write about their experience. This research investigates the effectiveness of these pre-generated comments, as well as how firms can better capitalize on these suggestions to increase volume and valence of online word of mouth. Drawing from the cognitive effort literature, the author demonstrates that when firms offer pre-generated comments to customers, this reduces the amount of effort involved, thus increasing the likelihood word of mouth is shared. The author also demonstrates that firms can push the envelope by generating positively-valenced comments rather than neutral suggestions, which will increase brand sentiment online. Further exploring the relationship between pre-generated comments and satisfaction, results show that there is surprisingly no backlash from dissatisfied customers who are asked to share overly positive comments generated by the firm. Taken together, the results of six studies show that firms should offer a single positive, pre-generated comment to their customers following a purchase or encounter, and this will increase the volume of positive word of mouth shared online.

Introduction

Word of mouth (WOM) has an incredible influence on what consumers choose to buy (Godes and Mayzlin 2009) and in recent years social media has become a key aspect of how WOM spreads across the Internet. Over 2 billion people around the globe use some form of social media (Edison Research 2019) and billions of conversations take place online every day (Berger 2014). Firms have embraced the increasing prominence of social media, and by having official accounts on Facebook, Twitter, and Instagram they are able to take initial steps toward controlling and influencing the online conversation. However, some firms have identified that simply having an account on social media is not enough. Instead, these firms are using technology to proactively manage their online presence—they are suggesting comments to share via social media, making it easier for their customers to post online. For example, when a purchase is made on Amazon.com, the confirmation screen offers the option to share the purchase via Facebook, Twitter, E-mail, or Pinterest, and the pre-generated tweet reads: "*I just bought [product name] via @amazon.*" Purchasing tickets to a show on VividSeats.com results in a suggested tweet with a link to the event: "*Just scored tickets to Jerry Seinfeld! [link]*." In these cases, the text is presented with a button to click and share the pre-generated comment, and if the link is clicked then the text is populated into the text box on the relevant social media platform. With these comment suggestions, firms have made it easier for customers to share WOM. My research examines the effectiveness of this marketing strategy, as well as how firms may be better able to utilize this tool and the possible backlash that could occur.

Prior WOM research has uncovered many reasons consumers share WOM. Research has found certain individual traits that indicate a consumer is more likely to engage in spreading

WOM (Anderson 1998; Berger 2014; Cheema and Kaikati 2010; Gregoire, Tripp, and Legoux 2009), while other studies have looked at managerial tools that are available, such as seeded marketing campaigns (Dost et al. 2019) and economic incentives (Hennig-Thurau et al. 2004; Ryu and Feick 2007; Sun, Dong, and McIntyre 2017), though results for the latter have been somewhat mixed. Prior WOM research has overlooked an underlying mechanism that influences behavior at a more fundamental level: effort. In the examples in the preceding paragraph, firms are offering pre-generated comments as a way to lower effort for their customers. Yet in the marketing literature the link between WOM behaviors and the amount of effort it takes to generate WOM has not been established.

The primary goal of my research is to test the effectiveness of these pre-generated comment suggestions. Do people share comments if they are suggested to them by the firm? Additionally, I expect that firms could be doing better if they are trying to increase WOM volume this way. Tang, Fang, and Wang (2014) found that a large amount of neutral comments online will weaken the effects of positive (and negative) WOM. A careful reading of the pre-generated comments used as examples will reveal that they are neutral, or slightly positive at best. My contention is that these pre-generated suggestions may serve as a baseline for future marketing strategy, but the current execution could be improved to avoid the trap of suggesting neutral comments. The purpose of my sequence of studies is to calibrate the best delivery of these pre-generated comments and assess any potential backlash that could occur. The results of my research demonstrate that, while current practice of neutral pre-generated comments may be increasing WOM, it is not as effective as it could be. Managers should suggest positive comments—rather than generic neutral comments—to their customers, since this will increase sharing and allow for the opportunity to prime customers with desirable behaviors.

To assess how effort affects WOM behaviors, I build on prior literature addressing how cognitive effort affects consumer decision-making, as well as explore likely outcomes when effort is adjusted for WOM communication. I then conduct six studies and show that suggesting comments to consumers lowers their effort, and that one suggested comment is optimal. Following this initial study, I show that cognitive effort is the mediating mechanism between pre-generated comments and posting behaviors. Then, I conduct two field experiments showing the main effects of pre-generated comments on sharing intentions. After establishing this main effect via replication and generalizability across settings, I build upon my findings using subsequent studies to examine the benefits of priming via text and the importance of accounting for satisfaction. I find that when firms solicit WOM behaviors from customers (whether organic or via pre-generated comments), customers are more likely to activate on the primed behaviors relative to a pure control group. While organic WOM and pre-generated comments both significantly increase spending, suggesting comments has a significant increase on sharing behaviors, so firms would gain the benefit of additional referrals by offering suggestions. Finally, while I expect that dissatisfied customers will retaliate against the firm if they are asked to share a positive comment, I find that when these customers share and edit their comments, they are not more likely to post, and the posts are not more negative than a typical organic negative WOM comment.

Conceptual Background

WOM has been perceived as a "naturally occurring phenomena" (Kozinets et al. 2010, p. 71), though firms have flirted with the idea of generating additional WOM through specific levers they can pull. These can include costly strategies such as economic incentives (Hennig-Thurau et al. 2004; Ryu and Feick 2007) and referral programs (Haenlein and Libai 2017; Schmitt, Skiera, and Van den Bulte 2011), or they may use seeded marketing campaigns (Dost et al. 2019), which have their own disclosure requirements and regulations which can provide challenges for firms. However, an emerging trend that firms have been using goes a step further than asking customers to share WOM. Instead, firms give customers the words to say themselves. While this is a step toward violating the natural occurrence of WOM behavior, this is free to the firm and still gives customers the ability to edit their own posts. At the same time, firms should be able to increase WOM volume and valence if customers are receptive to the suggestion. To assess the effectiveness of these pre-generated comment suggestions, I consider the role that cognitive effort plays in WOM generation and sharing, expecting that when comments are pre-generated this will reduce the amount of effort it takes customers to recall the experience, filter which aspects to write about, and then post the comment to social media. I then proceed to hypothesize on how firms can utilize these suggestions to prime customer behaviors. Finally, I look at the importance of customer satisfaction and how it influences the volume and valence of WOM when positive pre-generated comments are offered.

Cognitive Effort

Effort has been used as a framework across a wide spectrum of research in psychology and marketing, including effort exerted by customers (Moreau, Bonney, and Herd 2011; Nunes and Dreze 2006; Sweeney, Danaher, and McColl-Kennedy 2015), employees (Christen, Iyer, and Soberman 2006; Nahrgang, Morgeson, and Hofmann 2011), and firms (Bhaskaran and Krishnan 2009; Morales 2005). My research examines WOM generation and outcomes, thus I ground my work in the customer aspect of effort. An early definition of effort noted that it “includes the physical, mental, and financial resources" required of customers (Cardozo 1965, p. 244), which is consistent with later definitions that state effort can be classified as either physical or cognitive (Kanfer 1992). I make two notes regarding this initial conceptualization. First, I focus on the cognitive aspect for the purposes of my research into the role of effort in WOM activities. While there is the potential for physical obstacles to sharing WOM (e.g., meeting with a friend in-person to chat or typing and clicking to share online), these are minor hurdles relative to the cognitive effort required when generating and sharing WOM. Second, I note that Cardozo's original definition of effort was only applied to the acquisition of goods, not other activities that customers could engage in to benefit firms. To apply the effort construct to a broader range of consumer decisions, I adopt Johnson and Payne's (1985, p. 397) definition, where effort is "the total use of cognitive resources required to complete the task." Cognitive resources include time, thoughts, and emotions (Youngdahl and Kellogg 1997) and because effort and time are both finite resources, it's no surprise that consumers are cognitive misers and want to reduce effort as much as possible (Berry, Seiders, and Grewal 2002).

When assessing how much cognitive effort to allocate to complete a task, individuals typically only expend enough effort to make a satisfactory decision as opposed to an optimal one (Fiske and Taylor 1984). This is likely due to the error-effort trade-off, where effort reduction is achieved via the sacrifice of accuracy (Russo and Dosher 1983), so consumers must reconcile their effort expenditure with the threshold for a satisfactory outcome. In cases where the amount of cognitive effort required for a task is large but remains below a predetermined maximum, it is likely that a less demanding process would be preferred if the outcome is sufficiently satisfying. Alternatively, if required effort is greater than the amount of effort an individual is willing to expend, that person will give up (Bandura 1997; Brehm and Self 1989).

Finally, while humans will generally have different subjective evaluations of the cognitive effort cost needed to complete a task to satisfaction (Kool et al. 2010; Westbrook, Kester, and Braver 2013), there is nonetheless a non-zero cognitive cost for consumers to perform any activity. This non-zero cost is why cognitive effort has a large influence on human behavior (Naylor, Pritchard, and Ilgen 2013). In the following section, I establish how these underlying foundations of cognitive effort can affect consumer choice on whether they will engage in WOM behaviors.

Effort, Consumer Choice, and Word of Mouth

Consumers make multiple decisions in both the prepurchase and postpurchase stages (Lemon and Verhoef 2016). Notably, following a purchase, a consumer chooses whether to participate in nonpurchase behaviors, which include spreading WOM (Lemon and Verhoef 2016). Antecedents of WOM behaviors have been extensively researched (see Berger 2014 for a comprehensive overview), yet the connection between cognitive effort and WOM generation has not been established in the marketing literature. There have been two mentions of effort relative to WOM, albeit not cognitive effort specifically. Berger (2014) briefly mentions that written WOM takes more effort than oral WOM, and Van Doorn et al. (2010) note that customer engagement behaviors require customer expenditures of time, money, and effort.

To more formally account for the effects of effort on WOM behaviors, I draw from research on the consumer consideration set and its role in decision-making. Much like a purchase, where a consumer considers a set of alternatives, they also have varying choices when deciding whether to engage in WOM. When making these choices, there is a nested set of alternatives which are narrowed down until a choice is finally made (Kardes et al. 1993; Shocker et al. 1991). The consumer begins with the universal set of items, which includes the entirety of alternatives that can be obtained by any consumer. Next is the retrieval set, which includes items that a particular consumer is aware of via long-term memory. The retrieval set does not require that an item "come to mind" in a specific incident (Shocker et al. 1991), which indicates that this set still includes a sufficiently broad range of items. The model continues to filter through alternatives, and next is the consideration set, including "the [items] that a consumer would consider buying in the near future" (Roberts and Lattin 1991, p. 430). The consideration set includes a subset of the retrieval set that is purposely selected to be scrutinized before a final choice is made. Arriving at the consideration set has been described as a "relatively effortless" way of simplifying a complex final choice (Chakravarti and Janiszewski 2003, p. 245), though consumers also consider the opportunity cost where the risk of eliminating the best alternative is assessed relative to saved time and effort of using a heuristic (Huber and Klein 1991). In a WOM context, if consumers are faced with an abundance of choices, they will likely take the shortcut the firm provides them so that they can save time and effort.

I begin my hypothesis development by looking at current industry practice. Firms are attempting to motivate users to share WOM online by pre-generating comments, either via Twitter, Facebook, or e-mail, where the consumer is given a suggested tweet (or e-mail, or Facebook post) to share, which reduces the cognitive effort for the consumer by generating a consideration set of comments—effectively removing the need for retrieval. For example, if a consumer were to purchase a Sony Plasma TV on Amazon.com, a highlighted box on the confirmation page frames the message "*I just bought Plasma TV by Sony via Amazon @amazon*" and includes a button that asks the customer to 'Share this item.' Another example is the app for the movie website IMDb.com, where, once a film is rated, users are prompted to share their rating on social media: "*I rated Avengers: Infinity War (2018) 8/10 #IMDb*" will show up as a recommended tweet. This gives consumers an opportunity to boast about their purchase or share their opinion more easily. These two examples show that firms are trying to spur online WOM while also refining the consideration set to relevant characteristics about the customer's experience (i.e., the brand of TV purchased and where it was purchased from, or the movie that was seen and the rating given). Building on the notion that the decision-making process requires effort at each step, I expect that when a comment is pre-generated by the firm it requires less effort to consider sharing than organic (i.e., written from scratch) WOM. Formally, I hypothesize:

> H_1: Pre-generated comments suggested by firms require less effort to share than organic comments.

Another point of interest regarding the pre-generated comment examples is that the firms only offer one option to their customers. While I, as a researcher, can speculate that this may be due to technological limitations on the firm's end, there is also recent work providing a solid theoretical grounding for a smaller consideration set. Early marketing research adopted the mantra that giving humans more choices was better. As more choices are available, variety-seeking desires can be met (Inman 2001; Ratner, Kahn, and Kahneman 1999) and more opportunities exist for consumers to find an exact match to their preferences (Baumol and Ide 1956; Desmeules 2002; Kahneman, Wakker, and Sarin 1997). However, more recent work has shown that too many options can backfire for consumers. As noted by Iyengar and Lepper (2000), much research at the time used a relatively small number of choices in the experimental designs, which is not reflective of the reality of decision-making where humans encounter many more options; the authors found that having too many choices is demotivating. Beginning in the early 2000s, researchers explored the consequences of having too much choice. Schwartz's (2000) article, aptly titled *The Tyranny of Freedom*, makes the case that if we lived in a world with unlimited options, our desire for rational choice would overwhelm us.

In marketing, we have found that retailers offering a larger assortment of attractive goods decreases consumer preference (Chernev and Hamilton 2009), and a reduction of clutter and tertiary items actually increases sales across dozens of categories (Boatwright and Nunes 2001). This can be attributed to the extra cognitive effort required to examine attribute levels of all items in the assortment, as well as the trade-offs that must be accepted if one item is chosen over another (Chernev and Hamilton 2009). Of particular interest is that research has found that in some situations, choice itself may not be desirable: Regret and uncertainty cause decision avoidance, and sometimes it is even preferable to have others make an important decision (Beattie et al. 1994). In a WOM context, where comments are pre-generated by the firm, there should be benefits to the consumer for the reduction in choices (from the vast set of memories about a certain experience). A few suggestions should take less effort than an organic setting where a consumer writes a comment themselves, and complete refinement of the consideration set to one suggested comment should require the least amount of effort. I hypothesize:

> H_2: The number of pre-generated comments shown to a consumer affects cognitive effort, where fewer items are perceived as requiring less effort.

Word of Mouth and Priming Situational Cues

Positive WOM is a valuable asset to firms, typically as a means of bringing in new customers. Relative to non-referred customers, referred customers have a daily contribution margin at least 16% higher (Schmitt, Skiera, and Van den Bulte 2011), on social media platforms are worth more money per year in advertising revenue (Trusov, Bucklin, and Pauwels 2009), and also have a lower defection rate (Garnefeld et al. 2013). Given the value of WOM to firms, it is not surprising that research on the antecedents of WOM behaviors is aplenty. Studies have examined customer commitment, trust, satisfaction, and loyalty with the firm (De Matos and Rossi 2008), the valence and emotion of the WOM message (Berger and Milkman 2012), and individual traits such as need for uniqueness and self-enhancement (Berger 2014; Cheema and Kaikati 2010; Chen 2017).

What is lacking in most research on WOM are ways firms can influence WOM in the postpurchase phase of the consumption experience, rather than predict which customers are more likely to share WOM. Providing economic incentives has been explored briefly (Hennig-Thurau et al. 2004; Ryu and Feick 2007) but paying a fee per comment shared online can be costly to firms and time consuming to monitor. The same can be said of other incentives, such as referral programs or seeded marketing campaigns, which are expensive to maintain. Offering pre-generated comments takes advantage of current technological capabilities used by firms, while not requiring them to incur additional costs.

