The Power of Profanity:

The Meaning and Impact of Swearwords in Word-of-Mouth

by

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ABSTRACT

Swearwords are taboo words that are potentially offensive. However, they are used prevalently—and increasingly—online, suggesting that they are a useful communication tool. Prior work does not provide a comprehensive examination of how, why, or when swearwords might positively or negatively impact consumers engaging in online WOM. The current paper develops a framework that addresses these questions. Using six experiments and field data from Yelp and Amazon, this research demonstrates that swearwords in product reviews, even when compared to non-swearword synonyms ("This dishwasher is damn [super] quiet!)", can impact review readers' attitudes towards the review and the reviewed product. Specifically, when a swearword qualifies a desirable [undesirable] product attribute, it increases [decreases] review readers' attitudes towards the review and the reviewed product (e.g., "This dishwasher is *damn* quiet [loud]!"). The field data further suggest that uncensored and euphemistic swearwords add value to reviews, but censored swearwords do not. However, the effects are attenuated when the swearword is not diagnostic (e.g., when a review contains multiple swearwords or when the reviewed product is already expected to have the characteristic conveyed by the swearword). Swearwords affect reader's attitudes towards the product because they function as mixed-meaning expressions, which convey two meanings. Specifically, swearwords convey meaning about 1) the reviewer's feelings toward the product and 2) the product's attributes. The data show that these two meanings function as independent, parallel mediators of the unique effects of swearwords on readers' attitudes. Overall, these findings suggest that swearwords add value to reviews because they are particularly meaningful.

PREFACE

This thesis is an original work by Katherine Carol Lafreniere. The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Research Ethics Board, Project Name “Swearwords and Consumer Behavior”, No. Pro00059091, August 26, 2015. No part of this thesis has been previously published.

DEDICATION

To my parents, Margaret and Joseph Lafreniere, for making it all achievable and being an eternal beacon of light. To my husband, Michael Vercillo, for being my best friend, supporting my dreams, and offering endless comic relief. And to Drs. Doreen Der, Sameer Deshpande, and Sarah Moore for their profound impact on my journey through academia and life.

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INTRODUCTION

People hear and use swearwords more often than ever before (Jay and Janschewitz 2008; Stapleton 2010): 0.5% to 0.7% of all the words spoken in daily conversation are swearwords (Jay 2009). This percentage is considerable given that first-person plural pronouns (e.g., *we, us, our*)—a central part of speech—occur at a 1% rate (Mehl and Pennebaker 2003). Swearing is even more prevalent online (Subrahmanyam, Smahel, and Greenfield 2006): 7.7% of Twitter posts (Wang et al. 2014) and 8.3% of Yelp reviews[1] contain at least one swearword. Despite the frequent use of swearwords by consumers, little research has explored their impact in the context of word-of-mouth (WOM; but see Hair and Ozcan 2018), a primary and growing form of consumer-to-consumer communication, particularly online (e.g., Berger 2014; Chen and Xie 2008; Chevalier and Mayzlin 2006).

This limited amount of research is perhaps unsurprising, given the common view that swearwords are anti-social and offensive (Rassin and Muris 2005; Robbins et al. 2011; Stapleton 2010; Stephens, Atkins, and Kingston 2009). Consistent with this perspective, marketers have studied swearwords as a firm-to-consumer communication technique, where they can be used to produce offensive or shocking advertising (Brown and Schau 2001; Dahl, Frankenberger, and Manchanda 2003). Indeed, the denotative (i.e., literal) meanings of swearwords are related to taboo topics (e.g., sex, religion), and swearwords are often defined as taboo words that suggest a high level of emotional arousal (Andersson and Trudgill 2007; Jay 2009; Kwon and Cho 2015).

[1] This observation is from the 2017 Yelp Dataset Challenge. See the Field Data section for details.

Notwithstanding their taboo origins and definition, recent research in linguistics and marketing suggests that swearwords may not always have negative effects (e.g., Hair and Ozcan 2018). First, under certain conditions, swearwords are not considered offensive (Dynel 2012; Henry, Butler, and Brandt 2014; Johnson 2012; Kapoor 2014; Seizer 2011). For example, Daly, Holmes, and Stubbe (2004) found that swearwords used by a factory team could express politeness and solidarity, and Hair and Ozcan (2018) found that reviews with swearwords received more useful votes than those without swearwords. Second, swearwords have gone through a delexicalization process, such that their original (taboo) meanings have been lost gradually over time (Jay 1992; Fairman 2007).

These changes in offensiveness and meaning coincide with the frequent and increasing use of swearwords, which suggests that they are useful to communicators. If this is the case, swearwords may have the potential to evoke both negative and positive effects, as they lose their original denotative—and offensive—meanings. Indeed, psycholinguists maintain that swearing is neither meaningless nor random, but rule-governed and purposeful (Jay 2000), and research shows that people know the rules governing how and when to swear (Allan and Burridge 2006; Twomey 2010; Harrison and Hinshaw 1968; Jay 2000; Jay and Jay 2013). Yet, it remains unclear what specific meaning swearwords actually communicate (Jay and Jay 2015), or how the meaning inferred from swearwords might affect listeners, either positively or negatively.

This research explores the meaning conveyed by swearwords in order to test how, why, and when swearwords in online WOM (i.e., reviews) affect consumers. I theorize about how swearwords might affect review readers, depending on the product attribute the swearword qualifies. I hypothesize that a swearword qualifying a desirable attribute (e.g., the show is *damn* funny) should positively affect readers' attitudes toward the reviewed product, while a swearword qualifying an undesirable product attribute should negatively affect readers' attitudes toward the reviewed product (e.g., the show is *damn* boring). I suggest that this will occur because swearwords function as mixed-meaning expressions, or words that efficiently convey two meanings (Gutzmann and Turgay 2012). Specifically, in the context of online reviews, swearwords convey meaning about 1) the reviewer's feelings towards the product and 2) product attributes. I propose that these two inferred meanings function as independent, parallel mediators, such that swearwords convey both meanings, which both affect readers' product attitudes. I establish these effects by comparing the presence of swearwords to the absence of swearwords and to non-swearword synonyms (e.g., *so*). Finally, I explore when these effects are attenuated by identifying conditions under which swearwords are less diagnostic (Lynch 2006), and therefore less likely to affect readers (e.g., when a review contains multiple swearwords).

This research makes several contributions to marketing and linguistics. Foremost, despite their taboo nature and potential to offend (Andersson and Trudgill 2007; Jay 2009), I find that swearwords are useful to consumers. Critically, I provide a nuanced view of when swearwords in reviews will have positive, negative, or no effects on readers' attitudes. Further, I establish that swearwords have unique effects, even relative to non-swearword synonyms, because of the meanings they convey. In exploring why swearwords exert their effects, I also inform marketers about the inferences that readers draw from reviews. Specifically, this research is the first to demonstrate that a single word can efficiently communicate meaning about the reviewer and the product, and that these two inferences independently affect readers' attitudes. Further, the data show that inferences about the reviewer and the product affect consumers equally, suggesting that marketers should consider both inferred meanings in models of WOM. This research also introduces diagnosticity as a novel moderator of when swearwords will or will not affect review readers. Finally, the current work offers implications for marketers regarding how to manage swearing in online WOM.

Next, I develop the conceptual framework and hypotheses, beginning with an exploration of the meanings swearwords might convey. I then present six experiments and an analysis of Yelp and Amazon field data that test the predictions.

THEORETICAL BACKGROUND

Meaning refers to the idea or thing that one intends to communicate (Collins Dictionary 2017). Language philosophers posit that everything that is uttered in an ongoing conversation is relevant (Grice 1975; Searle 1976), and that utterances and symbols are made with specific intentions—they are not merely a natural phenomenon, which do not require deciphering (Searle 1965). Stated differently, when someone speaks or writes, others assume that she or he did so to convey meaning.

While a common lay theory about swearwords is that they are visceral, used only by speakers who lack vocabulary (Pinker 1994), and do not constitute genuine language (Jay and Jay 2015), linguistic researchers argue that swearwords ought to convey meaning because they obey syntactic and semantic rules (Dewaele 2015; Jay 2000; Jay and Jay 2013; Stephens et al. 2009). Currently, it is not clear what meaning swearwords actually convey (Jay and Jay 2015; Potts 2007), or how the meaning inferred from swearwords might affect listeners. I build on recent work in linguistics to argue that swearwords function as mixed-meaning expressions—that is, words that convey two meanings (Gutzmann and Turgay 2012).

First, linguists have theorized that swearwords convey meaning about the speaker (i.e., expressive meaning or language intensity; Andersson and Trudgill 2007; Blakemore 2011; Bower 1963; Kwon and Cho 2015; Hobbs 2013; Löbner 2013; Jay and Janschewitz 2008; Nasution and Rosa 2012; Potts 2007; Wajnryb 2005). Specifically, swearwords convey the *strength of the speaker's feelings* about some state of affairs (Löbner 2013). The inference of strong feelings arises from listeners' knowledge about swearwords' taboo status, as well as from beliefs, experience, and prejudices about the contexts in which swearwords are normally used (Allan and Burridge 2006; Stapleton 2010). Jay (2000) shows that people often use swearwords when they feel strong attitudes or emotions (e.g., "*Holy shit,* that was fun!"). Therefore, listeners understand that the speaker has strong feelings because they broke a taboo by using a swearword (Foolen 2015; Jay 2000). Even if the listener does not find swearing to be personally offensive, swearing still conveys meaning about the strength of the speaker's feelings because it is taboo (Hobbs 2013). Building on this literature, I suggest that when a reviewer uses a swearword, readers will infer that the reviewer has strong feelings about the product being reviewed. In turn, this should affect readers' attitudes toward the product. This link is demonstrated in the feelings-as-information literature, which shows that people update their judgments about a given object based on their inferences about the speaker's feelings towards that object (Schwarz and Clore 1983; 1996; van Kleef 2010).