When firms offer pre-generated comments to their customers, they are lowering the amount of cognitive effort required from consumers. Since humans are cognitive misers (Berry, Seiders, and Grewal 2002), actions with fewer effort requirements are more likely to be undertaken. In the context of WOM, if sharing pre-generated comments requires less effort than engaging in WOM organically, the difference should manifest in higher sharing rates in situations where pre-generated comments are offered. Given that I expect pre-generated comments reduce effort, I propose that these suggestions affect sharing via decreased effort (i.e., a mediating relationship). Thus, I hypothesize:

> H_3: The relationship between pre-generated comments and posting behavior is mediated by customer effort.

> H_4: Pre-generated comments suggested to customers increases the likelihood the customer shares a post about their experience.

In addition to the benefits of pre-generated comments bringing in additional customers via WOM, there is also reason to expect that suggesting positive comments to customers is an opportunity for firms to prime desirable behaviors. When humans are exposed to a certain word, trait, or action that is associated with a specific behavior, there is likely to be nonconscious activation of that particular behavior (Dijksterhuis and Bargh 2001). This has been conceptualized as a form of "automatic social behavior" that can be primed by using situational cues as simple as a few choice words (Bargh, Chen, and Burrows 1996). For example, in Bargh and colleagues' (1996) Study 2, when words of an elderly stereotype (e.g., old, wrinkle, retired, Florida) were used to prime participants, they exhibited slower walking behavior following the study (relative to the neutral condition).

Early work found two competing reasons for why priming works: Either motivational or semantic constructs are being activated (Sela and Shiv 2009). To address the inconsistencies, Sela and Shiv (2009) proposed the Activation-Striving Model, where if priming cues attempt to activate behavior which differs from one's active self-concept the effects of the prime will be persistent, whereas if the primes are inherently consistent with one's self-concept the activation will be fleeting. The longer-term effects are associated with goal motivation, while the more short-lived effects are an activation of semantic constructs (e.g., personality). A recent meta-analysis (Weingarten et al. 2016) has shown that priming effects are robust and that behavior priming has a stronger effect over less valued behaviors.

This presents an interesting opportunity for firms. As cognitive effort is reduced and pre-generated comments are suggested, firms are able to prime specific behaviors from their customers simply by suggesting the positive comment. Of particular interest to marketers is the priming of excitement, since excitement has been shown to increase approach tendencies as well as unplanned purchases (Dawson et al. 1990). If excitement is successfully primed, this could cause an increase in purchase frequency as well as amount. While the underlying mechanism for the activation of priming may be either goal motivation and others may have semantic constructs activated, there should still be a significant effect if priming excitement is done via pre-generated comments. I hypothesize:

> H_5: Priming excitement in consumers via pre-generated comments activates a) an increase in purchase frequency and b) an increase in purchase amount following the suggestion of the comment.

Misidentification of Customer Satisfaction

I expect that while positive suggested comments are likely to reflect the experience for satisfied consumers, mismatched comments could irritate dissatisfied customers and influence posting and retaliatory behaviors. Therefore, my research also explores the effects of satisfaction and potential retaliatory behavior that may occur in response to positive pre-generated comments that are incongruent with the customer experience.

In the early days of WOM research, scholars were disconnected regarding whether positive (Bitner 1990; Oliver 1980) or negative (Richins 1983; Anderson 1998) WOM is more widespread. To resolve these contradictions, researchers have split WOM behavior into two dimensions: generation (i.e., from a consumer's own experiences) and transmission of WOM (i.e., relaying information heard from others), and the results show that consumers will generate more positive WOM and transmit more negative WOM (Angelis et al. 2012). However, in the current research, I am not directly testing differences in WOM generation based on valence. Instead, I build on the concept that there is a U-shape for the relationship between satisfaction and WOM, where customers at either end of the satisfaction continuum are more vocal about their experiences than neutral customers (Anderson 1998).

When marketers choose to use pre-generated comments, they are trying to actively shape the valence by suggesting positive comments to their customers. Suggesting negative pre-generated comments would be counterintuitive. However, despite best efforts, not all customers will be satisfied following an interaction with the firm. Service failures can occur, or products may not meet customer expectations. I expect that customer satisfaction will play a role in affecting sharing behaviors, and that the push by firms to generated positive WOM via pre-generated comments will not be consistent across all customers.

More specifically, there should be a moderating effect of satisfaction on customer's sharing of pre-generated comments. Given that a positive comment will not correspond to the experience a dissatisfied customer had, I see no reason why a dissatisfied customer would share the pre-generated comment. Therefore, I anticipate that for satisfied customers pre-generated comments will increase sharing probabilities (consistent with H_4), but for dissatisfied customers the suggestion to share a pre-generated comment will turn them off from sharing and decrease posting numbers, resulting in an ordinal interaction. I hypothesize:

> H_6: The effect of pre-generated comment suggestions on posting probability is moderated by customer satisfaction, such that suggestions have a positive effect for satisfied customers and a negative effect for dissatisfied customers.

Despite lower relative posting rates for dissatisfied customers who follow through, I expect to see these dissatisfied customers take revenge against the firm based on the valence of the comments they share. I base this assumption of outcomes on prior work done on dissatisfaction behaviors such as customer revenge, which is a consumer's desire to harm a firm following a negative experience (Bechwati and Morrin 2003). When a dissatisfied customer is reminded about their experience, while they may want to take revenge against the firm, it is rare that people will act out these desires (Aquino, Tripp, and Bies 2001). Consumers may instead choose nonaggressive responses (Aquino, Tripp, and Bies 2006), and in cases of dissatisfaction this can be negative WOM (Zhang, Feick, and Mittal 2014). Negative WOM captures a customer's intentions to disparage a firm to others, and it's an indirect way for consumers to "tarnish a firm's reputation and to encourage others to avoid patronizing it" (Gregoire and Fisher 2008, p. 249; Wangenheim 2005).

In line with H_6, I expect that the potential backlash from an experience-suggestion mismatch to extend beyond mere posting probabilities. With current comment pre-generation technology, customers maintain the ability to edit posts before they are shared, despite the text being immediately populated into the field. For example, even if firms use the simple strategy of linking to https://twitter.com/intent/tweet?text=Firm's%20suggested%20text., an inaccurate comment is likely to be adjusted by the customer, and firms have done two things: They have reminded the customer of an unsatisfactory experience they may have forgotten and the firm has essentially made it easier for customers to share their own negative WOM by linking to Twitter.

In line with this conceptualization of negative WOM following an unsatisfactory experience, I expect that the retaliation from customers will be amplified in the case where positive pre-generated comments are suggested. These customers will have had a bad experience with the firm, and firms attempting to solicit positive WOM will be seen as opportunistic. This could ultimately lead to an increase in negative WOM volume, as well as the valence of comments shared. I hypothesize:

> H_7: Pre-generated comment suggestions to dissatisfied customers, relative to organic WOM activity, will a) increase the amount of negative comments shared by these customers, as well as b) have a more negative valence in the shared comments.

Overview of Studies

I assess the impact of pre-generated comments across six studies, which are listed in Table 1-1. In Study 1, I establish that by suggesting pre-generated comments, firms can lower a consumer's cognitive effort. Additionally, Study 1 explores how the number of pre-generated comments affects effort, where one suggestion is expected to be optimal. Study 2 builds on this foundation by formally establishing that effort is the mediating mechanism between pre-generated comments and sharing intentions. Next, I proceed to test the effects of positive pre-generated comment suggestions across two settings. Study 3 is an experiment with active gym members which shows that pre-generated comments suggested via an e-mail to members increases sharing intentions relative to a natural, "organic" solicitation. Study 4 expands on findings from Study 3 by incorporating control variables as well as a different context. Study 4 is a market research survey for a potential restaurant opening, and I am able to account for anticipated satisfaction, attachment to social media, and desire for self-enhancement to rule out alternative explanations, and I show robustness of the effect based on a separate setting (i.e., restaurant vs. gym) as well as contact method (i.e., post-survey confirmation screen message vs. e-mail to all members). Study 5 shows how firms are able to use the pre-generated comment to prime desirable behaviors Finally, in Study 6 I manipulate satisfaction to explore the potential negative outcomes which may occur if positive pre-generated comments are suggested to customers who had a negative experience. In total, these six studies provide a robust test of the benefits and consequences of positive pre-generated comment suggestions to customers.

Study 1: The Effect of Pre-generated Comments on Effort

As a foundation for the following five studies, Study 1 examines the extent to which pre-generated comments will be less effortful for customers who wish to share WOM (H_1), and fewer pre-generated comments will take the least effort (H_2).

Method

Three hundred seventy-six participants were recruited using Amazon Mechanical Turk (MTurk) workers to participate in the study. Participants were randomly assigned to one of the four consideration set conditions (consideration set: organic, one/three/five pre-generated comments). Participants read a scenario and imagined that they were shopping online for a new set of headphones. They imagined that they were browsing Amazon.com and found a pair of noise-cancelling headphones by the brand Cowin. Participants were given some product details (e.g., battery life, sound quality, noise reduction attributes). Participants were then told they decide to purchase these particular headphones.

On page following the scenario, participants were told that after their purchase Amazon asks them to write comments about their purchase to share via their Twitter account. The researcher explicitly states that the participant is confident in their decision and wishes to write comments about their purchase. Following this statement, the manipulations took place.

The first condition, which is referred to as “organic,” presented a blank box with the prompt: “Write your comments about your purchase here.” There was also a question asking if participants would share this comment to their Twitter, which was asked in this condition as a means of consistency across the latter conditions (i.e., three and five pre-generated comments where a choice is required). For the second condition, with one pre-generated comment, there was also a note stating “Amazon.com suggests the following tweet about your purchase” and the blank text box was absent. Instead, there was an image mimicking a typical online sharing template was shown (see Figure 1-1), with the pre-generated comment in the text field. Participants were asked if they would share this comment or not.

The remaining two conditions were similar to the single pre-generated comment condition, except the number of comments suggested was greater. The comments and examples of manipulations are shown in Figure 1. The additional comments were: “The new Active Noise Cancelling headphones I just ordered look awesome! I’m looking forward to them arriving! via @amazon,” “I ordered some new Active Noise Cancelling headphones on Amazon. They look great and I can’t wait to listen to my favorite music with them! via @amazon,” “I placed an order for new headphones on Amazon and I can’t wait to use them! via @amazon,” and “Check out these new headphones I bought through Amazon. They have Active Noise Cancelling and look really comfortable. I can’t wait for them to arrive! via @amazon.” In the latter two conditions, participants were asked which of the comments they would share or if they wouldn’t share any of them.

I use two measures of cognitive effort in Study 1 that have been established in the marketing and psychology literature: time to task completion and the Customer Effort Score. First, I use a measure of time, operationalized as the time taken for complete the task (Bettman, Johnson, and Payne 1990) measured in seconds (Garbarino and Edell 1997). The measurement of time began when participants arrived at the page asking them to write or select a comment and ended once they made a choice (whether to share or not; which comment to share or not share any). Following the manipulation and the participant's choice of comment I also surveyed them on perceptions of effort via the Customer Effort Score (CES), an index that asks: "How much effort did you personally put forth to handle your request?" on a 1–5 scale, where 1 = "Very Low Effort" (Dixon, Freeman, and Toman 2010; de Haan, Verhoef, and Wiesel 2015). Here, to fit the context of social media, the wording was adapted to: "How much effort did you personally put forth to write and share your comment?" Then, participants completed a simple manipulation check asking what type of product they were buying (incorrect responses were removed from the sample) and then I collected demographic information. Overall, after removing incomplete surveys and participants who failed the manipulation check, I ended up with a sample size of three hundred thirty-seven ($n = 337$, $M_{age} = 38$ years, 60% female).

Results

I first compare effort perceptions of the organic state of WOM relative to the conditions where comments were suggested. I conducted an analysis of variance (ANOVA) across all four conditions to examine differences across the two measures of effort, and found that significant differences existed for both the time measure ($F(3, 333) = 53.02$, $p < .001$) and the CES ($F(3, 333) = 13.22$, $p < .001$). The means and standard deviations across the conditions are displayed in Table 1-2, as well as graphically in Figure 1-2A and 1-2B, and I note that the correlation between the two effort measures was positive and significant ($r = .26$, $p < .001$). To test hypotheses 1 and 2, I conduct a series of planned comparisons. First, I compare time spent and the CES for the organic condition to the means of the other three conditions. These results were significant for the time measure ($t(333) = 10.93$, $p < .001$) and the CES ($t(333) = 4.67$, $p < .001$). The consistent results across both measures indicates that pre-generated comment suggestions require lower cognitive effort than the organic state of WOM, which supports H_1.

Next, when comparing one pre-generated comment to three pre-generated comments, results were significant across both cognitive effort measures ($t_{time}(333) = 4.94$, $p < .001$; $t_{CES}(333) = 3.66$, $p < .001$). Surprisingly, I did not find a significant difference between the three and five pre-generated comments conditions ($t_{time}(333) = .79$, $p = .43$; $t_{CES}(333) = .09$, $p = .93$). As expected, the difference between five pre-generated comments and the organic condition was significant ($t_{time}(333) = 6.90$, $p < .001$; $t_{CES}(333) = 2.73$, $p < .01$). These results provide partial support for H_2, where one pre-generated comment requires the least amount of effort, while three/five comments require more effort than one comment but are similar to each other perceptually (CES) and objectively (time).

Discussion

Study 1, as a test of hypotheses 1 and 2, shows two important outcomes which I build on in the subsequent studies. First, I find that suggesting pre-generated comments—relative to natural, organic WOM—requires less effort. This effect was robust across an objective (number of seconds) and subjective (the Customer Effort Score) measure of effort. Next, I found that offering one pre-generated comment requires the least amount of effort for customers, while three and five pre-generated comments are similar across both effort measures. These results speak to the importance of the size of the consideration set provided to customers, where more than one suggestion requires extra effort to analyze all of the options available. These suggestions are still perceived as being less effortful than organic WOM. Going forward, given the significant findings of one suggestion requiring the least amount of effort, I only use the one pre-generated comment option in the experimental designs.

Study 2: Establishing Effort as a Mediator

Following Study 1's findings of pre-generated comments reducing effort relative to organic WOM, I conduct a study to formally test effort as the mediator in the pre-generated comment → sharing likelihood relationship (H_3). I test this using a scenario-based study where participants make a purchase and then are asked whether they will share a comment, as well as timed for their actions and asked about perceived effort (as in Study 1). I predict that both of these effort measures will be significant mediators in the proposed relationship.

Method

A target of two hundred participants were recruited from MTurk to participate in Study 2. Participants were asked to imagine that they are looking for a tool set to use for basic assembly and repairs around their home, so they go online and use Google's shopping search feature to see the available options. They were shown a picture of the tool set in addition to relevant product information about their purchase (e.g., types of tools, storage box, weight). Ultimately, in the scenario, they decide to buy a 116-piece tool set.

Next, participants were randomly assigned to one of the two experimental conditions in the 2 (WOM type: organic vs. one pre-generated comment) x 1 between-subjects design. In the organic condition, participants were told that on the purchase confirmation page, they are asked to write comments about their purchase to share via social media. They were asked if they would be willing to write comments, and if they selected "Yes, I would write comments," participants were directed to a text box where they could type comments about their purchase (selecting the "no" option skipped directly to the subsequent measurement variables). On the page where participants could write their comments, there was also a question asking whether they would share this comment, which gave participants a continuing option to opt out (similar to having second thoughts and closing the browser). In the one pre-generated comment condition, participants were similarly told that they were being asked to share comments on the purchase confirmation screen. However, in this condition, participants were shown a suggested comment: "I just bought: Hyper Tough 116-piece Tool Set, and I can't wait for it to arrive!" The framing was consistent with Figure 1 above. Again, participants were asked if they would share this comment.

Consistent with Study 1, I measure effort across time and the CES. I also again asked what was being described in the purchase scenario (removing incorrect responses), and then measured demographic information at the end of the survey. One hundred ninety-one participants were included in the final sample, which consisted of participants who completed the survey and passed the simple manipulation check (n = 191, M_{age} = 37, 55% female).

Results

Mediation was tested by examining the indirect effect of pre-generated comment suggestions on posting intentions via the two measures of effort (time and CES)[1]. I conduct the analysis using Model 4 of the PROCESS macro (Hayes 2012), and I report the 95% bias-corrected confidence intervals following 10,000 bootstrap samples. The pre-generated comment condition was dummy coded as 1 relative to the organic condition as 0. Additionally, the dependent variable, decision to share, was dummy coded as well (base condition = do not share).

[1] I note that the correlation for the two effort measures was in line with the correlation from Study 1: $r = .21$, $p < .001$.

With time as the mediating variable, results show a significant mediating effect (b = -.26, SE = .22, CI_{95} = [-.80, -.02]) between pre-generated comments and posting intentions. Following a similar procedure with the CES as the mediator, I also find a significant indirect effect (b = -.28, SE = .16, CI_{95} = [-.63, -.01]). Based on these consistent results, I find support for H_3.

Discussion

Study 2 used an experimental design to establish the connection between pre-generated comments and sharing intentions, specifically, through effort as a mediator. The results confirm that both measures of effort can act as mediators between pre-generated comments and sharing intentions, which demonstrates that when firms are pre-generating comments to suggest to their customers, what they are doing is lowering effort. In the following studies, I expand on this premise by testing how the pre-generated comments will affect the spread of WOM from customers.

Study 3: Main Effects of Pre-generated Comments on WOM

In Study 3 I conduct a field experiment to assess the effects of pre-generated comment suggestions on WOM behaviors from consumers. I manipulate organic versus pre-generated comment suggestions when sending e-mail messages to members of a gym in the Boston area. The purpose of Study 3 is to establish the effects of pre-generated comments on consumer responses to a call to action to support the firm in social media.

Method

Data collection for Study 3 was done in collaboration with a gym in the Boston, Massachusetts area. The gym makes use of an e-mail system to send information to their members, and the researcher was able to utilize this system to e-mail members and manipulate whether comments were pre-generated or not.

For the purposes of Study 3, I created a promotional e-mail to send to the gym members with the goal of driving social media support for the gym. The e-mail itself was consistent across conditions other than the manipulation, which took place at the end of the e-mail. The message was sent from the official account of gym management. The body of the e-mail was primarily an appeal to members to engage with the gym on social media. The primary message was that the gym is looking for ways to improve the member experience, and by building up its social media presence they will be better able to satisfy their customers. I opt to use this type of solicitation as a way of increasing statistical power via a larger sample size, since I expect relatively small sharing percentages based on similar research done on click through rates on social media where percentages are often fractions of a percentage point and max out at 3.1% (Tucker 2014).

Following the opening paragraph, the e-mails differed based on experimental condition. In the organic condition, the e-mail stated, "If you are willing to help us out, please consider posting about us on Twitter, which you can do by clicking <u>here</u> or via the Twitter icon below:" followed by an image of the Twitter logo. Clicking either link opened a new browser window with a tweet box that members could type into. In the pre-generated comment condition, there was a similar message, replacing "please consider posting about us on Twitter" with "please consider sharing the following tweet on Twitter." The pre-generated tweet was: "If you're looking for a gym, check out [@GymName]! With the best equipment and trainers, I would definitely recommend [the gym] to anyone in the area!" The researcher was able to track clicks on the links via the e-mail platform, which served as the dependent variable.

A total of 1,665 e-mails were sent to active gym members who were randomly assigned to one of the two conditions. The e-mail open rate was 48.6% for all e-mails sent, where 410 e-mails were opened in the pre-generated comment condition and 400 in the organic condition. One week after the initial e-mail was sent, a second e-mail was sent to those who did not open the e-mail as a reminder. The e-mail was identical other than the e-mail subject, which included "Reminder:" before the subject line. The reminder e-mail generated an additional 156 message opens, resulting in a final total sample size of 966 observations (where 50.6% were in the organic condition).

Results

Given the binary nature of the outcome of interest (intentions to share WOM on Twitter), I analyze the data using logistic regression. If members clicked the link to go to Twitter the dependent variable was coded as 1 (no click = 0). I also dummy coded the experimental conditions, with the pre-generated comments condition coded as 1 and the organic condition as 0. Finally, while I do not expect a significant effect, I also added a dummy variable to account for whether the member opened a reminder e-mail (relative to the original e-mail).

Logistic regression results of sharing choice on the experimental condition showed a significant and positive effect for pre-generated comment suggestions (2.1% vs. 0.2%; $\beta = 1.63$, $\chi^2 = 6.55$, $p < .05$, Exp(B) = 5.11) on sharing intentions.[2] These results indicate support for H_3.

Discussion

The field experiment for Study 3 shows a significant lift in intentions to share WOM online when customers are suggested a positive, pre-generated comment. This supports hypothesis 4, and gives further credibility to the notion that if managers attempt to lower effort

[2] The Reminder coefficient was not significant ($\beta = -.65$, $p = .53$, Exp(B) = .52).

for their customers they can reap the benefits of additional positive WOM. While the percentages in this study are low in absolute value (i.e., 2.1% and 0.2%), these are above what is to be expected with social media click through rates (Tucker 2014), and if firms were to implement these strategies on a scale of thousands (or millions) of encounters with their customers, the boost to the firm's online engagement numbers would be substantially large.

Study 4: Robustness of the Effects of Pre-generated Comments on Sharing

In Study 4, I expand on the results shown in Study 3 by generalizing the effects of pre-generated comments to another setting, while also including a relevant set of control variables. The researcher conducts a controlled experiment using pre-generated comments and an organic WOM condition, and, rather than using e-mail (as in Study 3), the manipulation takes place at the end of a typical customer satisfaction survey. Significant results in Study 4, when accounting for control variables, would provide additional support for H_4 and show generalizability of the effects of pre-generated comments on sharing intentions.

Method

Study 4 was an experiment conducted by the researcher and disguised as a market research concept test for the potential opening of a restaurant named Simmer Down, which was considering locations in three large cities across the United States. Prior to launching the market research survey, the researcher built Twitter accounts for the three separate locations, which included a restaurant logo, banner image, description, and relevant tweets to make the account appear active. By launching these Twitter accounts myself, I was able to eliminate any potential confounds and have full control over all conditions to ensure consistent and effective manipulations. Figure 1-3 displays a screen capture of one of the Twitter accounts.

To ensure the accuracy of the restaurant concept test, I took a two-step approach when designing the study. First, I looked at population statistics for major cities around the United States on Wikipedia.org, and then I identified states where a large portion of the population resides in a single city. This allows for maximization of potential sample size since MTurk allows the researcher to limit participants geographically based on state of residence. The cities I used were Baltimore, MD, Phoenix, AZ, and Minneapolis, MN, where the metro area populations include 46.5%, 66.05%, and 63.38% of the state population, respectively. Second, in the MTurk recruitment, I asked participants to only accept the HIT if they lived in the city specific to the study. Finally, at the end of the survey, I also asked participants for their zip code, which allowed me to filter out participants based on geography.

After a brief introduction, participants were surveyed on their purchase intent for three items that may be on the restaurant menu (a burger, pasta dish, and salmon sandwich) using purchase intention items from Baker and Churchill (1977). Next, I asked participants a question about their anticipated satisfaction (using items from Spreng, MacKenzie, and Olshavsky (1996) and Eroglu and Machleit (1990)). I also measured multiple control variables as a way of ruling out other factors that could affect social media posting. Specifically, I asked about attachment to social media using items from VanMeter, Grisaffe, and Chonko (2015), desire for self enhancement using items from Wu and colleagues (2016), and the types of social media platforms the participant uses (with the goal of controlling for Twitter users). All items were measured on 7-point scales. Last, I collected demographic information such as age and sex.

The manipulation for the experiment took place after the survey questions; specifically, I manipulated the survey completion page after all of the questions had been answered. The experiment was a 2 (WOM type: organic vs. one pre-generated comment) x 1 design, and similar to Study 3, participants were randomly assigned to one of the two conditions. In the organic condition, the completion page stated, “If you would like to show support for Simmer Down’s upcoming opening, please go to Twitter and tweet about us,” followed by a link. Below the link was a standard message stating the survey response was recorded. There was no indication that clicking the Twitter link was required to complete the survey. In the pre-generated comment condition, the message was similar, but the latter part stated, “…, please go to Twitter and consider sharing the following Tweet: I just saw a preview of Simmer Down, a new [city] restaurant, and it looks awesome!” There was then a link to share the pre-generated tweet, and an identical “thank you” message followed. I tracked clicks on these links by adding JavaScript code into the survey software.

The target sample per city, prior to data cleaning, was 300 participants. Following data collection, I removed incomplete surveys and those which did not meet the geographic criteria based on zip code. In total, I collected 476 usable survey responses across the three cities ($N_{Baltimore}$ = 159, $N_{Minneapolis}$ = 139, $N_{Phoenix}$ = 178). The mean age of the sample was 36.2 and 58% of the sample was female.

Results

Logistic regression was used in my analysis, where the dependent variable was coded as 1 if participants clicked the Twitter link at the end of the survey and 0 if they did not. I regressed the choice to share on experimental condition (pre-generated comments = 1, organic = 0), anticipated satisfaction, desire for self enhancement, attachment to social media, if the participant had a Twitter account (yes = 1, no = 0), age, and then dummy variables for two of the locations (reference group = Phoenix). I first ran the model with only the control variables, and then added in the treatment variable in step 2 of the logistic regression model. Table 1-3 reports the full results of both steps. Overall, I found a positive and significant effect of pre-generated comment suggestions on sharing intentions (6.7% vs. 2.1%; $\beta = 1.24$, $p < .05$, Exp(B) = 3.45), as well as a significant difference in the χ^2 values between the control variable model and the full model when adding the single treatment effect variable ($\Delta\chi^2 = 5.66$, $p < .05$). Thus, I find further support for H_4 in an additional setting, robust to a strong set of control variables.

Discussion

Study 4 shows that pre-generated comments are a generalizable tool for firms, as well as their effect being robust to important control variables. The results of the test of H_4 from Study 3 remain significant when consumers are asked to participate at the end of a survey (rather than in an e-mail, as in Study 3). Additionally, these effects remain significant when accounting for control variables such as attachment to social media, desire for self enhancement, and satisfaction. In the following studies, I test other outcomes besides sharing intentions, while also ensuring replication of H_3 in further contexts.

Study 5: Priming Effects of Pre-generated Comments

Study 5 is the first of two studies to assess the effects pre-generated comments may produce other than increasing WOM volume. In a two-stage study, I am able to prime consumers with excitement in the first step (in one of the three conditions) and then I follow-up with participants to examine how priming affected purchase behaviors relative to an organic WOM condition and a pure control group (H_5). The pure control condition has no WOM activity involved, which allows for comparisons of the effects of pre-generated comment suggestions to both organic WOM and absent WOM situations. I expect that priming via pre-generated comments will lead to a significant increase in activating planned and unplanned purchases.

Method

MTurk workers ($n = 1,500$; $M_{age} = 37$, 55% female) were recruited to participate in a two-part survey, with a target of 500 participants per cell to have enough statistical power to detect small effect sizes. The study was structured as a 3 (WOM type: control vs. organic vs. one pre-generated comment) x 1 design, and similar to Study 4, the first stage of this experimental design provided participants with an identical task before exposure to the manipulations. The survey launched in December 2018, and asked participants to watch a two-minute trailer for the film *Aquaman*, which had not yet opened in the United States. After watching the trailer, I asked participants about their intentions to see the film based on using a 7-point bipolar behavioral intent items from Bansal, Taylor, and James (2004). I also asked participants about their desire for self enhancement using 7-point items consistent with Study 4 (Wu et al. 2016), and finally I asked about their involvement with super hero movies using four items from Lichtenstein, Netemeyer, and Burton (1990). Last, I asked about demographic information.

The manipulation took place following the demographic information questions. Participants were randomly assigned to one of the three conditions. In the control condition, participants were simply thanked for completing the survey and asked to click "next" to submit their results. The organic condition had a message stating, "If you would like to help us out by sharing the *Aquaman* trailer you just watched, you can go to Twitter and tweet about it," followed by a link to Twitter and a thank you-type message identical to the other conditions. The pre-generated comment condition was identical to the organic condition, except with the suggested tweet: "I just saw a new trailer for *Aquaman* and it looks awesome! Check it out: https://youtu.be/2wcj6SrX4zw" followed by a link to Twitter where this text would be pre-generated. I used this pre-generated comment as a simple way to prime excitement in the participants, based on the hypothesis. By suggesting that the movie will be awesome, the excitement generated should result in the participant being more likely to see the film, while also spending more money due to their predisposition to unplanned purchases (e.g., concession sales). For the organic and pre-generated comment conditions, I tracked if participants clicked the corresponding links.

In mid-January 2019, I reached out to these same participants for a follow-up survey about their experiences with *Aquaman*. In total, 654 participants responded and completed the second survey. In this survey, I asked participants if they went to see *Aquaman* in theaters. If they indicated that they saw the film, I then asked how many people they saw the movie with (including themselves) and how much money they spent on the movie-going experience. I also asked how many movies they had seen in the last year.

Results

First Wave Results (H_4 replication). I conducted a logistic regression in two steps, as in Study 4, where I first regressed sharing (clicking share = 1; not clicking = 0) on the control variables for self enhancement, involvement with superhero films, and intent to see the film.[3] This model was significant ($\chi^2 = 14.27$, $p < .01$), though the only significant predictor was intent to see the film ($\beta = .40$, $p < .05$, Exp(B) = 1.49). I next added the dummy variable for the pre-generated comment condition (pre-generated = 1; organic = 0). Results of this analysis replicated

[3] I note that I only used two conditions in this analysis since the control condition made no mention of Twitter or social media, thus the sample size was 999 rather than 1,500.

previous findings. I found a significant positive effect of pre-generated comments on sharing intentions (3.4% vs. 1.4%; $\beta = .99$, $p < .05$, Exp(B) = 2.70), as well as a significant difference to the overall model ($\Delta\chi^2 = 5.20$, $p < .05$). In the second model, intentions remained significant ($\beta = .42$, $p < .05$, Exp(B) = 1.52), while involvement and self enhancement were not ($\beta_{involvement} = .02$, $p = .92$, Exp(B) = 1.02; $\beta_{self\_enhancement} = .36$, $p = .13$, Exp(B) = 1.43).

Second Wave Results (H_5 test). I test two outcomes based on the priming condition for the 654 participants who completed the follow-up survey. First, to assess effects on spending behavior, I separated participants in the sample who went to see the movie (n = 265), and then used linear regression to regress total money spent on the two dummy variables for the WOM conditions (relative to the control group), as well as age (which may be correlated with disposable income) and number of people in the party as control variables. Results showed a significant effect of the pre-generated comments on spending ($\beta = 7.77$, $t = 2.03$, $p < .05$) while the effect of the organic condition was not significant ($\beta = 4.15$, $t = 1.07$, $p = .29$). The number of people in attendance was significant ($\beta = 11.39$, $t = 15.48$, $p < .001$), and I find a nonsignificant effect for the organic condition ($\beta = 4.15$, $t = 1.07$, $p = .29$) and age ($\beta = .14$, $t = 1.08$, $p = .28$).

Next, I used logistic regression to examine whether priming excitement increased the likelihood that the participant saw the movie in theaters. By regressing movie attendance (saw the film = 1; didn't see it = 0) on dummy variables for the pre-generated comment and organic conditions (reference group = control), as well as involvement with super hero films, I surprisingly find a significant positive effect for the organic condition (46.6% vs. 36.7%; $\beta = .46$, $p < .05$, Exp(B) = 1.58), but no significant effect for the pre-generated comment condition relative to the control group (39.0% vs. 36.7%; $\beta = .17$, $p = .42$, Exp(B) = 1.18), with a significant effect for the involvement control variable ($\beta = .51$, $p < .01$, Exp(B) = 1.66). I display these results graphically in Figure 1-4. Overall this provides mixed support for H_5, which I discuss below.