Second, Löbner (2013) recently theorized that swearwords in the form of nouns might function as mixed-meaning expressions (see also Blakemore 2011; 2015), which convey meaning not only about the speaker's feelings but also about the subject under discussion (i.e., descriptive or propositional meaning; Gutzmann and Turgay 2012; Reimer 2015). Specifically, Löbner (2013) suggested that when swearwords are used as nouns, they identify and describe the subject (e.g., "This *asshole* spilled their drink on me."). Even when swearwords take on forms other than nouns, I argue that they can convey meaning about not only about the speaker (i.e., the reviewer) but also about the subject under discussion (i.e., the product). This is because the meaning of an utterance is not solely contingent on the literal meaning of a word (Searle 1976); words can be modified grammatically to convey different meanings (Foolen 2015). For example, the word *torture* can be modified from a verb into an adverb, in order to convey a description rather than an action: "Her singing is *torturously* beautiful." Similarly, swearwords ought to convey meaning about the subject under discussion because they can be modified grammatically in different ways.

Consider, for example, the multiple ways one can use the word *fuck* (Pinker 2007). When the word is used descriptively (e.g., "Let's *fuck*") or abusively (e.g., "Go *fuck* yourself!"), it serves as a verb and asserts what action the speaker wants the listener to take (even if the action is not based on the word's original denotative meaning). When the word is used idiomatically (e.g., "That's *fucked* up."), it serves as an adjective conveying that the speaker thinks the situation is unfortunate and weird. Finally, when the word is used emphatically (e.g., "This is *fucking* amazing!") or cathartically (e.g., "*Fuck*! That hurt."), it serves as an adverb and emphasizes that the property under discussion (amazingness, pain) holds to a higher degree. In each of these cases, the swearword conveys meaning about not only the speaker (i.e., their strong feelings), but also about the subject under discussion—that is, the swearword functions syntactically like a content word and provides information about what is being discussed. The specific inferred meaning about the subject under discussion depends on how the swearword is modified grammatically (e.g., swearwords as nouns describe the subject, whereas swearwords as adjectives or adverbs describe the subject's attributes).

To explore swearwords in online WOM, I focus on swearwords when they are used emphatically (e.g., "*Fucking* awesome!") and cathartically (e.g., "*Holy shit*!"). I do so because speakers most often use swearwords in these grammatical forms (Jay 1992), and because these usages do not reflect the swearword's original meaning and therefore cannot be interpreted literally. Further, these forms constrain the number of ways in which a swearword might convey meaning about a product. Specifically, they function like degree words (e.g., *very*) and exclamations (e.g., *wow!*), two key types of intensifiers (Gutzmann and Turgay 2014). Intensifiers are adverbial content words that convey meaning about the subject by communicating that one of its attributes holds to a higher or lower degree than average (e.g., this dish is *very* tasty; Ghesquière and Davidse 2011; Gutzmann and Turgay 2012; van der Wouden and Foolen 2017). Thus, in a WOM context, an intensifier (e.g., *very*) changes the degree of the product attribute that it qualifies (e.g., level of tastiness). For simplicity, I label swearwords that are used emphatically or cathartically as *swearword intensifiers*.

Overall, I hypothesize that the presence (vs. absence) of a swearword intensifier in online WOM will convey meaning about the strength of the reviewer's feelings and about the intensity of the product's attribute (i.e., the degree to which a particular attribute holds). For example, in the sentence "the dishwasher is fucking quiet," the presence (vs. absence) of the swearword intensifier should convey not only stronger feelings on the part of the reviewer, but also a higher degree of quietness on the part of the dishwasher. Thus, swearword intensifiers that qualify desirable attributes (e.g., the dishwasher is *damn* quiet) should increase review readers' attitudes towards the reviewed product, whereas swearword intensifiers that qualify undesirable attributes (e.g., the dishwasher is *damn* loud) should decrease readers' attitudes. Formally, I hypothesize the following.

H1: The presence (vs. absence) of a swearword intensifier will increase readers' attitudes toward the product when it qualifies a desirable product attribute and decreases readers' attitudes when it qualifies an undesirable attribute.

H2a: The presence (vs. absence) of a swearword intensifier will convey that the reviewer has stronger feelings about the product.

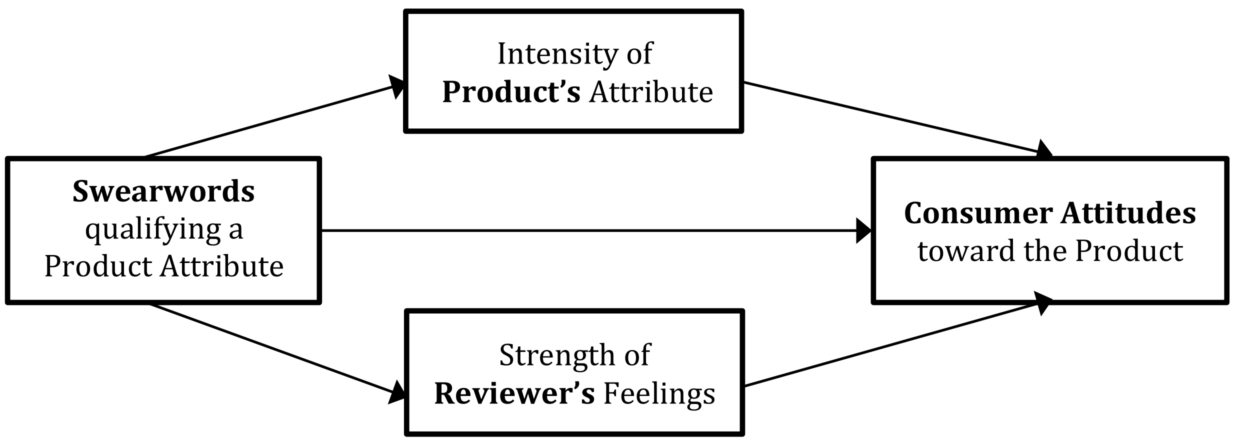
H2b: The presence (vs. absence) of a swearword intensifier will convey that the product attribute it qualifies holds to a higher degree.

Beyond comparing the effects of the presence or absence of swearword intensifiers, I suggest that even when they are compared to non-swearword intensifiers (e.g., *very*), swearwords should still have stronger effects on readers' attitudes towards the reviewed product. I present more detailed theorizing about these comparisons in the relevant studies (studies 2 and 3).

Critically, I predict that the two inferred meanings conveyed by swearwords (i.e., about the reviewer's feelings and the product's attributes) should function as independent, parallel mediators to affect readers' attitudes toward the reviewed product. Thus, compared to no swearwords and to non-swearword intensifiers, swearwords should convey meaning about the reviewer and the product, which should both affect readers' attitudes. I hypothesize that these inferred meanings will function independently to affect attitudes because they qualify different objects (the reviewer and the product; Figure 1), which have both been shown to affect readers in prior work (e.g., Hamilton, Vohs and McGill 2014; Kivetz and Simonson 2000). I confirm the independence of these two constructs empirically prior to testing for mediation in the studies, and I show via moderation that the two inferred meanings can be turned off independently. Formally, I hypothesize the following.

H3: Compared to the absence of a swearword intensifier and to non-swearword intensifiers, the effect of a swearword intensifier on readers' attitudes towards the product will be independently mediated by inferred meaning about the strength of the reviewers' feelings and the intensity of the product's attributes.

Figure 1. Proposed Mediation Model



OVERVIEW OF STUDIES

I test these hypotheses using six experiments and an analysis of Yelp and Amazon review data. Study 1 compares how the presence (vs. absence) of a swearword in a positive review affects readers' attitudes, while studies 2 and 3 compare the effects of swearword versus non-swearword intensifiers. Studies 1–3 provide evidence for the model via mediation by measuring the two meanings conveyed by swearwords. Study 4 tests the proposition that swearwords qualifying a desirable product attribute will positively affect readers' attitudes, whereas swearwords qualifying an undesirable product attribute will negatively affect readers' attitudes. The last two experiments investigate a boundary condition for the swearing effect. I propose that when the meanings conveyed by swearwords are not diagnostic, they should not affect readers. Study 5 explores diagnosticity using product category as a moderator, while study 6 does so using a reviewer characteristic—swearing multiple times—as a moderator. Finally, to investigate the external validity of the findings, I analyze field data from two online review sites: Yelp and Amazon. I examine the effect of swearing on the value of a review (i.e., its helpfulness) using different swearword categories (uncensored, euphemistic, and censored swearwords), multiple swearwords in a review, and swearwords in negative, neutral, and positive reviews.

STUDY 1

The purpose of this study was to test hypotheses 1 through 3 by comparing the presence versus absence of a swearword intensifier in a positive review. I hypothesized that when a swearword qualified a desirable product attribute, it would convey meaning about the strength of the reviewer's feelings and the intensity of the product's attribute, and that this would have a positive effect on product attitudes. Further, I expected these two inferred meanings to function as parallel, independent mediators of the effect of swearwords on product attitudes.

Participants, Design, and Measures

Two hundred and fifteen individuals were recruited to complete a single factor, 2-level (swearword: present vs. absent) between-subjects study (MTurk; $M_{age} = 35.5$; 53% male). Twenty-nine participants were excluded from analysis for failing the attention check (participants were asked to report how the reviewer described the product's size), leaving a final sample of 186.

Participants were asked to imagine that they wanted to buy a new external battery (i.e., power station) for their electronic devices. Then they were shown a seller's website with an image and a product description of an external battery, along with one positive review that rated the product 4 out of 5 stars. The title of the review contained the swearword manipulation. In the swearword present condition, the title read, "It charged my phone fucking fast." In the swearword absent condition, the title read, "It charged my phone fast." The remaining text of the review was the same across both conditions: "It's handy and portable. But it feels heavy. It holds a charge fine and its size is okay."

As a manipulation check, participants were asked if they found the review to be offensive (1 = *not at all*, 7 = *very much*; $M = 2.20$, SD = 1.96) and if they thought most people would find the review to be offensive (1 = *not at all*, 7 = *very much*; $M = 2.78$, SD = 2.01). Participants' attitude towards the power station was measured with six items using seven-point semantic differential scales, anchored as follows: negative—positive, dislike—like, good—bad, unfavorable—favorable, unappealing—appealing, and unpleasant—pleasant ($M = 5.70$, SD = .83, $\alpha = 0.91$). Participants also reported on a sliding scale how much (in dollars) they would pay for the power station on a \$0 to \$200 scale (M = \$43.92, SD = \$33.56). Reviewer feeling strength was measured with three items by asking participants if they would describe the reviewer's feelings about the product as strong, intense, and confident (1 = *not at all*, 7 = *very much*; $M = 5.28$, SD = 1.27, $\alpha = 0.86$). Finally, product attribute intensity (i.e., inferences about the battery's charging speed) was measured with six items. Participants reported the degree to which the power station's charging capabilities were fast-paced, high-speed, turbo, rapid, quick, and swift (1 = *not at all*, 7 = *very much*; $M = 5.56$, SD = 1.09, $\alpha = 0.95$).

Results

Offensiveness. One-way ANOVAs on review offensiveness ($M_{\text{fucking}} = 3.18$, SD = 2.29, $M_{\text{control}} = 1.21$, SD = .69; $F(1, 183) = 62.49$, $p < .001$, partial $\eta^2 = .255$) and perceived offensiveness of the review to others ($M_{\text{fucking}} = 4.26$, SD = 1.79, $M_{\text{control}} = 1.29$, SD = .67; $F(1, 183) = 222.12$, $p < .001$, partial $\eta^2 = .548$) both revealed a significant effect of swearword; participants found the review more offensive and perceived others to be more offended when the swearword was present versus absent.

Independence of mediator and dependent variables. A principal-component analysis with varimax rotation[2] was conducted on the items comprising the two inferred meaning measures and the product attitude measure; three factors emerged. The first factor captured product attribute intensity (31.85% of variance, eigenvalue = 7.33). All 6 items assessing product attribute intensity (i.e., charging speed) had a factor loading above .81 on the same factor and a factor loading below .22 on the other factors. The second factor captured product attitudes (29.35% of variance, eigenvalue = 2.60). All 6 items assessing product attitudes had a factor loading above .75 on the same factor and a factor loading below .20 on the other factors. The third factor captured reviewer feeling strength (15.94% of variance, eigenvalue = 1.49). All 3 items assessing reviewer feeling strength had a factor loading above .75 on the same factor and a factor loading below .26 on the other factors.

[2] A factor analysis with oblimin rotation produced similar results across studies.

Product attitude. A one-way ANOVA showed, as expected, a significant effect of swearword on attitude towards the product ($F(1, 184) = 6.17$, $p = .014$, partial $\eta^2 = .032$), such that participants held more favorable attitudes towards the product when the swearword was present ($M_{\text{fucking}} = 5.84$, SD = .83) compared to when it was absent ($M_{\text{control}} = 5.54$, SD = .83). [3]

Willingness-to-pay. A one-way ANOVA also revealed a significant effect of swearword on willingness-to-pay ($F(1, 184) = 7.22$, $p = .008$, partial $\eta^2 = .038$), such that participants were willing to pay more for the power station when the swearword was present (M_{fucking}= \$50.35, SD = \$40.47) versus absent (M_{control} = \$37.35, SD = \$22.99).[4]

Reviewer feeling strength. A one-way ANOVA on reviewer feeling strength revealed a significant effect of swearword ($F(1, 184) = 87.24$, $p < .001$, partial $\eta^2 = .322$), such that participants thought the reviewer had stronger feelings when the swearword was present (M_{fucking} = 6.00, SD = .82) compared to when it was absent (M_{control} = 5.28, SD = 1.27).

Product attribute intensity. A one-way ANOVA on product attribute intensity (i.e., charging speed) revealed a significant effect of swearword ($F(1, 184) = 16.37$, $p < .001$, partial $\eta^2 = .082$), such that participants thought the battery charged faster when the swearword was present (M_{fucking} = 5.87, SD = 1.01) versus absent (M_{control} = 5.56, SD = 1.09).

Mediation analysis. A parallel multiple mediation analysis (PROCESS, model 4; Hayes 2013) with 5,000 resamples tested whether the two inferred meanings explained the effect of swearwords on readers' attitudes. In this case, multiple mediation is useful since it tests the effect of each potential mediator while holding constant the other mediator. This lends more confidence

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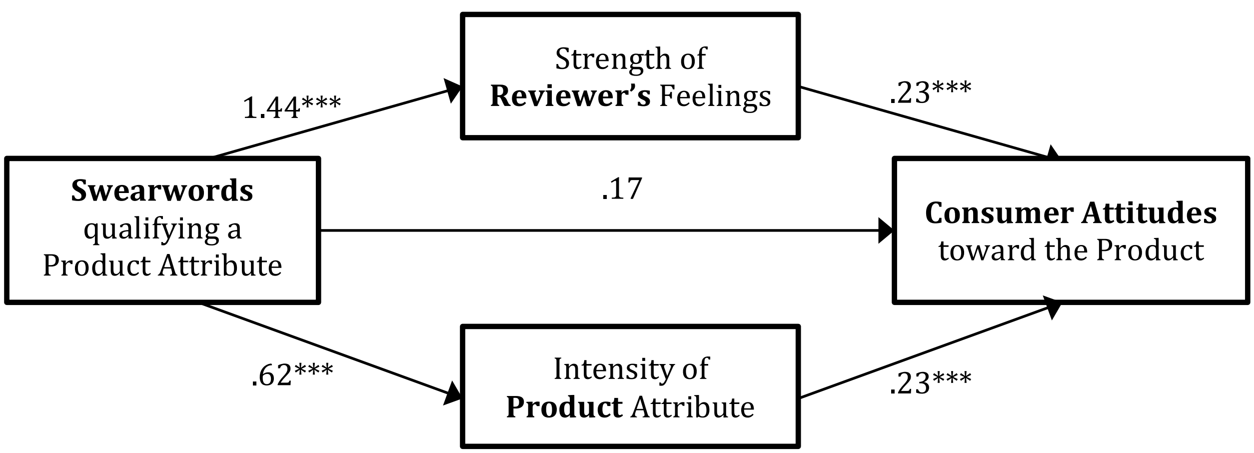
[3] The results for product attitudes hold when controlling for offensiveness, $F(1, 182) = 9.50$, $p = .002$, partial η^2 = .050.

[4] The results for willingness-to-pay are not significant when controlling for offensiveness, $F(1, 182) = .02$, $p = .89$.

to causal claims because it controls for endogeneity (Hayes, 2013). Further, this analysis allows a comparison of the size of the indirect effect for each mediator (Hayes, 2013).

Results indicated that a swearword (present = 1; absent = 0) increased product attribute intensity (i.e., charging speed; $\beta = .14$, 95% CI: .06 to .26) and reviewer feeling strength ($\beta = .33$, 95% CI: .16 to .52), which increased product attitudes[5] ($\beta = .48$, 95% CI for the total indirect effect: .30 to .68). A pairwise comparison between the two indirect effects was not significant ($\beta = .19$, 95% CI for the indirect effect contrast: -.03 to .42), suggesting that there was no difference in the strength of the mediators, and that both appear equally important to the model. The direct effect of swearwords on product attitudes became insignificant when controlling for the mediators ($\beta = -.17$, 95% CI for the direct effect: -.43 to .07; Figure 2).

Figure 2. Mediation Analysis (Study 1)



Note: The regression coefficients are superimposed on the model. ***$p < .001$

[5] Mediation with willingness-to-pay as the dependent variable revealed similar but weaker results across studies.

Discussion

The results of study 1 provided support for hypotheses 1 through 3. The data showed that compared to no swearword, the presence of a swearword that qualified a desirable product attribute increased review readers' product attitudes and willingness-to-pay. Further, the presence (vs. absence) of a swearword conveyed two meanings, about 1) the strength of the reviewer's feelings and 2) the intensity of the product's attributes in terms of charging speed. A factor analysis confirmed the independence of these two meanings, and a process analysis showed that they functioned as parallel mediators that each enhanced readers' product attitudes.

STUDY 2

The purpose of study 2 was twofold. First, I used a different product category and swearword from study 1 for generalizability. Second, I provided a more stringent test of hypotheses 1 through 3 by comparing a swearword intensifier to a non-swearword intensifier that could potentially convey the same meanings as a swearword. I selected the non-swearword intensifier *so* because it has been identified as a mixed-meaning expression (Foolen 2015; Gutzmann and Turgay 2012; Waksler 2012). I expected the two intensifier conditions to convey meanings about the product and the reviewer to different degrees, and therefore differentially affect readers' product attitudes.

For product attribute intensity, I expected the swearword intensifier (i.e., *damn*) to convey *higher* product attribute intensity than the non-swearword intensifier (i.e., *so*) because swearword intensifiers are negative words (van der Wouden and Foolen 2017). As in other areas of judgment and cognition, there is a negativity bias in information processing (Baumeister et al. 2001), wherein negative words draw more attention than neutral or positive synonyms (Foolen 2015; Garcia et al. 2012; Jing-Schmidt 2007). This is because such negative signals are potentially harmful (Foolen 2015; Jing-Schmidt 2007). Relatedly, there is a positivity bias in everyday discourse, such that positive words rather than neutral or negative words are more frequently used and therefore serve as the baseline of conversation (Garcia et al. 2012). This bias is also explained from an evolutionary perspective because positive words motivate us to perceive the world optimistically (Foolen 2015). However, it causes negative words to stand out even more (Garcia et al. 2012). Thus, when negative words (including swearwords) are used as intensifiers, they lead to a higher degree of intensification because they build on the literal meaning of the word to convey different degrees of intensity (Foolen 2015).

For reviewer feeling strength, I expected the swearword intensifier (i.e., *damn*) to convey higher reviewer feeling strength than the non-swearword intensifier (i.e., *so*) because of the swearword's taboo status. Speakers often use swearwords when they feel strongly (Jay 2000), and listeners infer that the speaker has strong feelings because the speaker broke the taboo (Foolen 2015; Jay 2000). Ultimately, I expected swearword intensifiers to have the strongest positive impact on readers' product attitudes, relative to non-swearword intensifiers.

This study also tested three possible alternative explanations for the observed effects of swearwords: arousal, believability, and interpersonal closeness. First, given that swearwords observed in isolation can increase arousal (Janschewitz 2008; Kensinger and Corkin 2004) and that arousal can affect product preferences (Di Muro and Murray 2012), these effects may be driven by review readers' arousal. Second, since swearwords are associated with truthfulness (Feldman et al. 2017; Hair and Ozcan 2018), they may increase product attitudes not because they convey meaning, but because they make the reviewer more believable. Third, interpersonal closeness (Aron, Aron, and Smollan 1992) may be an alternative explanation. Prior work demonstrates that swearwords can indicate shared group membership (Daly et al. 2004), which, in turn, has been found to affect purchase decisions (e.g., Berger and Heath 2008). Consequently, swearwords could increase readers' perceptions of closeness with the reviewer, which could enhance attitudes towards the product.