Discussion

Study 5 tested the effects of pre-generated comments on priming positive behavior in customers. The results were surprising when comparing the pre-generated comment condition to the organic and control conditions. First, I find that asking customers to share WOM organically has a significant impact on activating purchases, while pre-generated comments are essentially similar to the control condition. Next, I found that in the pre-generated comment condition, once in the purchase situation, customers would spend more money, while in the organic condition spending was not significantly different. This shows that while the two types of WOM have differing positive impact on customers, there are no observable downsides. However, I note that the sharing percentages were higher (3.4% vs. 1.4%) when pre-generated comments were suggested. To illustrate how these factors tie together, if I incorporate the sample's attendance percentages and money spent firms should expect to earn $4,183.80, $7,325.52, and $7,460.70 per 1,000 impressions in the control, organic, and pre-generated comment groups, respectively[4]. These results provide evidence that it's always beneficial for firms to ask customers to share WOM, and that by per-generating comments firms will be able to shape part of the online conversation, rather than rely entirely on it being organic.

[4] The calculations use the percentage attendance and average money spent in the conditions. Based on 1,000 impressions: Control group (1,000 x 0.367 x 11.40 = $4,183.80); Organic group (1,000 x 0.466 x 15.72 = $7,325.52); Pre-generated group (1,000 x 0.390 x 19.13 = $7,460.70).

Study 6: The Consequences of Customer Experience Misidentification

The previous studies have shown the beneficial effects of positive pre-generated comments for satisfied and neutral customers, and I now investigate the moderating effects of satisfaction on sharing in a controlled experiment. This enables me to capture the proposed interaction effect (H_6) and to look at potential backlash that could occur when the organic nature of WOM is violated and when there is a mismatch between the positive pre-generated comment and the customer's experience (H_7).

Firms strive to provide a consistently superior customer experience, but despite their best efforts failure inevitably occurs at some point in time. By manipulating satisfaction, I am able to assess sharing intentions based on levels of satisfaction while also identifying additional backlash that may occur when firms offer pre-generated comments to all customers, inevitably reaching those that were dissatisfied. I predict that when positive comments are offered to dissatisfied customers, these customers will take revenge against the firm for their presumptive behaviors (H_7). This revenge should manifest in writing, where the comments shared by those who were offered a pre-generated comment are more negative than their organic counterpart.

Method

Four hundred twenty-eight MTurk workers ($n = 428$, $M_{age} = 38.1$, 61% female) participated in Study 6. The study was a 2 (satisfaction: satisfied vs. dissatisfied) x 2 (WOM type: organic vs. one pre-generated comment) experimental design. First, participants were randomly assigned to one of the satisfaction conditions where they were asked to read a scenario about a hotel stay. In both conditions, the participant was going out of town for the weekend with two friends. They had made plans several weeks in advance, and they have finally arrived at where they are staying: the Seabreeze Hotel. In the satisfied condition, the participant is greeted by an employee who carries their bags to the front desk. The participant is also given a surprise room upgrade, and when asking the front desk employee for a restaurant recommendation, they recommend the Seabreeze Hotel's premium restaurant. The rest of the stay goes smoothly, and check-out at the end of the trip proceeds quickly.

In the dissatisfied condition, the participant has to carry their own bags up to the front desk, and the hotel clerk informs the participant that their reservation has been lost. After about ten minutes, they are given a room with one king bed. When asking where to eat nearby, the employee tells them that they can check Yelp for recommendations. They were also unable to upgrade to a proper room for the remainder of the trip. While the beach itself was nice, they were glad to check out and go home at the end of the weekend.

Following the scenario, participants were then randomly assigned to one of the WOM conditions, which were consistent with the previous studies. In the organic condition, participants were given a text box and the option to (hypothetically) share what they wrote on Facebook. The pre-generated comment condition had a text box pre-populated with a suggested post, which stated: "I stayed at the Seabreeze Hotel for my winter break getaway, and everything was great! The service was wonderful and my two friends and I had a fun time at the beach. I'd recommend the Seabreeze Hotel to anyone staying in the area!" While this comment was highly positive, it was clear to participants that they could edit it as they saw fit. I also asked if they would share this comment.

Following the manipulations, I asked satisfaction questions to assess the effectiveness of the manipulation using three items from Allen et al. (2014) measured on a 7-point scale. I also measured demographic information such as age and sex.

Preceding the analysis, two research assistants who were not familiar with the study's purpose independently coded the sentiment of the comments. Coding was done for all comments written in the organic condition, for the pre-generated comment suggested by the researcher, and any pre-generated comments which were edited, regardless of how much editing took place. The research assistants analyzed the comments across two dimensions. First, they indicated the overall sentiment of the comments on a 9-point scale, where 1 = very negative, 5 = neutral, and 9 = very positive. Then, they were asked to count the number of positive and negative thoughts mentioned in each comment. Correlation between the two coders was high: $r_{rating} = .96$ ($p < .001$), $r_{positive\_thoughts} = .93$ ($p < .001$), $r_{negative\_thoughts} = .93$ ($p < .001$). Given these high correlations, I average the rating and count variables between the two coders to form the three separate variables for the analysis.

Results

Manipulation Check. I used ANOVA to test the effectiveness of the manipulation of satisfaction and to rule out potential confounds. The goal was to confirm a successful manipulation of satisfaction, as well as a nonsignificant main effect of the WOM type condition and its interaction with satisfaction, which would establish that the manipulation was successful and would rule out potential confounds (Perdue and Summers 1986). The main effect of the satisfaction was significant ($M_{satisfied} = 6.08$ vs $M_{dissatisfied} = 2.19$; $F(1, 424) = 1140.79$, $p < .001$), the main effect of the WOM type condition was not significant ($M_{organic} = 3.94$ vs. $M_{pre\text{-}generated} = 4.40$; $F(1, 424) = 2.78$, $p > .05$), and the interaction was not significant ($F(1, 424) = .05$, $p = .83$). This suggests that the manipulation was successful.

Satisfaction Effects on Sharing Intentions (H_6 test). Logistic regression was used to test the effects of satisfaction on sharing. I regressed the choice to share on dummy variables for the satisfaction condition (dissatisfied = 1; satisfied = 0), WOM type (pre-generated = 1; organic = 0), as well as the interaction between pre-generated comment and dissatisfaction. Consistent with prior studies, I find a significant effect of pre-generated suggestions on sharing intentions (β = .90, $p < .01$, Exp(B) = 2.45). I also find a positive effect of dissatisfaction on sharing intentions that approaches significance (β = .49, $p = .09$, Exp(B) = 1.63), and in support of H_6, I find a significant interaction between pre-generated comments and dissatisfaction (β = -2.02, $p < .001$, Exp(B) = .13). I display the observed posting frequencies in Figure 1-5 to better display the interaction effect.

Pre-generated Comment Effects on Sentiment (H_7 test). For the second stage of analysis, I took the initial sample and reduced it to only participants who chose to share their comments and those who made changes to the pre-generated comment (regardless of how many characters were changed). The research assistants also coded the pre-generated comment to ensure it was accomplishing the goal of priming positive sentiment, and it had a rating of 8.5/9.0, 3.5 positive thoughts, and 0 negative thoughts. This resulted in 170 observations.

I used ANOVA and linear regression to test H_7, where I included the same dummy variable coding for the conditions and interaction as in the preceding test of H_6. First, I used ANOVA to assess if the pre-generated comment condition affected the number of negative thoughts for participants in the dissatisfaction condition.[5] Results show that pre-generated comments did not have a significant effect ($M_{organic} = 3.27$ vs $M_{pre\text{-}generated} = 3.52$; $F(1, 100) = .46$, $p = .50$) on the number of negative thoughts, thus I do not find support for H_{7a}. Next, I regressed valence on the dummy variables for the experimental conditions. I found a significant main

[5] I use ANOVA rather than linear regression here since none of the satisfied condition participants mentioned negative thoughts, thus giving a coefficient of zero for the pre-generated comment condition (i.e., all variance in number of negative thoughts is attributed to the satisfaction condition).

effect for the dissatisfaction dummy ($\beta = 5.67$, $t = 26.41$, $p < .001$) on valence, as one would expect, but neither the pre-generated comment condition ($\beta = .21$, $t = .52$, $p = .61$) nor the interaction ($\beta = .20$, $t = .42$, $p = .68$) significantly affected valence. Therefore, I fail to find support for the negative effects hypothesized in H_{7b}.

For completeness, I also disclose the results of analysis on how many positive thoughts were mentioned. Regressing positive thoughts on the experimental conditions, I find a significant effect for pre-generated comments ($\beta = 1.22$, $t = 4.01$, $p < .001$), dissatisfaction ($\beta = -3.12$, $t = 19.21$, $p < .001$), and the interaction effect ($\beta = -.77$, $t = 2.08$, $p < .05$). I display the results of the positive comments and valence graphically in Figures 1-6A and 1-6B, respectively.

Discussion

Study 6 answered two important questions: How does a mismatch of pre-generated comment sentiment and customer satisfaction affect sharing, and how much will consumers change the pre-generated comment? The results show that offering pre-generated comments can curtail negative WOM volume and valence. In failing to find support for H_7, Study 6 presents a lack of observable downside for firms who wish to spur positive sentiment online.

General Discussion

Across six studies, I have shown that when firms offer a positive, pre-generated comment to customers, these customers are more likely to share WOM (Studies 3-6). Ideally, firms will offer a single pre-generated comment suggestion (Study 1), and the mechanism by which this occurs is a reduction in cognitive effort on the customer's part (Study 2). Across three studies in the field (Studies 3-5), I show robustness of the positive effect pre-generated comments have on sharing. By using pre-generated comment suggestions, managers can also prime positive behaviors from their customers (Study 5). However, the effect on sharing is contingent on the customer not having an unsatisfactory experience with the firm (Study 6), though fortunately dissatisfied customers will not overreact negatively when they are offered the positive pre-generated comment (Study 6). These results have implications for future marketing research, as well as for practitioners, and I discuss those implications in the following sections.

Marketing Implications

This work has multiple implications for firms and marketing managers. First, I find that current industry practice of suggesting relatively neutral comments about a purchase is sub-optimal and could be more effective. Rather than suggesting neutral comments such as "I just bought Product ABC," firms should work to shape valence by pre-generating positive comments to share online. I find that offering these suggestions results in a higher share percentage relative to organic WOM, which can lead to increased online volume and positive sentiment, as well as customer referrals. Additionally, by offering these pre-generated comments, it allows firms to highlight specific aspects of the customer experience via social media. For example, a hotel may want to mention its prime location one week, while spurring sales for luxury services like spa treatments the next. By suggesting pre-generated comments that mention these different benefits of patronizing the business, the firm will be able to shape the online conversation.

I also find that there is no observable downside to these suggestions in the event of a mismatch where a dissatisfied customer is offered a positive pre-generated comment suggestion. Prior research has shown that customers will retaliate against the firm in cases of dissatisfaction. While this remains true to some degree, offering pre-generated comments can curtail the backlash online. Dissatisfied customers who are offered a pre-generated positive comment were less likely to post online, and even if they chose to do so, the valence was not more negative than it would be in an organic WOM state. Therefore, managers can safely nudge their customers to share positive WOM by lowering effort without fear of backlash.

My findings also give managers a tool to prime desirable behaviors in their customers. By offering pre-generated comments, customers will read what is suggested by the firm, and primes such as excitement can spur additional spending for customers. This strategy could be used in conjunction with a call to action, where managers aim to increase repurchase behaviors or customer referrals. By mentioning these actions in the suggested comments, regardless of whether they are shared or not, the behavioral response will be triggered in the customers and the firm will achieve a desirable outcome.

Theoretical Contributions

My work has several important theoretical contributions. First, I show the importance of assessing customer effort when accounting for WOM behaviors. A rich body of literature has been established on why customers choose to share WOM about their experiences, but prior work has not taken into account how much effort is required by customers to do so. I show that effort is an important consideration for customers, and when effort is reduced they are more likely to share comments online. Future research should capture the amount of effort expended in WOM situations, as this could lead to interesting results and interpretations.

Next, my work adds to current WOM research by addressing the consumer decision-making process. I propose that the consideration set of all possible alternatives and comments that could be mentioned via WOM may overwhelm a customer, and refining the consideration set to fewer comments will increase the likelihood that these customers share WOM. My work shows that offering pre-generated suggestions requires less effort from customers, and that one suggested comment that they can accept or reject takes the least amount of effort. Therefore, this research advances the literature on the consideration set in a new context.

Finally, my research adds to the literature on how customer satisfaction affects WOM sharing behavior. Consistent with prior work, I expected that in cases of dissatisfaction, customers who are offered a positive pre-generated comment would retaliate against the firm. I find that this is not the case, and if the comments are altered the valence is no different than organic negative WOM. I also find a unique interaction when effort is considered as a WOM dimension. When the positive comment matches the customer's experience, they are more likely to share WOM, but when customers are dissatisfied their sharing likelihood drops. This interaction provides a starting point for future research that assesses how satisfaction and effort interact in WOM situations.

Limitations and Future Research

I acknowledge a few limitations of my work. First, while I tested the main effects of pre-generated comments on posting behaviors, I did not include every context in which a customer may share WOM. Future research may expand on this by testing potential moderators of when and where pre-generated comments are offered. Second, I did not find a significant difference in spending behaviors when priming was used, relative to organic WOM. While the benefits of increased sharing for pre-generated comments are consistent, perhaps better results may be obtained from other forms of priming. Additional work on priming behaviors via pre-generated comments could shed light on this issue. Finally, while I did not find an increase in negative WOM or stronger negative valence for comments shared by dissatisfied customers, there may be other potential negative side effects. My assumption is that dissatisfied customers would not purchase from the firm again, regardless of the WOM type, but there may be some dissatisfied customers who will give the firm another chance if they share WOM organically versus are offered a pre-generated comment.