Participants, Design, and Measures

Two hundred and ten individuals were recruited to complete a 2 level (intensifier: swearword [*damn*] vs. non-swearword [*so*]) between-subjects study (MTurk; $M_{age} = 35.4$; 50% male). Thirty participants were excluded from analysis for failing the attention check (participants were asked to report how the reviewer described the product's price in the text of the review), leaving a final sample of 180.

In each condition, participants were asked to imagine that they needed to hire a plumber. Then they were shown a plumbing business on a popular review website, which included one positive review. The title of the review contained the intensifier manipulations "they were [damn/so] handy!" The remaining text of the review was the same across both conditions: "We used this company for scheduled jobs in the past, but a few days ago we had an emergency (sewer backing up) and they responded quickly. They got the job done and were relatively affordable." Participants then responded to questions about the review's taboo status, product attitudes, reviewer feeling strength, product attribute intensity (in this case, degree of handiness), arousal, believability, and interpersonal closeness.

Review offensiveness (M = 1.47, SD = 1.17), perceived offensiveness to others (M = 1.63, SD = 1.22; manipulation checks), product attitudes (M = 5.85, SD = .86, α = 0.91), and reviewer feeling strength (M = 5.40, SD = 1.03, α = 0.86) were measured as in study 1. Product attribute intensity (i.e., inferences about the business' handiness) was measured with four items. Participants reported the degree to which the business was handy, skilled, capable, and able (1 = *not at all*, 7 = *very much*; M = 6.15, SD = .87, α = 0.95). Arousal was measured by asking participants how they were feeling on a 1-7 *calm* to *excited* scale (M = 3.23, SD = 1.87). Believability was measured using seven items adapted from prior research (e.g., "the reviewer is trustworthy"; 1-7 scales; Lawrence, Fournier and Brunel 2013; Poels, Janssens and Harrwig 2013; M = 5.75, SD = .99, α = 0.95). Finally, interpersonal closeness between the participant and the reviewer was measured using Aron, Aron, and Smollan's (1992) 7-point interpersonal closeness scale, wherein higher values indicate greater self-other overlap (M = 3.50; SD = 1.86).

Results

Offensiveness. One-way ANOVAs on review offensiveness (M_{damn} = 1.43, SD = 1.09, M_{so} = 1.52, SD = 1.26; $F(1, 177)$ = 62.49, p = .64) and perceived offensiveness of the review to others (M_{damn} = 1.74, SD = 1.19, M_{so} = 1.53, SD = 1.26; $F(1, 176)$ = 1.25, p = .26) were not significant.

Independence of mediator and dependent variables. A principal-component analysis with varimax rotation was conducted on the items comprising the two inferred meaning measures and the product attitude measure. Eigenvalues indicated that three factors explained 60.03%, 11.36%, and 10.60% of the variance. The first factor captured product attitudes (60.03% of variance, eigenvalue = 7.80). All 6 items assessing product attitudes had a factor loading above .81 on the same factor and a factor loading below .31 on the other factors. The second factor captured product attribute intensity (11.36% of variance, eigenvalue = 1.48). All 4 items assessing product attribute intensity (i.e., handiness) had a factor loading above .76 on the same factor and a factor loading below .40 on the other factors. The third factor captured reviewer feeling strength (10.60% of variance, eigenvalue = 1.38). All 3 items assessing reviewer feeling strength had a factor loading above .68 on the same factor and a factor loading below .26 on the other factors.

Product attitude. A one-way ANOVA showed, as expected, a significant effect of swearword on attitude towards the product ($F(1, 178) = 7.55$, $p = .007$, partial $\eta^2 = .041$), such that participants held more favorable attitudes towards the product when the swearword was present ($M_{\text{damn}} = 6.02$, SD = .78) compared to when it was absent ($M_{\text{so}} = 5.67$, SD = .91).

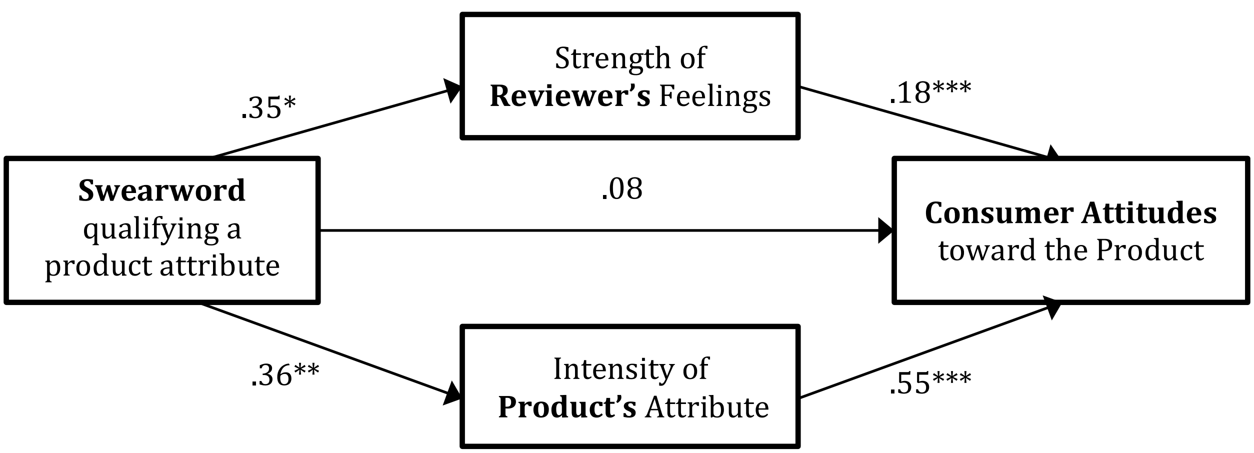
Reviewer feeling strength. A one-way ANOVA on reviewer feeling strength revealed a significant effect of swearword ($F(1, 178) = 5.32$, $p = .022$, partial $\eta^2 = .029$), such that participants thought the reviewer had stronger feelings when the swearword was present ($M_{\text{damn}} = 5.57$, SD = .96) compared to when it was absent ($M_{\text{so}} = 5.22$, SD = 1.08).

Product attribute intensity. A one-way ANOVA on product attribute intensity (i.e., handiness) revealed a significant effect of swearword ($F(1, 178) = 8.26$, $p = .005$, partial $\eta^2 = .044$), such that participants thought the battery charged faster when the swearword was present ($M_{\text{damn}} = 6.34$, SD = 1.01) versus absent ($M_{\text{so}} = 5.97$, SD = .89).

Mediation analysis. A parallel multiple mediation analysis (PROCESS, model 4; Hayes 2013) with 5,000 resamples tested whether the two inferred meanings explained the effect of swearwords on readers' attitudes. Results indicated that a swearword intensifier (swearword = 1; non-swearword = 0) increased product attribute intensity (i.e., charging speed; $\beta = .20$, 95% CI: .06 to .36) and reviewer feeling strength ($\beta = .06$, 95% CI: .01 to .14), which increased product attitudes (β = .27, 95% CI for the total indirect effect: .10 to .44). A pairwise comparison between the two indirect effects was not significant (β = -.14, 95% CI for the indirect effect contrast: -.31 to .01), suggesting that there was no difference in the strength of the mediators, and that both appear equally important to the model. The direct effect of swearwords on product attitudes became insignificant when controlling for the mediators (β = .08, 95% CI for the direct effect: -.11 to .27; Figure 3).

Alternative explanations. One-way ANOVAs on arousal (M_{damn} = 3.18, SD = 1.92, M_{so} = 3.29, SD = 1.83; $F(1, 178) = .16$, $p = .69$), believability (M_{damn} = 5.80, SD = .97, M_{so} = 5.70, SD = 1.02; $F(1, 178) = 1.51$, $p = .48$), and interpersonal closeness (M_{damn} = 3.36, SD = 1.80, M_{so} = 3.64, SD = 1.91; $F(1, 178) = 1.09$, $p = .30$) were not significant.

Figure 3. Mediation Analysis (Study 2)



Note: The regression coefficients are superimposed on the model.
*$p < .05$, **$p < .01$, ***$p < .001$

Discussion

Study 2 tested the impact of swearwords in reviews for a different product category (i.e., plumbing services) by comparing a swearword intensifier (i.e., *damn*) to a non-swearword intensifier (i.e., *so*). The results provided additional support for hypotheses 1 through 3. Even when compared to a non-swearword intensifier—rather than to the absence of a swearword—a swearword intensifier increased review readers' product attitudes. Further, the swearword (vs. non-swearword) intensifier conveyed higher reviewer feeling strength and product attribute intensity in terms of handiness. A factor analysis confirmed the independence of these two meanings, and a process analysis showed that they functioned as parallel mediators that each enhanced readers' product attitudes. This study also ruled out arousal, believability, and interpersonal closeness as alternative explanations.

STUDY 3

The purpose of study 3 was twofold. First, I used a different product category from studies 1 and 2 for generalizability. Second, I retested hypotheses 1 through 3 by comparing a swearword intensifier to two other non-swearword intensifiers that could potentially convey the same meanings as a swearword. I selected the non-swearword intensifier *super* because it has been identified as a mixed-meaning expression (Waksler 2012; see also Foolen 2015; Gutzmann and Turgay 2012; Gutzmann and Turgay 2014), and I selected the negative intensifier *insanely* to match the negative valence of swearwords (Foolen 2015). I expected the three intensifier conditions to convey meanings about the product and the reviewer to different degrees, and therefore differentially affect readers' product attitudes.

For product attribute intensity, I expected the swearword intensifier (i.e., *damn*) to convey *higher* product attribute intensity than the non-swearword intensifier (i.e., *super*; similar to study 2) and the *same* product attribute intensity as the negative intensifier (i.e., *insanely*) because both swearword intensifiers and negative intensifiers are negative words (van der Wouden and Foolen 2017). Building on the negativity bias in information processing (Baumeister et al. 2001; see study 2), when positive words are used as intensifiers, they lead to a lower degree of intensification (e.g., "a *nice* amount"). In contrast, when negative words (including swearwords) are used as intensifiers, they lead to a higher degree of intensification (e.g., "an *insane* amount") because they build on the literal (negative) meaning of the word to convey different degrees of intensity (Foolen 2015).

For reviewer feeling strength, I expected the swearword intensifier (*damn*) to convey higher reviewer feeling strength than both the non-swearword intensifier (*super*) *and* the negative intensifier (*insanely*). This is because of the swearword's taboo status. Speakers often use swearwords when they feel strongly (Jay 2000), and listeners infer that the speaker has strong feelings because the speaker broke the taboo (Foolen 2015; Jay 2000).

Ultimately, because of their greater impact on strength of the reviewer's feelings, I expected swearword intensifiers to have the strongest positive impact on readers' product attitudes, relative to non-swearword and to negative intensifiers.

Participants, Design, and Measures

Three hundred and seventeen participants were recruited from MTurk (M_{age} = 36.2; 52% male). Twenty-one participants were excluded from analysis for failing the attention check (asking participants to report how the reviewer described the product's wash cycle), leaving a final sample of 296.

This study was a single factor, 3-level (intensifier: swearword [*damn*] vs. non-swearword [*super*] vs. negative word [*insanely*]) between-subjects design. Participants were asked to imagine that they needed to buy a new dishwasher. Then they were shown an image of a dishwasher on a seller's website which included one positive review. The title of the review contained the manipulation, and read, "The dishwasher is [damn/insanely/super] quiet!" The remaining review text was the same across conditions ("Cycles work as expected. Layout is okay."). After reading the review, participants reported on the review's offensiveness, product attitudes, willingness-to-pay, reviewer feeling strength, and product attribute intensity (i.e., degree of quietness).

Offensiveness (manipulation check; review offensiveness [$M = 1.53$, SD = 1.21], perceived review offensiveness to most people [$M = 1.50$, SD = 1.07]), product attitudes ($M = 5.71$, SD = .89, $\alpha = 0.95$), willingness-to-pay (\$0 to \$1200 scale; $M = \$409.42$, SD = \$185.96), and reviewer feeling strength ($M = 4.68$, SD = 1.41, $\alpha = 0.95$) were measured as in study 1. Product attribute intensity was measured by asking participants to report the degree to which the dishwasher was quiet, silent, inaudible, muted, unobtrusive, suppressed, and faint on a 1 = *not at all* to 7 = *very much* scale ($M = 5.24$, SD = 1.38, $\alpha = 0.91$).

Results

Offensiveness. A one-way ANOVA revealed a significant effect of intensifier on review offensiveness ($F(2, 288) = 3.61$, $p = .028$, partial $\eta^2 = .024$). The review was more offensive in the swearword condition ($M_{\text{damn}} = 1.78$, SD = 1.46) compared to the non-swearword condition ($M_{\text{super}} = 1.32$, SD = .87, $t(288) = 2.65$, $p = .009$) and the negative word condition ($M_{\text{insanely}} = 1.48$, SD = 1.18), $t(288) = 1.71$, $p = .087$). For perceived offensiveness to others, an ANOVA also revealed a significant effect of intensifier ($F(2, 288) = 24.36$, $p < .001$, partial $\eta^2 = .145$), such that participants perceived others to be more offended in the swearword condition ($M_{\text{damn}} =$

2.56, SD = 1.61), relative to the non-swearword (M_{super} = 1.39, SD = 1.02, $t(288) = 6.39$, $p < .001$) and the negative word conditions ($M_{insanely}$ = 1.53, SD = 1.15), $t(288) = 5.63$, $p < .001$).

Independence of mediators and dependent variable. A principal-component factor analysis with varimax rotation was conducted on the inferred meanings and product attitude items; three factors emerged. The first factor captured product attitudes (29.3% of variance, eigenvalue = 6.53). All 6 items for product attitude loaded above .83 on this factor and below .17 on the others. The second factor captured was product attribute intensity (28.7% of variance, eigenvalue = 3.46). All 7 items for product attribute intensity loaded above .72 on this factor and below .23 on the others. The third factor captured reviewer feeling strength (15.9% of variance, eigenvalue = 1.83). All 3 items for reviewer feeling strength loaded above .81 on this factor and below .21 on the others.

Product attitude. An ANOVA revealed a significant effect of intensifier on product attitudes ($F(2, 293) = 8.54$, $p < .001$, partial $\eta^2 = .055$). Participants liked the dishwasher more in the swearword condition (M_{damn} = 6.00, SD = .78), compared to the non-swearword (M_{super} = 5.64, SD = .89, $t(293) = 2.85$, $p = .005$) and to the negative word conditions ($M_{insanely}$ = 5.50, SD = .93, $t(293) = 4.02$, $p < .001$).[6]

Willingness-to-pay. An ANOVA on willingness-to-pay also revealed a significant effect ($F(2, 293) = 3.13$, $p = .045$, partial $\eta^2 = .021$), such that participants were willing to pay more for the dishwasher in the swearword condition (M_{damn} = \$447.25, SD = \$225.30), compared to the non-swearword condition (M_{super} = \$392.06, SD = \$164.96, $t(293) = 2.10$, $p = .037$) and the negative word condition ($M_{insanely}$ = \$388.76, SD = \$155.69, $t(293) = 2.23$, $p = .027$).

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[6] The results for product attitudes hold when controlling for offensiveness ($F(1, 287) = 10.73$, $p < .001$, partial $\eta^2 = .070$). The results for willingness-to-pay are only directionally significant when controlling for offensiveness ($F(1, 287) = 2.22$, $p = .111$, partial $\eta^2 = .015$)

Product attribute intensity. An ANOVA revealed a significant effect of intensifier on product attribute intensity (i.e., degree of quietness; $F(2, 293) = 3.37$, $p = .036$, partial $\eta^2 = .022$), such that participants perceived the dishwasher to be quieter in the swearword condition ($M_{\text{damn}} = 5.49$, SD = 1.33) compared to the non-swearword condition ($M_{\text{super}} = 4.99$, SD = 1.43, $t(293) = 2.60$, $p = .010$). As predicted, there was no difference in quietness between the swearword and the negative word conditions ($M_{\text{insanely}} = 5.23$, SD = 1.32, $t(293) = 1.23$, $p = .22$).

Reviewer feeling strength. An ANOVA revealed a significant effect of intensifier on reviewer feeling strength ($F(2, 293) = 6.62$, $p = .002$, partial $\eta^2 = .043$). Participants perceived the reviewer's feelings to be stronger in the swearword condition ($M_{\text{damn}} = 5.07$, SD = 1.40) compared to the non-swearword condition ($M_{\text{super}} = 4.38$, SD = 1.37, $t(293) = 3.54$, $p < .001$) and the negative word condition ($M_{\text{insanely}} = 4.58$, SD = 1.38), $t(293) = 2.51$, $p = .013$).

Mediation. A parallel mediation model with a multi-categorical independent variable (model 4; Hayes 2013) showed significant effects when comparing the swearword condition (*damn*) to the non-swearword condition (*super*) and to the negative word condition (*insanely*).

First, relative to the non-swearword, the swearword increased inferences of reviewer feeling strength ($\beta = .15$, 95% CI for the indirect effect: .06 to .25) and product attribute intensity (i.e., degree of quietness; $\beta = .04$, 95% CI for the indirect effect: .001 to .10), which increased product attitudes ($\beta = .35$, 95% CI for the total effect: .11 to .60). Consistent with studies 1 and 2, a pairwise comparison between the two indirect effects was not significant ($\beta = .05$, 95% CI for the indirect effect contrast: -.002 to .11), suggesting that there was no difference in the strength of the mediators. The direct effect of swearwords on product attitudes became insignificant when controlling for the mediators ($\beta = .17$, 95% CI for the direct effect: -.06 to .40).

Second, relative to the negative word, the swearword increased inferences of reviewer feeling strength (β = .10, 95% CI for the indirect effect: .02 to .20), which increased product attitudes (β = .49, 95% CI for the total effect: .25 to .74). The indirect effect of the swearword via product attribute intensity (i.e., degree of quietness) was not significant (β = .02, 95% CI for the indirect effect: -.008 to .07), showing that, as predicted, the swearword and the negative word conveyed similar meaning about quietness. The direct effect of swearwords on product attitudes remained significant when controlling for the mediators (β = .37, 95% CI for the direct effect: .14 to .60).

Discussion

Study 3 tested the impact of swearwords in reviews by comparing a swearword intensifier (i.e., *damn*) to a non-swearword intensifier (i.e., *super*) and a negative intensifier (i.e., *insanely*). The results of this study supported hypotheses 1 through 3 and demonstrated the unique effects of swearwords. Similar to study 2, even when compared to a non-swearword intensifier—rather than to the absence of a swearword—a swearword intensifier conveyed meaning about the reviewer's strong feelings and the product's attribute of quietness, and these inferences independently enhanced review readers' attitudes. Further, while both negative intensifiers and swearword intensifiers conveyed similar meaning about the product's attribute, only the swearword intensifier increased inferences of reviewer feeling strength, which also enhanced readers' attitudes. Finally, study 3 offered additional evidence that the two meanings conveyed by swearwords function as independent mediators, first by replicating the factor analysis from studies 1 and 2, and second by showing that the indirect pathway for product attribute intensity can be turned off independently of reviewer feeling strength.

In sum, study 3 replicated and extended the previous studies by showing that relative to non-swearword intensifiers and negative intensifiers, swearword intensifiers positively influenced readers' attitudes because they conveyed greater reviewer feeling strength and product attribute intensity. Studies 1-3 tested the hypotheses in the context of positive reviews where swearwords qualify positive product attributes. I did so because of the abundance of research suggesting that swearwords have negative effects (e.g., Pinker 1994; Rassin and Muris 2005) and because there are far more positive than negative reviews (Woolf 2014). However, review readers generally consider negative reviews more helpful than positive reviews (Sen and Lerman 2007). For this reason, and for generalizability, in the next study (and the field data), I test hypothesis 1 in the context of a negative review.