APPENDICES

APPENDIX A: TABLES

Table 1-1
Overview of Studies

Study	Hypothesis Tested (Replicated)	Expected Contribution	Context (n)
1	H_1, H_2	Pre-generated comments require less cognitive effort than organic WOM; One pre-generated suggestion requires the least amount of effort.	Online Purchase of Headphones (367)
2	H_3	Effort mediates the relationship between pre-generated comment suggestions and posting behaviors.	Online Purchase of Tool Set (191)
3	H_4	Positive pre-generated comments significantly affect sharing intentions when used in an e-mail to customers.	Gym Members (966)
4	H_4	The effects of pre-generated comments on sharing intentions is generalizable across contexts (an end-of-survey solicitation) as well as when accounting for control variables.	Restaurant Concept Test (476)
5	H_5 (H_4)	Pre-generated comments are able to prime behaviors in customers by highlighting relevant, positive aspects of the customer experience.	Movie Experience (1500)
6	H_6, H_7 (H_4)	Accounting for satisfaction is critical: A mismatch between satisfaction levels and comment sentiment will decrease WOM sharing and increase customer revenge via negative WOM.	Hotel Experience (428)

Table 1-2

Study 1 Results per Condition

Condition	**Cell Size**	**Time**		**CES**	
		Mean	*SD*	*Mean*	*SD*
Organic	79	69.02	42.90	3.30	0.91
One Comment	87	15.91	10.62	2.16	1.15
Three Comments	84	36.49	25.66	2.82	1.27
Five Comments	87	39.80	21.37	2.80	1.32

Notes: CES = Customer Effort Score; Time measured in seconds; n = 337

Table 1-3

Study 4 Results

Predictor	Model 1 Estimate		Model 1 S.E.	Model 2 Estimate		Model 2 S.E.
Dependent Variable = if Share						
Intercept	-13.12	**	(2.70)	-14.13	**	(2.84)
Attachment to Social Media	-0.07		(.22)	-0.06		(.22)
Desire for Self Enhancement	0.28		(.30)	0.35		(.31)
Anticipated Satisfaction	1.10	**	(.38)	1.04	**	(.38)
Age	0.03		(.02)	0.04	*	(.02)
if Twitter user	1.56	**	(.59)	1.56	**	(.59)
if Baltimore (dummy)	-0.3		(.56)	-0.25		(.57)
if Twin Cities (dummy)	-0.11		(.03)	-0.09		(.62)
if Pre-generated Comment				1.24	*	(.56)
Model χ^2	33.71	**		39.37	**	
Model $\Delta\chi2$				5.66	*	

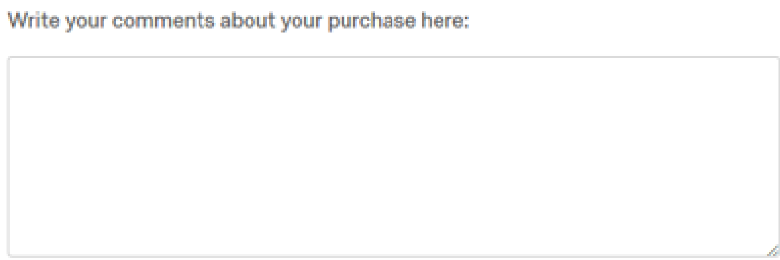
Notes: *n* = 476; * = *p* < .05; ** = *p* < .01

APPENDIX B: FIGURES

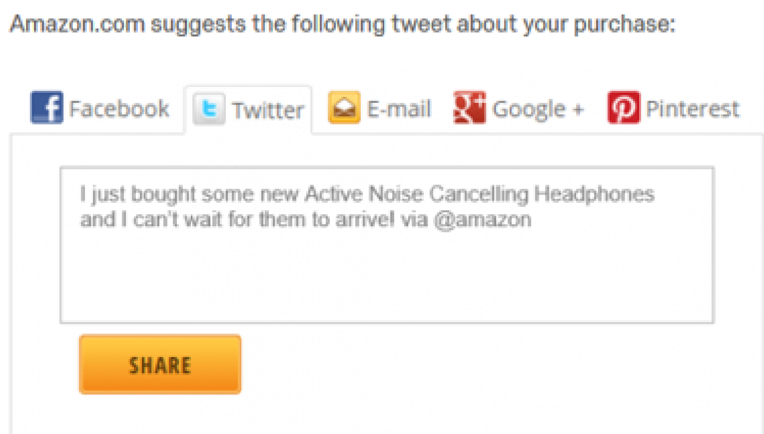
Figure 1-1

Study 1 Manipulations

Organic Condition



Baseline manipulation: One pre-generated comment



Additional comments for three suggested condition

"The new Active Noise Cancelling headphones I just ordered look awesome! I'm looking forward to them arriving! via @amazon"

"I ordered some new Active Noise Cancelling headphones on Amazon. They look great and I can't wait to listen to my favorite music with them! via @amazon."

Additional comments for five suggested condition

"I placed an order for new headphones on Amazon and I can't wait to use them! via @amazon"

"Check out these new headphones I bought through Amazon. They have Active Noise Cancelling and look really comfortable. I can't wait for them to arrive! via @amazon."

Figure 1-2A

Study 1 Results: Effort Score

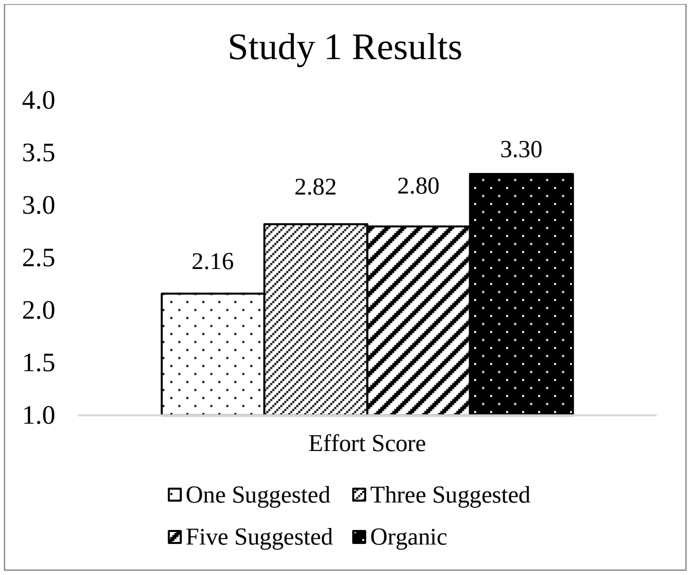


Figure 1-2B

Study 1 Results: Time (Seconds)

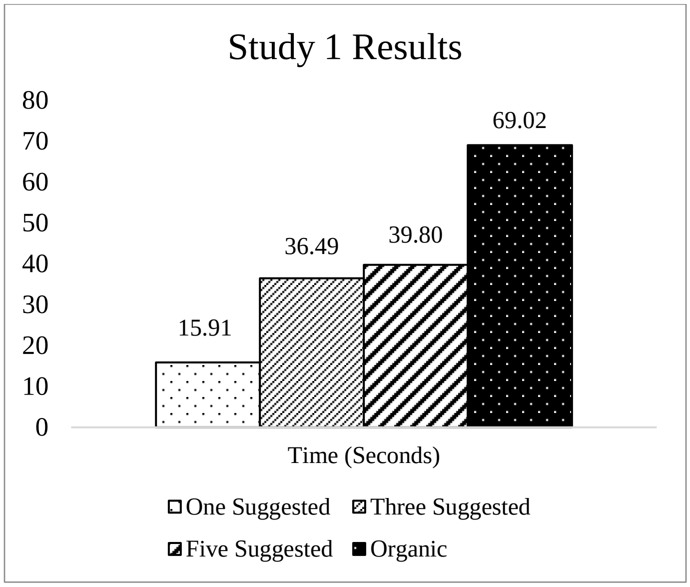


Figure 1-3

Study 4 Twitter Page Example

Figure 1-4

Study 5 Results

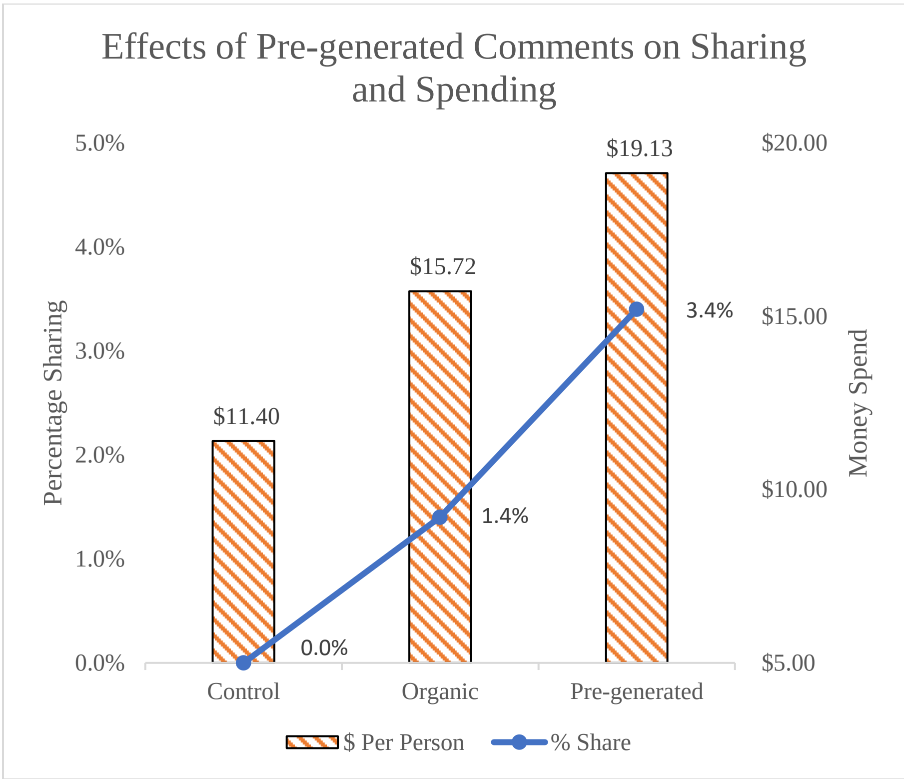
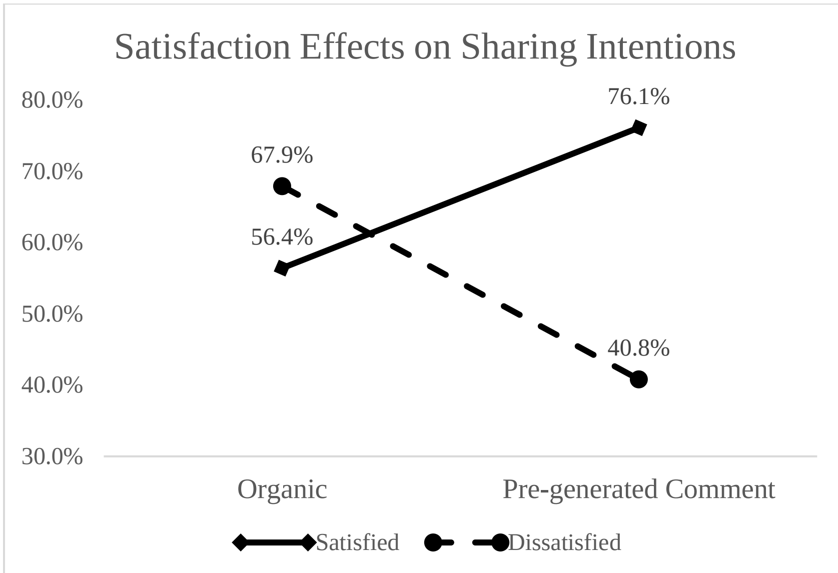


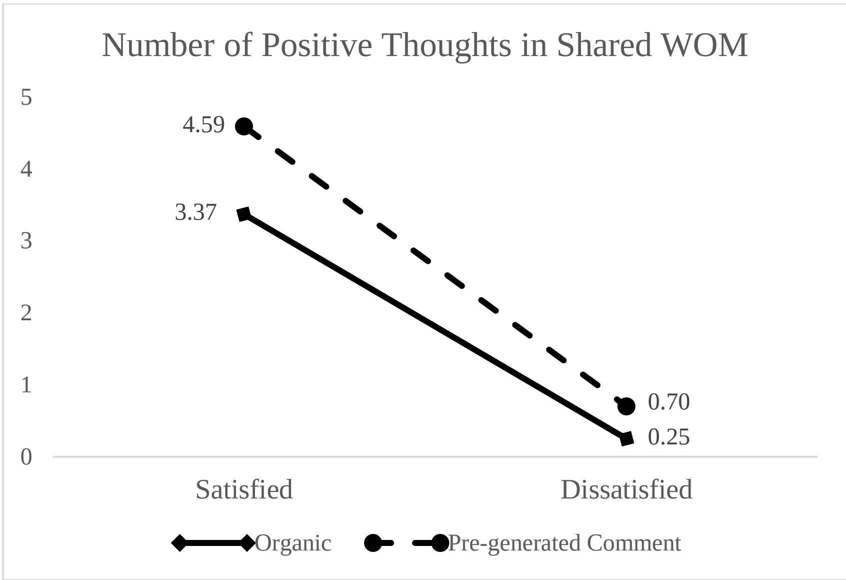
Figure 1-5

Study 6 Interaction Plot



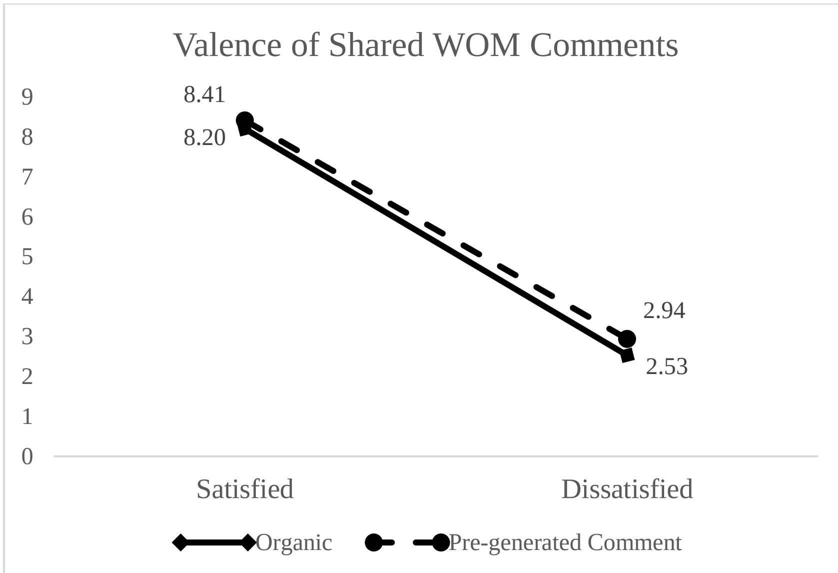
Figures 1-6A

Study 6: Number of Positive Thoughts in Shared WOM



Figures 1-6B

Study 6: Valence of Shared WOM



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ESSAY TWO

Consumer Spending Following the Posting of an Online Customer Review

Abstract

Online customer reviews (OCRs) are the new norm for e-commerce, with 97% of consumers needing to read at least two reviews before they trust a business. An abundance of research has investigated how OCRs are perceived and why certain consumers elect to write OCRs, but little research has investigated the impact of OCR-writing on the behavior of the reviewers themselves. This is surprising because reviewers are content generators and effectively half of the consumer-to-consumer exchange of information. The author presents a conceptual model to assess how the act of posting an OCR influences future behaviors of the reviewers. Using data from over 60,000 customers of a large quick-service restaurant, this research shows that when customers post an OCR, they are more likely to exhibit differentially higher spending and transactions than those who did not. The author also tests moderating effects of this relationship, showing that relationship length affects these outcome variables. In a follow-up experiment, the author shows that managerial responses to OCRs increase interactional justice, which proves to be a mediator in the relationship between posting and financial outcomes. These results indicate that firms must pay attention not only to the OCRs themselves, but to the customers who take the time to write them as well.

Introduction

Online customer reviews (OCRs) are a critical component to business success. With 82% of consumers reading OCRs before purchases (Smith and Anderson 2016) and eight in ten consumers trusting online reviews as much as a personal recommendation (eMarketer 2017), it's no surprise that a single review website, Yelp.com, has over 184 million cumulative reviews posted by the first quarter of 2019 (Yelp 2019). The importance of OCRs has driven researchers to examine the relevance of OCR characteristics (i.e., volume, valence, and variance) on sales, and a recent meta-analysis of 96 studies has found that volume is more impactful than valence, and high variability can depress sales (Babic Rosario et al. 2016). Yet, despite this large quantity of literature focusing on OCRs' effects on sales or why consumers feel the need to post their opinions online (e.g., Berger 2014, Cheema and Kaikati 2010; Chen 2017), little research has taken into account how the reviewer will behave once they choose to post an OCR. This is an important topic, since 51% of consumers at least occasionally post reviews online about products and services, and between 5-10% of a firm's customers will almost always post a review (Smith and Anderson 2016; Weise 2017; Yelp Blog 2011).

The current OCR research literature, while expansive, has failed to account for half of the consumer-to-consumer interaction (i.e., the reviewer's behavior). This underdevelopment is surprising given the hundreds of millions of consumers that post OCRs. The two literature streams that come closest to analyzing the content generators of OCRs are the service recovery literature and work done on customer engagement. With issues of service recovery, once consumers voice their dissatisfaction with the firm, successful efforts by the firm to recover have been shown to engender a stronger relationship via satisfaction (Bitner, Booms, and Tetreault

1990; De Matos et al. 2007), though a meta-analysis shows no significant lift in repurchase intentions after recovery (De Matos et al. 2007). Customer engagement, which captures customer activities with a focus on a brand or firm after purchases are made (Van Doorn et al. 2010), comprises of activities such as customer referrals and influence (Kumar et al. 2010). This influence customers have on others is similar to OCRs, in that this influence goes beyond close friends and can affect firm profits (Kumar and Pansari 2016), but, to date, engagement research has focused on its effects on overall performance and has not split out the effects on the individual customers who write OCRs and spread influence. My goal is to expand the prior service recovery and customer engagement literature by assessing future purchase behaviors for all consumers that post OCRs, not only those who are dissatisfied and participate in complaining behaviors, and to split out these effects on an individual reviewer level.

To examine the effects of writing an OCR on reviewer behaviors, I conduct two studies. First, I leverage data from a large retailer that tracks participation in an online feedback forum in conjunction with individual spending. Next, I conduct a separate lab experiment to make inferences about reviewer behavior, determine causality, and measure perceptions in relation to OCRs. Based on the tenants of the commitment-consistency principle (Cialdini 2007), my first study confirms that if a consumer is an active reviewer, they behave consistently by spending more with the firm while also patronizing the business more often. Next, I test how relationship length may moderate these effects, and I find that longer relationships amplify the effects, substantially increasing interactions and spending with the firm. Finally, I show that managerial acknowledgement is valued by consumers, where replies to OCRs increase interactional justice, which mediates the effects between posting a review and consumer spending.

I make several contributions. First, my research provides an in-depth examination of reviewer behaviors, specifically through their future purchase behaviors. By using sample matching procedures and longitudinal data, I am able to show robust results for the main effects of OCR-writing on reviewer behaviors, as well as the relationship length moderator. Second, I show that it is in the benefit of the firm to encourage consumers to actively voice their opinions, especially those who have a longstanding relationship with the firm. Third, I show that interactional justice is an important mediator in the writing-purchasing relationship, so it is crucial for managers to stay involved and engage with their customers. Taken together, the results of my paper show that managers must pay more attention to the reviewers themselves, not only the OCR content and its readers, to increase firm sales in the future.

Literature Review

I begin by reviewing the online customer review (OCR) literature and highlighting how most of the OCR research has focused on OCR valence, volume, and variance in relation to sales. I then demonstrate the gap in the literature regarding the effects of writing an OCR on the reviewer themselves. Next, I introduce my theoretical framework, which is based on the commitment-consistency principle (Cialdini 2007).

Relevant OCR Research Background

Research in marketing has shown that OCRs provide value to firms across two intertwined research streams: OCRs' overall impact on sales, as well as the theoretical underpinnings that justify why certain OCR characteristics influence OCR readers' (i.e., the audience) purchases. The earliest research into OCRs focused on establishing that variance in the online conversation has explanatory power in contexts relevant to marketers. For example, Godes and Mayzlin (2004) find that the online conversation can explain variance in TV ratings. Other early work established the robustness of these findings. OCRs and recommendation styles influence behavior for consumers reading reviews (Senecal and Nantel 2004), and Chevalier and Mayzlin (2006) demonstrated that OCRs affect book sales online. Perhaps more importantly, Chevalier and Mayzlin (2006) established that consumers do not only pay attention to star ratings—they also rely on review text when making decisions. While Chevalier and Mayzlin (2006) show that negative OCRs have more impact on sales than positive OCRs, Clemons, Gao, and Hitt's (2006) work found that positive OCRs have more predictive power for new product growth than negative OCRs. The first major investigations into the power of OCR volume found that the power lies in its social influence (Salganik, Dodds, and Watts 2006; Salganik and Watts 2008), where more reviews will reduce customer uncertainty (Ho-Dac, Carson, and Moore 2013). Liu (2006) found similar results when studying OCR volume, and showed that for box office revenues, the volume of the online conversation has more predictive power than valence.

Once these effects were established, later OCR research took a more nuanced approach. Some researchers have continued to dissect the extremes of OCR valence and attempted to distinguish which type of OCR (i.e., positive versus negative) has a stronger effect on sales. Empirical studies have found that negative OCRs have a much stronger impact on sales than positive OCRs (e.g., Cui, Lui, and Guo 2012; Yang and Mai 2010), which is likely due to a "negativity effect," where negative information "stands out and is weighted more heavily than positive information" (van Doorn and Verhoef 2008, p. 126; Kanouse and Hanson 1972; Mittal, Ross, and Baldasare 1998). Others have looked at the relationship between volume, valence, and variance to see which is the strongest predictor or has a moderating effect on the others. Khare, Labrecque, and Asare (2011, p. 111) concluded that OCR volume is a “decision-making cue,” and when volume is high it amplifies outcomes of OCR valence. Considering all three traits, Sun (2012) found that the effects of OCR variance on sales is dependent on the overall valence, where higher variance will increase sales for poorly-rated products (e.g., lower than 4.1 stars on Amazon) since they are perceived as products either loved or hated. Most recently, when accounting for valence in conjunction with volume and variance, it appears valence directly affects consumer choice, while volume and variance moderate this effect (Kostyra et al. 2016).

Finally, researchers have also explored how the website where OCRs appear will influence the OCR’s effectiveness. Senecal and Nantel’s (2004) early work found no difference based on whether an OCR was published on a retailer or third-party website, though later work determined that the affiliation of the website where the OCR is posted will affect the magnitude of the OCR’s impact. The three avenues where consumers will typically see OCRs for a specific product are the retailer’s website (a.k.a., internal OCRs), a third-party website (a.k.a., external OCRs), or an expert, critic, or professional review (Floyd et al. 2014). Gu, Park, and Konana (2012) tested the difference in internal versus external OCRs for high-involvement products, and they found that external OCRs have a much higher impact than internal OCRs. Finally, a recent meta-analysis by Floyd and colleagues (2014) found that the three most impactful OCR characteristics were critics’ reviews, third-party reviews, and review valence, respectively, which demonstrates the importance for managers to not only encourage customers to post OCRs on their own website, but on external websites as well.

Table 2-1 accounts for the research relevant to my work. As I have demonstrated in my review of the literature, there is clearly a need for a shift in the focus of OCR research. Marketers are well-aware of the effects of OCRs and how they are viewed, but when over 26,000 reviews are posted every minute to Yelp.com alone (James 2014), investigation into reviewer behavior post-OCR is warranted.

The Commitment-Consistency Principle

A large swath of the commitment literature is built on the idea of consistency, where individuals seek to avoid cognitive dissonance by being consistent with both their internal beliefs and subsequent behavior (Cialdini 2007; Festinger 1962). This is the nature of the commitment-consistency principle (Cialdini 2007). Internally, conflicting thoughts create discomfort (Festinger 1962) and people are likely to avoid this psychological tension by resisting information that would distort their current perceptions (Crosby and Taylor 1983), especially since evaluating unfamiliar viewpoints requires a psychological cost of cognitive effort and reorganization (Festinger 1962; Salancik 1977). Once these internal beliefs are established, there is a firm commitment, and people are likely to behave in a way that is consistent with those beliefs to "self-signal" that they are in line with their perceived self-identity (Baca-Motes et al. 2012, p. 1071-72). This behavior is not only a signal to the person themselves, though. Behavior is public, albeit to varying degrees, and the strength of advocacy for these beliefs is dependent on how "public" these commitments are (Cialdini 2007; Deutsch and Gerard 1955). This publicness is important, since people desire to appear consistent in the eyes of others. Thus, while private commitments still induce consistent behavior, public commitments have a stronger effect on behavior than private ones (Cialdini and Trost 1998).

The commitment-consistency principle has seen some application in marketing. Consumers that actively commit to a charitable cause (e.g., environmentally-friendly products) will show increased preference for products linked to that cause, despite minor cost increases (Vaidyanathan and Aggarwal 2005). Similarly, if consumers give a brief commitment to ecofriendly behavior at hotel check-in—and are given a lapel pin signifying commitment—they are more likely to act on their commitment (Baca-Motes et al. 2013). Garnefeld and colleagues (2013) showed that customers that have committed to taking part in a firm's referral program will have increased loyalty (i.e., reduced churn). In a sales context, a salesperson will utilize this principle to secure a commitment at one price and be reasonably sure the customer will not back out of their commitment when a modified deal is presented (Cialdini et al. 1978).

Despite extensive past research into how valence, volume, and variance affect product sales and the audience of OCRs, as well as work in marketing using the commitment-consistency principle and customer loyalty/churn (i.e., Garnefeld et al. 2013), my goal is to stitch together these subsections of marketing research to explore how reviewers behave when they post an OCR online. My research is among the first to shift the focus of OCR research to the reviewer-level of analysis and test individual sales-level outcomes. Recent work has shown that consumers who write emotional reviews are more inclined to make impulse purchases in the future (Motyka et al. 2018), but I expand on this work to examine purchases across all reviews and types of purchases. I examine how the act of posting an OCR affects future purchases by the reviewer, and I also contribute to the commitment-consistency literature by establishing another context where consumers will behave in accordance with their own declared behavior.

Hypothesis Development

Effect of Review Writing on Future Purchases

Online customer reviews (OCRs) are a tool for consumers to share their personal experience and level of satisfaction with others. There is no shortage of reasons for why consumers will post reviews online. Some consumers share their opinions based on their personal traits, like self-enhancement (e.g., Cheema and Kaikati 2010; Chen 2017) or to identity-signal (e.g., Berger 2014; Packard and Wooten 2013), while others feel the need to regulate their emotions through venting to feel better (e.g., Anderson 1998; Wetzer, Zeelenberg, and Pieters 2007), take vengeance to punish the company (e.g., Gregoire and Fisher 2008; Gregoire, Tripp, and Legoux 2009), or encourage rehearsal as a way to relive a positive experience (e.g., Hennig-Thurau et al. 2004; Rime 2009). Taken together, the combination of these consumer motivations shapes OCR valence (Berger 2014).

Once the initial step of writing the OCR has been completed, at this point the commitment-consistency principle (Cialdini 2007) should manifest. When a customer has invested the effort to share their thoughts and experience with others, internally this should trigger a sense of involvement with the firm—the customer is now invested in their relationship with the firm and any future interactions which may take place. Externally, the customer has put their reputation on the line by publicly declaring their commitment to the firm they are writing about. I expect that this internal and external commitment will drive the customer to behave consistently with their increased sense of involvement, which will be done to avoid internal conflict or being perceived as a fraud by others who have read their OCR. This commitment will express itself via increased visit frequency with the firm as well as increased customer spending. Formally, I hypothesize:

> H_1: Customers who post an OCR will show increased a) purchase frequency and b) spending compared to customers who do not post an OCR.

Moderating Effects: Customer Loyalty and Managerial Responses

Relationships with firms develop over time for consumers, and over a series of interactions firms strive to increase the investment of their customers, which increases dependency and switching costs (Berry and Parasuraman 2004; Dick and Basu 1994). Switching costs are what customers perceive as the sacrifice needed to switch to a competitor (Ping 1993), and they can be either economic or psychological (Morgan and Hunt 1994; Sharma and Patterson 2000). Economically, firms can introduce switching costs by introducing loyalty programs that reward relationship length, which would increase the switching costs if a customer were to choose to leave (Verhoef 2003). However, in the absence of a loyalty program, there are still significant switching costs if a customer wishes to switch providers. Over time, encounters with a firm become more stable, predictable, and less prone to frustration. This will result in the creation of psychological switching costs that will make the customers more loyal (Dick and Basu 1994) and less likely to switch to alternatives. Therefore, as the length of the customer-firm relationship increases, there should be an inherent increase in customer loyalty as well.

As a relationship with a brand matures, it is likely that a stronger self-brand connection develops. Self-brand connection is the "extent to which individuals have incorporated brands into their self-concept" (Escalas and Bettman 2003, p. 340), and it is a way in which consumers shape their identity while also communicating their image to others (Escalas 2004). A stronger self-brand connection is more likely to develop over time, and when consumers post about their experience with the brand it also signals their identity. Identity-signaling has been identified as one reason consumers share word of mouth (Berger 2014). While consumers can signal their identity with publicly visible items that have a style or bear a logo, not all firms have such an option (e.g., service providers). Instead, customers must convey their identity via word of mouth by sharing their opinion with others.

Writing a review should be more meaningful for customers who have higher self-brand connection, as the opinion they share will be more strongly tied to their own identity. It should be expected that when a declaration of support is made for a brand that more closely reflects one's own identity, the customer is more likely to follow through. I therefore expect that the length of the relationship with the firm will moderate the main effects of writing a review on spending. There should be an amplification as the length of the relationship increases.

Thus, I hypothesize:

> H_2: Relationship length moderates the effects of review writing on consumer behavior, such that a) purchase frequency and b) consumer spending are greater as relationship length increases.

Managerial responses to consumer voice should have an influence on consumer attitudes and behavior, especially since 30% of consumers believe a firm's response to OCRs is important (BrightLocal 2017). One of the most prevalent examples of firm responses to consumers is in the service environment, where following a service failure the compensation, response speed, apology, and initiation of contact influence customer satisfaction (Smith, Bolton, and Wagner 1999). Yet, when a service failure occurs, firms may be unaware since consumers often elect not to express their dissatisfaction (Stephen and Gwinner 1998; Voorhees, Brady, and Horowitz 2006). These challenges may also manifest in a retail context, since once a consumer purchases a product, dissatisfaction may not be observable until a consumer files a complaint or posts an OCR. This disables the firm's ability to recover proactively, which can be problematic since early research has shown that proactive intervention is an important in the service recovery

(Hart, Heskett, and Sasser 1990; Kelley, Hoffman, and Davis 1993). However, with the development of the Internet, more decisions must be made before communicating with consumers online. In an OCR context, it is still challenging to observe firm failure or consumer dissatisfaction before a complaint is filed or an OCR is written, but the conversation channel and tone of response must be considered since they affect consumers' brand evaluation. Specifically, "human voice" in responses is beneficial, and this benefit holds in both proactive and reactive instances when the conversation occurs on a brand-generated platform (Van Noort and Willemsen 2011, p. 138). This is good news for managers: Responses to OCRs on their website are always welcome, provided they do not sound automated.

While relevant in the domain of service recovery, these previous examples are all under the umbrella of failures by the firm. My research asks the question: What role do managerial responses play across all forms of online sentiment? Theoretically, I expect that when a firm responds to an OCR on their website, repurchase intentions will increase due to interactional justice. Interactional justice involves communication behavior, and accounts for the expectations of truth and respect in communication (Bies and Moag 1986; Bies and Shapiro 1987), as well as the fairness people receive during the execution of procedures (Gilliliand 1993). Past research has shown that when firms reach out to customers, future satisfaction is increased through perceptions of interactional justice (Goodwin and Ross 1992; Smith, Bolton, and Wagner 1999; Tax, Brown, and Chandrashekaran 1998), although again these instances were during service failure and when an apology was issued. However, interactional justice is broad, and deals with communication aspects such as honesty, politeness, effort, and empathy (Tax, Brown, and Chandrashekaran 1998). My expectation is that when a firm responds to a consumer's OCR, this will signal a desire to communicate respectfully, either through acknowledgement of a compliment or apology for a failure. This response, when compared to a non-response from the firm, will be a signal to the consumer that the firm cares about respectful communication. However, if a firm fails to respond, a customer may feel ignored and their perceptions of interactional justice will be much lower than if they had not made any comment at all. Following this, it's likely that interactional justice influences future spending behavior; thus, I expect that interactional justice is a mediating mechanism between writing an OCR and consumer spending. I hypothesize:

> H_3: The effects of posting a review on consumer spending are mediated by perceptions of interactional justice.

Study 1

Study 1 tests hypotheses 1 and 2. I use data from a quick-serve restaurant including almost 3 million transactions across over 60,000 loyalty program members. Coarsened Exact Matching (Blackwell et al. 2009) is used to develop treatment and control conditions and then I proceed with linear regression analysis to assess the effects of writing an OCR and how relationship length moderates these effects.

Data and Measurement

The data set is obtained from a quick-service restaurant. The data contains a random sampling of customers and their purchases across a two-year period. In total, the data includes 2,920,762 transactions across 60,123 unique customers. The firm provided data on the total yearly, monthly, and weekly expenditures, as well as a transaction counter across the two-year time period. In addition to spending data, I operationalize relationship length based on data from the firm that indicated the number of days since a customer enrolled in their retail payment system. Discussions with firm executives suggested that this data point is an effective proxy for customer loyalty and relationship strength. I determine whether the customer is a reviewer by their membership in the firm's online community. The sole purpose for joining this community is to post reviews, as no registration was required to read reviews. Thus, it is a reliable flag to identify individuals who post reviews (dummy coded, where member = 1).