STUDY 4

The purpose of study 4 was to test hypothesis 1 in the context of negative as well as positive reviews. In a positive review where the swearword qualifies a desirable product attribute, I hypothesized that the swearword would have a positive effect on readers' attitudes towards the reviewed product. In a negative review where the swearword qualifies an undesirable product attribute, I hypothesized that the swearword would have a negative effect.

Participants, Design, and Measures

This study was a 2 (swearword: present vs. absent) by 2 (review valence: negative vs. positive) between-subjects design. Three hundred and ninety-eight individuals from Amazon's

Mechanical Turk (MTurk; M_{age} = 36.9; 48% male) were recruited to participate. Thirty-three were excluded from analysis for failing the attention check (participants were asked to report how the reviewer described the product's size), leaving a final sample of 365.

This study employed the same online shopping scenario as study 1. The title of the review contained the swearword manipulations. In the swearword present condition, the title read, "It charged my phone fucking fast." In the swearword absent condition, the title read, "It charged my phone fast." Across both conditions, the product was rated 4 out of 5 stars and the text of the review read, "It's handy and portable. But it feels heavy. It holds a charge fine and its size is okay." Participants then answered questions related to offensiveness, product attitudes, and willingness-to-pay. Review offensiveness (M = 2.03, SD = 1.65), perceived offensiveness to others (M = 2.69, SD = 1.96; manipulation checks), product attitudes (M = 4.49, SD = 1.55, α = 0.98), and willingness-to-pay (M = \$34.10, SD = \$27.70) were measured as in study 1.

Results

Offensiveness. A full factorial ANOVA with review offensiveness as the dependent variable showed a significant main effect of swearword ($M_{fucking}$ = 2.77, SD = 1.90; $M_{control}$ = 1.32, SD = .93; $F(1, 361) = 86.10$, $p < .001$, partial $\eta^2 = .193$). Neither the main effect of review valence ($F(1, 361) = 1.53$, $p = .22$) nor the interaction ($F(1, 361) = .006$, $p = .94$) were significant. Further, a full factorial ANOVA with perceived offensiveness of the review to others as the dependent variable showed significant effects of swearword ($M_{fucking}$ = 3.98, SD = 1.76; $M_{control}$ = 1.44, SD = 1.18; $F(1, 360) = 262.59$, $p < .001$, partial $\eta^2 = .422$) and valence ($M_{negative}$ = 2.88, SD = 2.03; $M_{positive}$ = 2.50, SD = 1.88; $F(1, 360) = 5.32$, $p = .022$, partial $\eta^2 = .015$). The interaction was not significant ($F(1, 360) = .0002$, $p = .99$).

Product attitudes. A full factorial ANOVA showed a significant main effect of review valence on product attitudes ($F(1, 361) = 410.16$, $p < .001$, partial $\eta^2 = .532$) and a significant interaction ($F(1, 361) = 8.88$, $p = .003$, partial $\eta^2 = .024$). When the review was positive, participants held more favorable product attitudes when the swearword was present ($M_{\text{fucking}} = 5.80$, SD = .91) versus absent ($M_{\text{control}} = 5.45$, SD = .86, $t(361) = 2.22$, $p = .027$, partial $\eta^2 = .014$). When the review was negative, participants held less favorable product attitudes when the swearword was present ($M_{\text{fucking}} = 3.22$, SD = 1.05) versus absent ($M_{\text{control}} = 3.53$, SD = 1.35, $t(361) = 1.99$, $p = .048$, partial $\eta^2 = .011$).

Willingness-to-pay. An ANOVA on willingness-to-pay revealed a significant main effect of review valence ($F(1, 361) = 44.43$ $p < .001$, partial $\eta^2 = .110$) as well as a significant interaction ($F(1, 361) = 8.32$ $p = .004$, partial $\eta^2 = .023$). When the review was positive, participants were willing to pay more for the product when the swearword was present (M_{fucking}= \$47.34, SD = \$29.46) versus absent (M_{control} = \$39.18, SD = \$25.50, $t(361) = 2.11$, $p = .036$, partial $\eta^2 = .012$). When the review was negative, participants were willing to pay less for the product when the swearword was present (M_{fucking}= \$21.34, SD = \$16.65) versus absent (M_{control} = \$28.89, SD = \$30.14, $t(361) = 1.97$, $p = .05$, partial $\eta^2 = .011$).[7]

Discussion

The results of study 4 provided further support for hypothesis 1. The presence (vs. absence) of a swearword affected readers' attitudes towards—and willingness-to-pay for—the

[7] The results for product attitudes and willingness-to-pay hold when controlling for offensiveness (interaction effect for product attitudes: $F(1, 358) = 8.68$, $p = .003$, partial $\eta^2 = .024$; interaction effect for willingness-to-pay: $F(1, 358) = 7.95$, $p = .005$, partial $\eta^2 = .022$).

product under review. Specifically, in a positive review where the swearword qualified a desirable product attribute, readers held more favorable product attitudes and were willing to pay more for the reviewed product. However, in a negative review where the swearword qualified an undesirable product attribute, readers held less favorable product attitudes and were willing to pay less for the reviewed product. In short, study 4 demonstrated that relative to no swearwords, swearword intensifiers could exert positive or negative effects on review readers. Studies 5 and 6 investigated boundary conditions for the swearing effect.

STUDY 5

The purpose of study 5 was to examine when the effects of swearwords in reviews might be attenuated. I hypothesized that swearwords would be used as an input for judgment only when the meanings they conveyed were diagnostic (Feldman and Lynch 1988; Lynch, Marmorstein, and Weigold 1988). Diagnostic information helps consumers distinguish between alternative hypotheses, interpretations, or categorizations, such as whether a product is high or low quality (Ahluwalia and Gürhan-Canli 2000; Herr, Kardes, and Kim 1991).

I predicted that swearwords would not be diagnostic when the product under review had inherently intense attributes (e.g., white-water rafting). Kronrod and Danzinger (2013) demonstrated that consumers use emotionally intense language when describing highly hedonic experiences, and such activities has been shown to increase swearing (e.g., Anderson and Carnagey 2009). Accordingly, a swearword in a review about an intrinsically intense consumption experience should not be diagnostic (i.e., redundant or non-discriminatory) because product attribute intensity is not novel; it should therefore not affect readers' product attitudes.

Specifically, a swearword (vs. non-swearword) intensifier should convey *higher* product attribute intensity when the swearword is diagnostic (i.e., the product is not inherently intense) and the *same* product attribute intensity when the swearword is not diagnostic (i.e., the product is inherently intense; moderated mediation). Given that diagnosticity in this case is related to the product category and not to the reviewer, I expect reviewer feeling strength to remain a mediator across both diagnosticity conditions.

For generalizability, study 5 used a different swearword (*holy shit*) and a different non-swearword intensifier (*wow*) from prior studies. *Wow* was selected as the non-swearword intensifier because it is commonly used to convey that the speaker is very impressed by something (Ekpe, Offong, and Okon 2014). This study also tested an alternative explanation: conversational norms. Adhering to conversational norms or communication expectations leads to more favorable product attitudes (Grice 1975; Kronrod and Danziger 2013; Reece 1989). If swearwords are conversationally normative, this could lead to the observed positive effects of swearwords. Finally, this study included a measure of attitudes towards the review website to see if swearwords negatively affected perceptions of the host website.

Participants, Design, and Measures

This study employed a 2 (intensifier: swearword [*holy shit*] vs. non-swearword [*wow*]) by 2 (diagnosticity: diagnostic [class 1 rafting] vs. non-diagnostic [class 5 rafting]) between-subjects design. Two hundred and forty one undergraduates completed the study in exchange for partial course credit (M_{age} = 20; 55% male). Thirteen participants were excluded from analysis for failing the attention check (asking them to report the valence of the review, which was positive across all conditions), leaving a final sample of 228.

Participants were asked to imagine that they were planning a rafting trip with their friends and wanted to check out rafting companies online. Participants in all conditions were then shown the profile of a fictitious rafting company on a popular customer review website, accompanied by a customer review. The title of the review contained the intensifier manipulation. The title in the swearword condition read, “Holy shit, that was fun!” while the title in the non-swearword condition read, “Wow, that was fun!”

Diagnosticity of meaning about the product was manipulated by describing the rafting excursion as Class 1 (diagnostic) or Class 5 (non-diagnostic). In the diagnostic conditions, the company’s profile was titled, “WaterMax – Class 1 Rafting” and the definition of a class 1 rapid read, “very relaxing … gentle moving water. Very small waves requiring little or no maneuvering.” Since such an excursion is ambiguous in terms of fun, the meaning conveyed by the swearword intensifier (vs. the non-swearword intensifier) should offer discriminating information, and should positively affect readers’ product attitudes. In the non-diagnostic conditions, the company’s profile was titled, “WaterMax – Class 5 Rafting” and the definition of a class 5 rapid read, “adrenaline junkies only … class 5 enters the ‘kinda scary’ scale. Confused and erratic waves or holes. Small drops, ledges or waterfalls are present.” Since such an excursion is unambiguously fun, the meaning conveyed by the swearword intensifier (vs. the non-swearword intensifier) should be redundant and should not affect readers’ product attitudes. The imagery in each condition reflected these descriptions. The subsequent review was the same across all conditions: “This was my first time rafting. I was terrified at first, but the guides were really well prepared and gave me the confidence I needed to do it. So glad I did.”

Review offensiveness ($M = 1.63$, SD = 1.24), perceived offensiveness to others ($M = 2.16$, SD = 1.49; manipulation checks), product attitude ($M = 5.60$, SD = 1.23; $\alpha = 0.95$), and reviewer feeling strength (M = 5.63, SD = 1.12; α = 0.81) were measured as in prior studies. Product attribute intensity (i.e., degree of fun) was measured using three 7-point semantic differential scales anchored: not fun/fun, dull/exciting, and not thrilling/thrilling; M = 5.14, SD = 1.57; α = 0.88)[8]. To measure conversational norms, participants reported how expected, normal, average, and typical the language in the review was (1 = *strongly agree*, 7 = *strongly disagree*; M = 5.14, SD = 1.38, α = 0.89; Kronrod and Danziger 2013). Finally, participants' attitude towards the review website was measured with six items using seven-point semantic differential scales with the following anchors: negative—positive, dislike—like, good—bad, unfavorable—favorable, unappealing—appealing, and unpleasant—pleasant (M = 5.20, SD = 1.26, α = 0.97).