The data also include a number of additional variables which I use in my matching procedures (described below). This includes the customer's age, whether they use the mobile app, if they chose to auto-reload their account, if they opted in for e-mail messages, and if they opted in for mail promotions. For my analysis, I focus specifically on the second year of data (time = *t*), which has two benefits. First, I am able to use the average cart size from time *t-1* as a matching variable to represent potential differences in customer traits such as income or purchase habits. Also, this allows me to control for the dependent variable (i.e., transactions or expenditures) in the previous time period, and this lag will address any unobserved differences which may not be captured with the other variables in the model. Table 2-2 provides descriptive statistics and correlations for the data.

I proceed with my analysis as follows: I discuss the analysis and results using the entirety of the data set to provide a benchmark with which to compare the matched-sample results. Then I discuss my matching procedures and the characteristics of the new sample to be used for analysis. Finally, I move on to present the more robust analysis using Coarsened Exact Matching (Blackwell et al. 2009), which is my formal test of the hypotheses.

Pre-matching Analysis and Results

Prior to conducting the matching procedures (described below), I conduct an ordinary least squares regression analysis using the complete data set. I conducted this analysis stepwise using three models for each of the two dependent variables (expenditures and transactions at time *t*). First, I included only the reviewer main effect as the sole predictor of the dependent variables. Second, I added in the standardized relationship length predictor, as well as its interaction with the reviewer dummy variable, which was calculated using the standardized relationship score times the reviewer dummy. Third, I included the relevant control variable from the previous period (i.e., $expenditures_{t-1}$ or $transactions_{t-1}$) to account for unobserved differences which may be present but unaccounted for in the other variables. Following the third step, I conducted a Breusch-Pagan test and found significant heteroskedasticity for the models predicting both dependent variables ($p < .001$ in both cases), thus I took one final step and included robust standard errors in my analysis. After this final step, I find a significant main effect for the reviewer dummy ($\beta = 87.32$, $p < .01$), loyalty ($\beta = 29.22$, $p < .01$), and the interaction ($\beta = 68.89$, $p < .01$) on expenditures. I find similar results with the transactions dependent variable regarding reviewer status ($\beta = 19.10$, $p < .01$), loyalty ($\beta = 7.11$, $p < .01$), and the interaction ($\beta = 16.89$, $p < .01$). Full results are displayed in Table 2-3.

Matching Procedure, Analysis, and Results

Matching procedures. While the previous results are promising, an issue of primary concern with the data for Study 1 is that consumers self-select whether they choose to post OCRs or not. Ideally, there would be random assignment to the treatment condition where consumers post an OCR (and the control group where they did not), but when using secondary data this is not always possible. If this self-selection is not addressed, there could be substantial bias in my results (Rosenbaum 2002). To address this bias, I employ Coarsened Exact Matching (CEM; Blackwell et al. 2009) using Stata. CEM works to reduce imbalances in the data between treated and control groups by matching observations on traits specified by the researcher, and through pruning of the data, the analysis will be less prone to statistical bias.

I use six variables for the matching procedure. I first note that the dependent variables are in time *t* and I use those same variables at time *t-1* as controls, which means they should not be used for matching procedures. However, I do include average cart size in time *t-1* since this could contain relevant purchase habits over time. I also include customer age and dummy variables for whether the customer would auto-reload their program card, whether they used the mobile app, if they opted in for e-mail messages, and if they opted in for mail promotions. As a benchmark, I first assessed the overall imbalance of the data using these six variables. The imbalance is measured as the joint distribution of all the variables, and merely served as a comparison for the post-CEM data. The initial imbalance is 0.942.

I test two different CEM methods for matching the data. I first use the automated CEM method, which reduces the imbalance (0.687). However, I find that *k*-to-*k* matching (which produces an equal number of treatment and control observations) provides significantly more imbalance reduction (0.512). In this sample, the imbalance is reduced to zero across the auto-reload, mobile app, e-mail, and mail dummies. The final difference in mean age was 0.04 and average cart size in time *t-1* was 0.14. Thus, I proceed with the *k*-to-*k* CEM sample for the analysis, which includes 2,494 total observations, equally split between reviewers and control customers.

Analysis and Results. I proceed with the analysis of the matched data similar to my process using the pre-matched data. I report full results in Table 2-4. Using the matched data, I regressed the dependent variables on the reviewer dummy, relationship length, the interaction, and the relevant *t-1* control variable. I then tested for heteroskedasticity with the Breusch-Pagan test and results were significant for both models ($p < .001$), thus I proceed using robust standard errors. I also checked for multicollinearity using the variance inflation factor (VIF), and in both models the VIF for all variables was less than 10, indicating no issues with multicollinearity (Kutner et al. 2005).

The regression results show that reviewers have significantly greater expenditures over the year ($\beta = 63.86$, $p < .01$) than non-reviewers. Relationship length was not significant ($\beta = 10.49$, $p > .50$), but the interaction was significant ($\beta = 62.04$, $p < .05$). With transactions as the dependent variable, reviewer status was significant ($\beta = 12.98$, $p < .01$), relationship length was not significant ($\beta = 0.74$, $p > .50$), but the interaction was significant ($\beta = 16.97$, $p < .05$). These interactions are displayed graphically in Figure 2-1A and 2-1B. Based on these results, I find support for H_{1a} and H_{1b}, as well as H_{2a} and H_{2b}.

Discussion

The results of Study 1 show robust support for the effects of writing a review on future spending with the firm. Following a matching procedure to reduce imbalance in the sample, I found that customers who write reviews spend significantly more money than those who do not over the course of a year. The same is true for the number of transactions, indicating that once a customer posts a review they will patronize the firm more often. I also find a significant moderating effect of relationship length. This interaction between reviewers and their tenure with the firm shows that it is beneficial to encourage reviews from their most loyal members, since this can yield the highest return. One limitation is that I do not test causality with the data and analysis, and I address that, as well as my third hypothesis, in Study 2.

Study 2

The purpose of Study 2 was to test the causality of writing OCRs and its influence on future spending in a controlled environment. One limitation of Study 1 is that, while I approach random assignment via matching, the study does not determine causality. Study 2 addresses this limitation. In addition, I explore how a manager response to an OCR will affect perceptions of interactional justice and subsequently future spending. Study 2 was conducted with data collected from Amazon's Mechanical Turk (MTurk).

Design and Method

Study 2 uses a 3 (reviews: control vs. review written vs. review written and reply) x 1 experimental design. Participants were told that a new coffee shop has opened near where they live, which they found out about via Yelp. At the time, the coffee shop didn't have many reviews, so the participants make plans with their friends to give the new place a chance. They were then told about their experience at the coffee shop, which I describe next. The scenario mentioned the nice décor and friendly cashier that greeted them once they arrived. There is a short line and the drinks are slightly more expensive than what they are used to, but it's not a significant factor in their decision. Once their coffee is ready, the barista brings it to the participant and their friends. Their coffee tastes different than they are used to. It could be because the coffee is an unusual roast, or something else, but everyone else's coffee seems fine. They chat with each other and then the participant leaves.

The manipulation took place following the description of the customer experience. In the control condition, there was no further information in the scenario. In the "review written" condition, the participant goes back to the Yelp page later that evening and they decide to write a review. The review is about a paragraph long and echoes the customer experience, pointing out the pros and cons of the experience. They decide to post their review to Yelp. In the "review written and reply" condition, the same review is posted, but the next day the participant receives a reply from the manager. The reply apologizes for the suboptimal experience and mentions that they will try to take better care of them the next time they stop by.

Following the scenario, I surveyed participants on variables relevant to my study. First, I measure interactional justice with the four scale items from Smith, Bolton, and Wagner (1999) on a seven-point scale, where 1 = "Strongly Disagree" and 7 = "Strongly Agree." Next, I measured repurchase intentions with items from Hess, Ganesan, and Klein (2003), also using a seven-point scale. I conducted a check where I asked participants to identify what they were doing, and at the end of the survey I asked demographic information.

My goal was to collect a minimum of 60 responses per condition. I collected 223 responses via MTurk. I then removed incomplete surveys and those that did not pass the manipulation checks. In total, this resulted in a final sample size of 198. The sample had a mean age of 37.72 and 51% of the sample was female.

Results

Main Effects. ANOVA was used to assess the main effects of the conditions on interpersonal justice and repurchase intentions. Results indicate an overall significant difference for interpersonal justice ($F(2, 195) = 24.99$, $p < .001$) and repurchase intentions ($F(2, 195) = 27.67$, $p < .001$). The means and standard deviations are reported in Table 2-5. These significant differences allow me to proceed with the rest of the analysis.

To further examine the hypothesized effect of OCR-writing on repurchase intentions I used planned contrasts. I compared the effects of the control condition to the two review conditions, which were grouped together. Using a t-test, I find a significant difference between the conditions (M_{Control} = 3.13, M_{Written} = 4.46; t = 6.45, p < .001). This result provides additional support for H_1 as a test of causality between OCR-writing and future spending.

For completeness, I conduct three more planned contrasts and report the 95% confidence interval for the estimate of the difference. First, I find a significant difference between the control condition and the written condition (Estimate = .94, CI_{95} = [.48, 1.40]). Second, there is a significant difference in the written vs. written and reply conditions (Estimate = .78, CI_{95} = [.33, 1.23]). Finally, I also find a significant difference between the control condition and the written and reply condition (Estimate = 1.72, CI_{95} = [1.26, 2.17]). Next, I proceed with mediation analysis to formally test H_3.

Mediation Analysis. To test the hypothesized mediation effect of interpersonal justice between review writing and future purchases, I used PROCESS (Hayes 2012) model 4 with 10,000 bootstrapped samples. For the independent variable, I treated the conditions as multicategorical where the control group was the base condition and the two review written conditions were represented with indicator coding. I report the 95% bias-corrected confidence intervals and full results are displayed in Table 2-6.

First, I find a significant direct effect of the conditions on interpersonal justice (written: b = -.54, SE = .19, CI_{95} = [-.92, -.17]; written and reply: b = .79, SE = .19, CI_{95} = [.41, 1.16]). Second, I find significant effects or interpersonal justice on repurchase intentions (b = .49, SE = .08, CI_{95} = [.33, .64]) while controlling for the experimental conditions. Finally, the paths from the conditions to repurchase intentions remained significant while accounting for the interpersonal justice mediator (written: b = 1.20, SE = .22, CI_{95} = [.77, 1.63]; written and reply: b = 1.33, SE = .22, CI_{95} = [.90, 1.77]).

The mediation assessment showed a significant indirect effect via both written conditions (written: b = -.26, SE = .10, CI_{95} = [-.47, -.09]; written and reply: b = .38, SE = .12, CI_{95} = [.17, .64]). The total effects of the conditions on repurchase intentions were also significant (written: b = .94, SE = .23, CI_{95} = [.48, 1.39]; written and reply: b = 1.72, SE = .23, CI_{95} = [1.26, 2.17]). Based on the significant indirect effect, I find support for H_3.

Discussion

Study 2 makes two contributions to my research. First, it tests causality by explicitly manipulating whether the customer posts a review or not. By showing that the effect still holds in a controlled environment, this further supports hypothesis 1. Second, I show that interpersonal justice is a key mediator in the relationship between reviews and repurchase intentions. Interpersonal justice is affected by managerial responses, and customers likely feel ignored if there is no response to their review—which holds when compared to the control group. Thus, managers should take care and make thoughtful replies to their customers online if they wish to see the benefits of increased spending following an online review.

General Discussion

Online reviews are an impactful factor in determining a firm's success. Much prior research has examined the influence OCRs have as consumers read them, but little work has shown the effects of writing a review on the behavior of the review themselves. I conducted two studies and showed that after a review is posted, the reviewer will spend more and patronize the firm more frequently. In a follow-up experiment, I show causality by manipulating the reviewer condition. I also show that consumers value managerial responses, which increase perceptions of interactional justice. Interactional justice serves as a mediator in the relationship between OCR-writing and repurchase behaviors. Below, I discuss the implications my research has for marketing managers, as well as how my work contributes to theory development.

Marketing Implications

My first and most important implication for marketers is that once a customer posts an OCR, they will spend more and patronize the firm more often in the future. This is a function of the reviewer being consistent with their declared behavior, which is in line with the commitment-consistency principle (Cialdini 2007). Prior work in marketing has focused almost exclusively on how customers react to the review they read and why people choose to post OCRs, but the behavior of the reviewers themselves has been largely overlooked. I find that customers who post an OCR will spend as much as $63.86 over a year-long interval than those who don’t post. Additionally, they will have almost 13 more transactions with the firm over a year, which gives the firm more opportunities to touch base with their key customers and build a stronger relationship through their interactions.

I also assessed how relationship length would affect these spending and repurchase behaviors for those who share OCRs. In Study 1, I test a moderating effect of relationship length on the OCR-writing effects. I find a significant moderating effect where customers who have been with the firm longer and post an OCR will show differentially higher spending and number of transactions. This suggests that managers should focus on their long-standing members and have them post reviews online. Incentives could be used to generate additional posts, and mechanisms such as loyalty programs that increase relationship length could show additional benefits as customers write more reviews over time.

The results of my research also give managers guidance on how to handle OCRs once they are posted. Study 2 shows that customers value responses from managers to their reviews; they will react positively if there's a response to the OCR and negatively when they are ignored. A managerial response will increase perceptions of interactional justice from the reviewer, and this is one mechanism by which future repurchases are affected. Therefore, I recommend that managers be diligent and monitor the reviews that are posted online so they can capitalize on the opportunity to increase interactional justice and repurchase intentions with personalized responses.

Theoretical Contributions

This research has multiple theoretical contributions in addition to its implication for practitioners. My work is the first to bring the commitment-consistency principle (Cialdini 2007) to an OCR context. While the commitment-consistency principle has been the crux of much research, it has not been applied extensively in marketing. By showing how consumers who post an OCR are more likely to behave consistently with their public statements, I lay the foundation for future scholars to test more complex models of consumer behavior following the posting of an OCR.

I am also among the first to examine behavioral consequences of reviewers posting an OCR for others to see. Initial work by Motyka et al. (2018) showed that customers who write emotional reviews are more inclined to make impulse purchases. I extend this by examining the behaviors of all reviewers, not simply those who write emotional reviews. My results show that the increases in spending can be attributed to the act of posting a review, regardless of emotional state and type of follow-up purchase. With these significant results, researchers can push forward and additional moderators that may influence these increased purchases beyond the expected emotionality of the review itself.

Last, I propose and test the mediating effect of interactional justice when explaining why reviewers spend more in the future. Interactional justice is a significant mediator, and the level of interactional justice can be influenced by the presence or absence of a managerial response to the OCR. To date, interactional justice has not been considered in an OCR context, despite receiving attention in other literature streams such as service recovery. By showing that interactional justice has an effect on future spending following an OCR, work can now be done to compare this explanatory variable in relation to other factors that may influence spending.

Limitations and Future Research

My work does include some minor limitations. First, in Study 1 I use membership in an online community where consumers post reviews as an indicator of review activity. I use this variable given the limitations of data availability, however if researchers are able to tie posting behaviors to individual consumer spending then a stronger test of my hypotheses could be conducted. Second, I did not have the valence of sentiment of the customers who are involved in the online community, i.e., I do not know whether they are sharing "positive" or "negative" OCRs. Based on the theoretical backdrop of the commitment-consistency principle, if consumers were to post negative reviews, I would expect a steeper drop in future purchases and repatronage relative to control groups. Third, there could potentially be other mediators and moderators to the relationship between OCR-writing and purchase behaviors. I accounted for interactional justice and showed that managerial responses will increase interactional justice, which is a key mediator, but there could be other potential mediators. Future research could explore other potential mechanisms.

APPENDICES

APPENDIX A: TABLES

Table 2-1
A Review of Relevant OCR Literature

Article	Level of Analysis	Dependent Variable(s)	Context	Reviewer Characteristics Considered
Godes and Mayzlin 2004	Product	Ratings	TV Shows	x
Senecal and Nantel 2004	Customer	Product Choice, Reviewer Expertise	Computer Mice, Calculators, and Red Wine	Human Expert vs. Recommender System vs. Other Consumers
Chevalier and Mayzlin 2006	Product	Sales Rank	Books	x
Clemons, Gao, and Hitt 2006	Product	Sales Growth Rate	Beer	x
Salganik, Dodds, and Watts 2006	Product	Market Share	Music Downloads	x
Duan, Gu, and Whinston 2008	Product	Daily Box Office Performance	Movies	x
Liu 2006	Product	Box Office Revenues	Movies	x
Hu, Liu, and Zhang 2008	Product	Sales	Books, DVDs, and Videos	Reviewer Reputation and Exposure
Yang and Mai 2010	Product	Reader's Feedback and Rating	Online Video Game	Reviewer Experience and Reviewer Time
Khare, Labrecque, and Asare 2011	Product	Persuasion	Movies	x
Cui, Lui, and Guo 2012	Product	Sales	Video Games and Consumer Electronics	x
Naylor, Lamberton, and West 2012	Brand	Brand Evaluations, Purchase Intentions	Facebook, social network websites	Reviewer Identity and Similarity to Viewers

Table 2-1 (cont'd)

Ho-Dac, Carson, and Moore 2013	Product	Sales, OCR Volume	Blu-Ray and DVD Players	x
Floyd et al. 2014	Product	Sales Elasticity	Meta-Analysis	Critics
Agnihotri and Bhattacharya 2016	Product	Reviewer Helpfulness	Electronics	Reviewer Expertise
Kostyra et al. 2016	Brand	Brand Choice	eBook Readers	x
Minnema et al. 2016	Product	Return Decisions	Electronics and Furniture	x
Packard and Berger 2017	Customer	Persuasiveness, Choice	Books, Hotels, Restaurants, Wine	Consumer Knowledge (i.e., experts vs. novices)
Motkya et al. 2018	Customer	Impulsive Behaviors	Documentary Films, General Amazon.com Purchases	Reviewer vs. Non-reviewer
This Study	Customer	Expenditures, Transactions	Quick-serve food retailer	Reviewer vs. Non-reviewer

Table 2-2

Study 1 Descriptive Statistics and Correlations

Descriptive Statistics and Correlations: Pre-matched Data

	Variables	Mean	S.D.	1	2	3	4	5	6	7
1	Y_0 Transactions	60.90	90.11	—						
2	Y_1 Transactions	73.71	98.58	0.66*	—					
3	Y_0 Expenditures	244.12	394.63	0.91*	0.60*	—				
4	Y_1 Expenditures	323.09	457.51	0.60*	0.92*	0.67*	—			
5	Reviewer	0.03	0.18	0.12*	0.14*	0.10*	0.14*	—		
6	Relationship Length	44.34	13.90	0.11*	0.25*	0.10*	0.23*	0.08*	—	
7	$z_{\text{Relationship Length}}$	0.00	1.00	0.11*	0.25*	0.10*	0.23*	0.08*	1.00*	—

Descriptive Statistics and correlations: Matched Data

	Variables	Mean	S.D.	1	2	3	4	5	6	7
1	Y_0 Transactions	89.00	111.36	—						
2	Y_1 Transactions	125.97	130.78	0.73*	—					
3	Y_0 Expenditures	350.74	472.21	0.93*	0.66*	—				
4	Y_1 Expenditures	553.32	593.08	0.70*	0.92*	0.74*	—			
5	Reviewer	0.50	0.50	0.19*	0.19*	0.16*	0.18*	—		
6	Relationship Length	49.75	8.31	0.11*	0.17*	0.11*	0.17*	0.06*	—	
7	$z_{\text{Relationship Length}}$	0.40	0.41	0.11*	0.17*	0.11*	0.17*	0.06*	1.00*	—

Notes: * = $p < .05$

Table 2-3

Study 1 Preliminary Analysis

	Models							
	1		2		3		4	
Variable	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**Robust S.E.**
DV = Expenditures$_t$								
Constant	311.75**	(2.32)	313.73**	(2.27)	182.12**	(4.44)	182.12**	(3.06)
Reviewer	347.36**	(12.86)	267.79**	(16.36)	87.32*	(40.35)	87.32**	(15.65)
Loyalty			100.64**	(2.24)	29.22**	(7.04)	29.22**	(3.24)
Reviewer x Loyalty			82.67**	(24.93)	68.89	(71.89)	68.89**	(22.49)
Expenditures$_{t-1}$					0.87**	(0.01)	0.87**	(0.01)
Observations	39,326		39,326		22,932		22,932	
R^2	0.02		0.07		0.47		0.46	
DV = Transactions$_t$								
Constant	71.10**	(0.50)	71.55**	(0.49)	41.28**	(0.96)	41.28**	(0.62)
Reviewer	80.08	(2.77)	59.38**	(3.51)	19.10*	(8.67)	19.10**	(3.47)
Loyalty			23.14**	(0.48)	7.11**	(1.52)	7.11**	(0.66)
Reviewer x Loyalty			24.7	(5.34)	16.89	(15.46)	16.89**	(5.09)
Transactions$_{t-1}$					0.80**	(0.01)	0.80**	(0.01)
Observations	39,326		39,362		22,932		22,932	
R^2	0.02		0.08		0.44		0.45	

Notes: * = p < .05, ** = p < .01

Table 2-4

Study 1 Post-CEM Final Analysis

	Models							
	1		**2**		**3**		**4**	
Variable	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**Robust S.E.**
DV = Expenditures$_t$								
Constant	437.23**	(16.36)	-33.28	(102.72)	190.34**	(21.77)	195.52**	(12.64)
Reviewer	229.36**	(23.08)	200.69**	(28.78)	71.89	(48.45)	63.86**	(21.64)
Loyalty			9.45**	(2.04)	18.94	(35.47)	10.49	(15.77)
Reviewer x Loyalty			57.92	(42.75)	57.30	(85.14)	62.04*	(30.51)
Expenditures$_{t-1}$					0.93**	(0.02)	0.94**	(0.02)
Observations	2,465		2,465		2,200		2,200	
R^2	0.04		0.06		0.56		0.57	
DV = Transactions$_t$								
Constant	100.50**	(3.70)	-1.37	(23.18)	49.93**	(5.09)	43.36**	(2.78)
Reviewer	52.51**	(5.22)	43.31**	(6.49)	13.28	(11.32)	12.98**	(4.71)
Loyalty			2.05**	(0.46)	2.46	(8.29)	0.74	(3.70)
Reviewer x Loyalty			19.61*	(9.65)	16.33	(19.89)	16.97*	(6.74)
Transactions$_{t-1}$					0.86**	(0.02)	0.87**	(0.02)
Observations	2,465		2,465		2,200		2,200	
R^2	0.04		0.06		0.53		0.56	

Notes: * = $p < .05$, ** = $p < .01$

Table 2-5

Study 2 Descriptive Statistics

	Control		**Review Written**		**Review Written and Reply**	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Interpersonal Justice	5.08	1.12	4.54	1.00	5.87	1.15
Repurchase Intentions	3.13	1.61	4.06	1.16	4.84	1.17

Table 2-6

Study 2 PROCESS Results

Relationship	Coefficient	SE	CI
Step 1:			
Constant	5.08**	0.14	[4.82, 5.35]
Review → IJ	-0.54**	0.19	[-.92, -.17]
Review & Reply → IJ	0.79**	0.19	[.41, 1.16]
Step 2:			
Constant	0.66	0.43	[-.20, 1.51]
Review → Repurchase	1.20**	0.22	[.77, 1.63]
Review & Reply → Repurchase	1.33**	0.22	[.90, 1.77]
IJ → Repurchase	0.49**	0.08	[.33, .64]
Indirect Effects via IJ:			
Review → Repurchase	-0.26**	0.09	[-.46, -.09]
Review & Reply → Repurchase	0.38**	0.12	[.17, .64]
Total Effects:			
Review → Repurchase	0.94**	0.23	[.48, 1.39]
Review & Reply → Repurchase	1.72**	0.23	[1.26, 2.17]

Notes: Review = dummy variable indicating the "review written" condition; "Review & Reply" = dummy variable indicating the "review written and reply" condition; both dummy variables are relative to the control condition; IJ = interpersonal justice; Repurchase = repurchase intentions; CI = 95% bias-corrected confidence interval; * = $p < .05$; ** = $p < .01$; $n = 198$

APPENDIX B: FIGURES

Figure 2-1A

Study 1 Interactions: Transactions

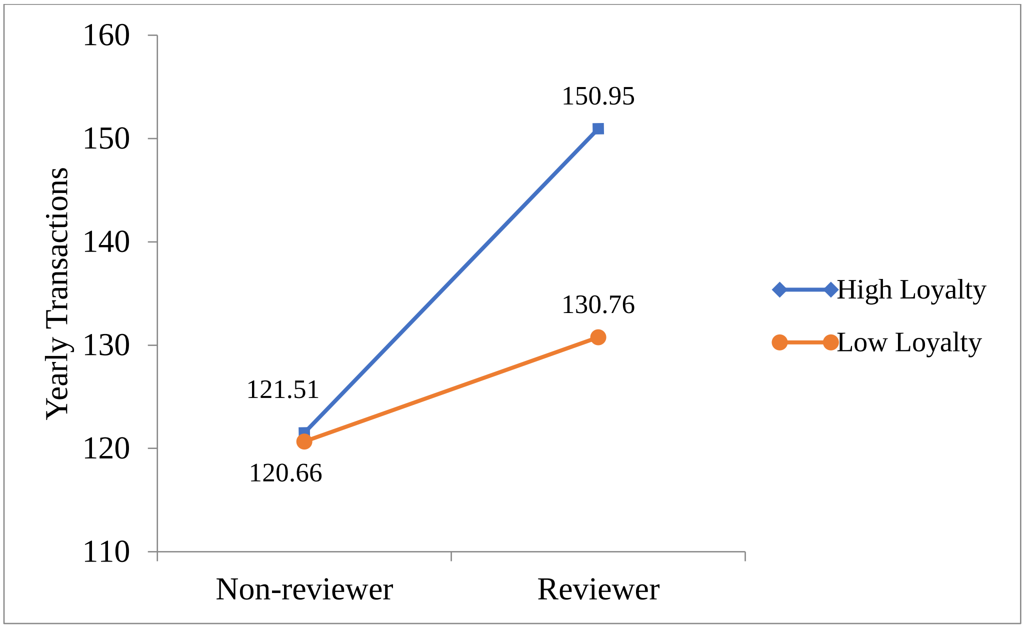
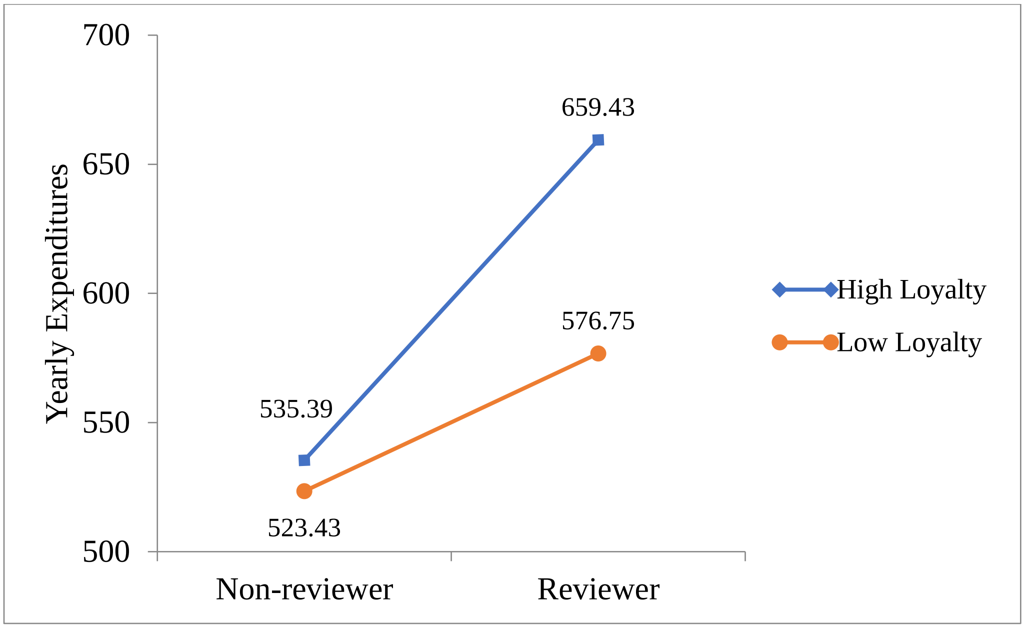


Figure 2-1B

Study 1 Interactions: Expenditures



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DISSERTATION CONCLUSION

The goal of my dissertation is to generate knowledge for marketing scholars and managers that can be used to improve firm performance in the digital space. Word of mouth (WOM) and online customer reviews (OCRs) inherently involve a relationship between the reviewer (i.e., sender) and other customers (i.e., receivers). My dissertation focuses on the motivation and behavior of the reviewers, which has received considerably less attention in the marketing literature than work on the receivers. My first essay tests the role of cognitive effort in the online WOM generation process. Current industry practice is for firms to reduce cognitive effort for their customers by suggesting comments that can be shared. This makes things easier for the customer and more likely that they convert from a customer to a reviewer. My second essay measures financial outcomes that are tied to reviewer behavior. Specifically, how does spending change when a customer converts to a reviewer and shares their opinion online? Below, I provide a summary of the managerial and theoretical contributions of these two essays.

Managerial Contributions: Essay One demonstrates the importance of cognitive effort in customers' decisions to share WOM across six studies. When firms suggest a single positive comment to their customers, cognitive effort is reduced, and customers are more likely to share this comment online. The benefits are twofold. First, firms will benefit from increased positive online WOM, which can increase customer referrals and future sales. Second, firms are also able to shape the online conversation by adjusting the suggested comments sent to customers. If firms were to alter the pre-generated comment suggestions based on what aspect of the experience they want customers to talk about, this could lead to WOM that benefits the firm in specific ways rather than generic comments such as "I just bought [Product ABC] from [Company XYZ]." My work shows that current industry practice is on the right track, but managers can be more proactive when engaging their customers and attempting to generate positive WOM by reducing cognitive effort.

While Essay One seeks to better understand why customers become reviewers, Essay Two enriches our understanding of how customer behavior changes once they decide to post an OCR. Using a large sample of customers over a two-year period, my second essay demonstrates that once customers post a review, they show differentially higher spending than customers who did not. For managers, this is a strong incentive to encourage customers to share their opinions online. In addition to prior work that has shown referred customers are valuable, my work indicates that there is also increased spending from the reviewers following an OCR in addition to the potential for increased revenue from other customers. Thus, managers should focus their efforts on incentivizing their customers to post reviews, since once they become reviewers they will spend more and patronize the firm more frequently in the future.

Theoretical Contributions: My dissertation also makes significant contributions to theory in marketing research. While prior WOM research has looked extensively at antecedents explaining why consumers choose to share WOM, my work is the first to consider the amount of cognitive effort required in the consumer's decision to share WOM. Effort is the foundation of most human behavior, and my work shows that cognitive effort is an obstacle that must be overcome if customers are to share WOM. While firms can alter the amount of effort required for customers to share WOM, future research should also account for how much effort was required for customers to share WOM. This could provide additional insights to existing relationships as well as new avenues of potential contribution for future researchers.

Essay Two also contributes to marketing theory. Using the commitment-consistency principle (Cialdini 2007) as a theoretical backdrop, my work shows that when customers post an OCR (i.e., commitment), they will exhibit greater spending in the future (i.e., consistency). Much prior work has only focused on financial outcomes for firms and the customers who read OCRs, and my second dissertation essay completes the picture by showing how reviewer spending changes as well following an OCR. Theoretically, future research analyzing how OCRs affect firm performance should account for how reviewer spending changes as well, since their spending (in addition to spending from non-reviewer customers) is a significant portion of the overall increases in revenue that results from OCRs.