Results

Offensiveness. As expected, a full factorial ANOVA on perceived offensiveness to others revealed a significant main effect of intensifier ($M_{\text{holy shit}}$ = 2.62, SD = 1.59; M_{wow} = 1.71, SD = 1.21; $F(1, 224) = 46.43$, $p < .001$, partial $\eta^2 = .094$). The main effect of diagnosticity ($F(1, 224)$ = .07, p = .80) and the interaction effect ($F(1, 224) = 1.00$, p = .32) were not significant. For review offensiveness, the main effect of intensifier was not significant ($M_{\text{holy shit}}$ = 1.75, SD = 1.35; M_{wow} = 1.50, SD = 1.10; $F(1, 224) = 2.45$, p = .12, partial $\eta^2 = .011$). The main effect of diagnosticity ($F(1, 224)$ = .01, p = .92) and the interaction effect ($F(1, 224)$ = .47, p = .49) were also not significant.

Independence of mediators and dependent variable. A principal-component factor analysis with varimax rotation was conducted on the inferred meanings and product attitude

[8] This measure originally contained 5 scale items, but not delightful/delightful and not enjoyable/enjoyable were removed due to high cross-loadings, particularly with the product attitude measure.

items; three factors emerged. The first factor captured product attitudes (42.29% of variance, eigenvalue = 6.41). All 6 items for product attitude loaded above .84 on this factor and below .25 on the others. The second factor captured was product attribute intensity (19.5% of variance, eigenvalue = 1.81). Two of the 3 items for product attribute intensity loaded above .90 on this factor and below .29 on the others. The item *fun* loaded highest on the product attribute intensity factor (.61), but also loaded fairly high on the product attitude factor (.59). It was retained in the analysis, but the results hold without this item. The third factor captured reviewer feeling strength (19.2% of variance, eigenvalue = 1.51). All three items for reviewer feeling strength loaded above .77 on this factor and below .24 on the others.

Product attitude. A full factorial ANOVA on product attitudes revealed a significant interaction ($F(1, 224) = 5.66$, $p = .018$, partial $\eta^2 = .025$). As hypothesized, product attitudes were more favorable in the swearword condition (vs. non-swearword condition) when the swearword was diagnostic (i.e., class 1 rafting; $M_{\text{holy shit}} = 5.88$, SD = 1.08; $M_{\text{wow}} = 5.37$, SD = 1.37; $t(224) = 2.27$, $p = .024$, partial $\eta^2 = .022$), but not when the swearword was non-diagnostic (i.e., class 5 rafting; $M_{\text{holy shit}} = 5.58$, SD = 1.19; $M_{\text{wow}} = 5.71$, SD = .99; $t(224) = 1.10$, $p = .27$).[9]

Product attribute intensity. A full factorial ANOVA revealed a significant main effect of diagnosticity on product attribute intensity (i.e., degree of fun; $M_{\text{class 5}} = 5.88$, SD = 1.13; $M_{\text{class 1}} = 4.42$, SD = 1.62; $F(1, 224) = 62.20$, $p < .001$, partial $\eta^2 = .22$) as well as a marginally significant interaction ($F(1, 224) = 3.70$, $p = .056$, partial $\eta^2 = .016$). As expected, inferences of fun were higher in the swearword condition (vs. non-swearword condition) when the swearword was diagnostic (i.e., class 1 rafting; $M_{\text{holy shit}} = 4.74$, SD = 1.62; $M_{\text{wow}} = 4.13$, SD = 1.57; $t(224) = 2.37$, $p = .019$, partial $\eta^2 = .024$), but not when the swearword was non-diagnostic (i.e., class 5

[9] The results for product attitudes hold when controlling for offensiveness (interaction effect: $F(1, 223) = 6.20$, $p = .014$, partial $\eta^2 = .027$).

rafting; $M_{\text{holy shit}}$ = 5.83, SD = 1.33; M_{wow} = 5.93, SD = .86; $t(224) = .36$, $p = .72$, partial η^2 = .001).

Reviewer feeling strength. A full factorial ANOVA revealed, as expected, a significant main effect of intensifier on reviewer feeling strength ($M_{\text{holy shit}}$ = 6.05, SD = .95; M_{wow} = 5.23, SD = 1.14; $F(1, 224) = 33.97$, $p < .001$, partial η^2 = .132). The main effect of diagnosticity ($F(1, 224) = 3.23$, $p = .074$, partial η^2 = .014) and the interaction effect ($F(1, 224) = .44$, $p = .508$, partial η^2 = .002) were not significant.

Moderated mediation. A moderated mediation model with product attribute intensity and reviewer feeling strength as the mediators (model 7; Hayes 2013) revealed, as expected, a significant index of moderated mediation for product attribute intensity (Index = -.235, 94% CI: -.505 to -.012) but not reviewer feeling strength (Index = -.049, 94% CI: -.226 to .082). The effect of swearwords on product attitudes via product attribute intensity was significant when the swearword was diagnostic (class 1; β = .203, 94% CI: .013 to .426) but not when it was non-diagnostic (class 5: β = -.031, 94% CI: -.173 to .092). The effect of swearwords on product attitudes via reviewer feeling strength was significant both when the swearword was diagnostic (class 1; β = .240, 94% CI: .082 to .450) and when it was non-diagnostic (class 5; β = .191, 94% CI: .069 to .335). The direct effect of swearwords on product attitudes became insignificant when controlling for the mediators (β = -.189, 94% CI: -.466 to .089).

Alternative explanations. A full factorial ANOVA on conversational norms was not significant (all $p > .31$).

Attitude towards review website. A full factorial ANOVA on attitudes towards the review website revealed a significant main effect of intensifier ($M_{\text{holy shit}}$ = 5.37, SD = 1.27; M_{wow} = 5.04, SD = 1.22; $F(1, 223) = 3.97$, $p = .047$, partial η^2 = .018) and a significant interaction effect (F(1,

223) = 5.46, p = .020, partial η^2 = .024). Attitudes were more favorable in the swearword condition (vs. non-swearword condition) when the swearword was diagnostic (i.e., class 1 rafting; $M_{\text{holy shit}}$ = 5.59, SD = 1.04; M_{wow} = 4.88, SD = 1.27; $t(223)$ = 23.07, p = .002, partial η^2 = .041), but there was no change in effect when the swearword was non-diagnostic (i.e., class 5 rafting; $M_{\text{holy shit}}$ = 5.15, SD = 1.43; M_{wow} = 5.21, SD = 1.17; $t(223)$ = .24, p = .81).

Discussion

Using a different swearword (*holy shit*) versus non-swearword (*wow*) comparison, study 5 replicated the previous studies by demonstrating that swearwords can positively affect reader's product attitudes. It also showed that the presence of a swearword in a review did not negatively affect the reader's attitude towards the review website. Most critically, study 5 demonstrated that swearwords do not affect review readers when the meaning they convey is not diagnostic. Specifically, swearwords increased product attitudes when it was diagnostic (i.e., when the excursion was ambiguous in terms of fun; class 1) but not when it was non-diagnostic (i.e., when the excursion was unambiguously fun; class 5). Finally, this study ruled out conversational norms as an alternative explanation.

STUDY 6

The purpose of study 6 was to retest hypotheses 1-3 and further explore when swearwords would affect review readers. Rather than using a product characteristic (study 5), this study tested diagnosticity of meaning as a moderator using a reviewer characteristic:

multiple swearwords. Based on the Yelp and Amazon field data (described next), I compared a review with no swearwords to reviews with two and five swearwords. I expected swearwords to be non-diagnostic when a review contained many swearwords versus a few swearwords, because reviews with different numbers of swearwords should differentially affect inferred meanings.

Specifically, given that the act of swearing breaks a taboo and therefore conveys strong reviewer feelings (Allan and Burridge 2006; Stapleton 2010), I predicted that two swearwords in a review would convey the *same* reviewer feeling strength as five swearwords, but *greater* reviewer feeling strength than no swearwords. However, compared to no swearwords or to five swearwords, I predicted that two swearwords would convey the highest product attribute intensity. This is due to a change in causal attribution, whereby review readers should attribute the use of multiple swearwords to characteristics of the reviewer rather than the product (He and Bond 2015). That is, multiple swearwords in a review should be non-diagnostic because, for any single swearword, it is less clear if the reviewer is swearing to convey information about the product's attribute or for some other reason (e.g., the reviewer is exaggerating or is simply prone to strong feelings). Thus, the meaning the swearword conveys about the product's attribute is less discriminating and should have an attenuated effect on product attitudes.

Participants, Design, and Measures

Three hundred and sixty-one North American participants recruited from Prolific Academic completed the study in exchange for fifty cents ($M_{\text{age}} = 35.6$; 49% male). Nineteen participants were excluded from analysis for failing the attention check (asking participants to report how the reviewer described the product's size), leaving a final sample of 342.

This study was a single factor, 3-level (number of swearwords: zero vs. two vs. five) between-subjects design. It employed the same product and scenario as study 1: a portable battery on a popular electronics website. In the zero swearwords condition, the review title read, "It charged my phone fast." In the two and five swearwords conditions, the review title read, "Holy shit, it charged my phone fucking fast." The remaining review text was the same in the zero and two swearwords conditions: "But, it feels heavy. Still, it's handy and portable. It holds a charge fine and its size is okay." In the five swearwords condition, the text included three additional swearwords that qualified other desirable product attributes: "But, it feels heavy. Still, the fucker is fucking handy and portable. It holds a charge damn fine and its size is okay."

After reading the review, participants answered questions related to offensiveness (manipulation check; review offensiveness [M = 1.53, SD = 1.21] and offensiveness to most people [M = 3.54, SD = 2.11]), product attitudes (M = 5.57, SD = 1.03, α = 0.95), willingness-to-pay ($0 to $200 scale; M = $42.50, SD = $33.99), reviewer feeling strength (M = 5.54, SD = 1.40, α = 0.90), and product attribute intensity (charging speed; M = 5.58, SD = 1.17, α = 0.95). All items were measured as in study 1.

This study also included some additional measures. First, the five swearwords condition had three swearwords that qualified other desirable product attributes: handiness, portability, and holding a charge. To test whether the swearwords changed the degree of these attributes, all participants reported on the degree to which the power station was handy (M = 5.75, SD = 1.19) and portable (M = 5.55, SD = 1.28; both 1 = *not at all*, 7 = *very much*), and on how well they thought the power station could hold a charge (1 = *far below average* to 7 = *far above average*; M = 5.36, SD = .98; these three items are analyzed separately below due to lower reliability, α = 0.67). Second, I predicted that five (vs. two) swearwords in a review would be non-diagnostic for any single swearword because it would be less clear if the reviewer used swearwords to convey meaning about the product's attributes or if the reviewer used swearwords because of their disposition. Thus, I measured causal attribution using a bipolar 7-point scale adapted from He and Bond (2015). Participants in the two and five swearwords conditions reported if they thought the swearwords in the review were caused by the reviewer's disposition towards swearing (1) or the reviewer's genuine assessment of the product (7). Therefore, higher (lower) scores indicated greater product (reviewer) attribution ($M = 3.39$, SD = 2.16).

Results

Offensiveness. A one-way ANOVA revealed a significant effect for the number of swearwords on review offensiveness ($F(2, 339) = 23.97$, $p < .001$, partial $\eta^2 = .124$): the review was more offensive in the two swearwords condition ($M_{\text{two}} = 2.70$, SD = 2.01) compared to the zero swearwords condition ($M_{\text{zero}} = 1.42$, SD = 1.20; $t(339) = 5.46$, $p < .001$). There was no difference between the two and five swearwords conditions ($M_{\text{five}} = 2.93$, SD = 1.94; $t(339) = .99$, $p = .32$). For perceived offensiveness of the review to most people, an ANOVA also revealed a significant effect ($F(2, 339) = 169.49$, $p < .001$, partial $\eta^2 = .500$). Participants perceived most others to be more offended in the two ($M_{\text{two}} = 4.15$, SD = 1.78) versus the zero swearwords condition ($M_{\text{zero}} = 1.47$, SD = 1.20, $t(339) = 13.53$, $p < .001$), but more offended in the five versus the two swearwords condition ($M_{\text{five}} = 4.97$, SD = 2.11; $t(339) = 4.18$, $p < .001$).

Independence of mediator and dependent variables. A principal-component analysis with varimax rotation was conducted on the items composing the two inferred meanings measures and the product attitude measure; three factors emerged. The first factor captured product attitudes (32.49% of variance, eigenvalue = 7.85). All 6 items comprised of product attitudes had a factor loading above .82 on the same factor and a factor loading below .24 on the other factors (eigenvalue = 7.85). The second factor captured product attribute intensity (i.e., charging speed; 31.92% of variance, eigenvalue = 2.72). All 6 items comprised of product attribute intensity (i.e., charging speed) had a factor loading above .81 on the same factor and a factor loading below .24 on the other factors. The third factor captured was reviewer feeling strength (17.23% of variance, eigenvalue = 1.68) All 3 items comprised of reviewer feeling strength had a factor loading above .79 on the same factor and a factor loading below .23 on the other factors (eigenvalue = 1.68).

Product attitude. An ANOVA revealed a significant effect of the number of swearwords on product attitudes ($F(2, 339) = 4.48$, $p = .012$, partial $\eta^2 = .026$), such that participants liked the battery the most in the two swearwords condition ($M_{two} = 5.80$, SD = .94), compared to both the zero swearwords ($M_{zero} = 5.50$, SD = .87; $t(339) = 2.20$, $p = .028$) and the five swearwords conditions ($M_{five} = 5.41$, SD = 1.22; $t(339) = 2.84$, $p = .005$).[10]

Willingness-to-pay. An ANOVA on willingness-to-pay also revealed a significant effect ($F(2, 338) = 4.97$, $p = .007$, partial $\eta^2 = .029$). As above, participants were willing to pay the most for the battery in the two swearwords condition (M_{two} = \$50.53, SD = \$44.26), compared to the zero swearwords (M_{zero}= \$38.59, SD = \$27.20; $t(338) = 2.68$, $p = .008$) and the five swearwords conditions (M_{five} = \$38.22, SD = \$25.94; $t(338) = 2.77$, $p = .006$).

Reviewer feeling strength. An ANOVA on reviewer feeling strength revealed a significant effect ($F(2, 339) = 154.97$, $p < .001$, partial $\eta^2 = .478$). Participants perceived the reviewer's feelings to be stronger in the two swearwords condition ($M_{two} = 6.18$, SD = .82) than the zero swearwords condition ($M_{zero} = 4.16$, SD = 1.30; $t(339) = 15.07$, $p < .001$). There was no

[10] The results for product attitudes and willingness-to-pay hold when controlling for offensiveness (product attitudes; $F(2, 338) = 4.47$, $p = .012$, partial $\eta^2 = .026$; willingness-to-pay: $F(2, 337) = 5.76$, $p = .003$, partial $\eta^2 = .033$).

difference between the two and five swearwords conditions ($M_{\text{five}} = 6.25$, SD = .86; $t(339) = .51$, $p = .61$).

Product attribute intensity. An ANOVA on product attribute intensity (i.e., charging speed) also revealed a significant effect ($F(2, 339) = 22.41$, $p < .001$, partial $\eta^2 = .117$), such that participants perceived the battery to charge faster in the two swearwords condition ($M_{\text{two}} = 5.99$, SD = 1.01) compared to the zero swearwords condition ($M_{\text{zero}} = 5.04$, SD = 1.19; $t(339) = 6.57$, $p < .001$) and the five swearwords conditions ($M_{\text{five}} = 5.69$, SD = 1.10; $t(339) = 2.01$, $p = .045$).

ANOVAs on inferences about the other desirable attributes did not reveal significant effects for handy ($F(2, 339) = 1.18$, $p = .31$) or portable ($F(2, 339) = 1.44$, $p = .24$). The exception was ability to hold a charge ($F(2, 338) = 3.84$, $p = .022$, partial $\eta^2 = .022$), where participants perceived the battery to hold a charge better in the five swearwords condition ($M_{\text{five}} = 5.49$, SD = .92) than the zero swearwords condition ($M_{\text{zero}} = 5.15$, SD = .97; $t(339) = 2.58$, $p = .01$). However, as expected, there was no difference between the five and two swearwords conditions ($M_{\text{two}} = 5.43$, SD = 1.02; $t(339) = .44$, $p = .66$), suggesting that multiple swearwords in a review reduce the diagnosticity of any single swearword.

Causal attribution. Only participants in the two and five swearwords conditions reported on causal attribution of the swearwords. An ANOVA revealed a significant effect of the number of swearwords on attribution ($F(2, 227) = 6.90$, $p = .009$, partial $\eta^2 = .030$). Participants were more likely to attribute swearing to the reviewer than to the product when the review contained five swearwords ($M_{\text{five}} = 3.02$, SD = 2.02) rather than two swearwords ($M_{\text{two}} = 3.72$, SD = 2.24).

Mediation. A parallel mediation model with a multi-categorical independent variable (model 4; Hayes 2013) revealed significant effects when comparing two swearwords to zero and five swearwords.

First, two (vs. zero) swearwords in the review increased inferences of reviewer feeling strength (β = .51, 95% CI for the indirect effect: .29 to .74) and product attribute intensity (i.e., charging speed; β = .38, 95% CI for the indirect effect: .25 to .54), which increased product attitudes (β = .30, 95% CI for the total effect: .03 to .56). A pairwise comparison between the two indirect effects was not significant (β = .06, 95% CI for the indirect effect contrast: -.31 to .20), indicating that there was no difference in the strength of the mediators. The direct effect of swearwords on product attitudes remained significant when controlling for the mediators (β = -.60, 95% CI for the direct effect: -.32 to -.87).

Second, two (vs. five) swearwords increased product attribute intensity (i.e., charging speed; β = .12, 95% CI for the indirect effect: .01 to .26), which increased product attitudes (β = .38, 95% CI for the total effect: .12 to .65). The indirect effect of two (vs. five) swearwords via reviewer feeling strength was not significant (β = -.02, 95% CI for the indirect effect: -.07 to .05), suggested the two and five swearwords conditions conveyed similar meaning about the reviewer's feelings. The direct effect of swearwords on product attitudes remained significant when controlling for the mediators (β = .28, 95% CI for the direct effect: .07 to .50).

Discussion

Study 6 tested the diagnosticity of swearwords by comparing reviews containing zero, two, and five swearwords. First, these results replicated prior studies and supported hypotheses 1-3. Compared to reviews with zero swearwords, reviews with two swearwords increased inferences of reviewer feeling strength and product attribute intensity (i.e., charging speed). Ultimately, these inferences independently enhanced product attitudes and willingness-to-pay. Second, compared to reviews with five swearwords, those with two swearwords had the greatest effect on readers. Two (vs. five) swearwords in the review conveyed higher product attribute intensity and the same reviewer feeling strength, and inferences of product attribute intensity increased readers' attitudes. Further, while the five (vs. two) swearwords condition had swearwords qualifying additional desirable product attributes (handy, portable, and the ability to hold a charge), there were no differences in inferences about these attributes across conditions. Together, these findings suggest that multiple swearwords in a review reduce the diagnosticity of any single swearword. Indeed, participants reported greater attribution to the reviewer when the review contained five (vs. two) swearwords. Third, study 6 offered additional evidence that the two proposed mediators function independently, by again showing that the two constructs load on different factors, and by showing that the indirect pathway for meaning about the reviewer's feelings can be turned off independently of meaning about the product's attributes.

While these experiments have provided strong causal support for the proposed model via mediation and moderation, they used experimenter-generated reviews and non-consequential dependent variables. Thus, the final study used an externally valid context—an analysis of Yelp and Amazon reviews—to demonstrate that swearwords provide value to review readers.

FIELD DATA

To corroborate the idea that swearwords can be useful to review readers, I obtained data from two leading review websites: Yelp and Amazon. Yelp reviews were obtained from the 2017 Yelp Dataset Challenge. This publically available dataset contained all reviews as of January 20th, 2017 that cleared Yelp's software, which automatically screens out fake or untrustworthy reviews (Yelp 2017a). The dataset consisted of approximately 4.7 million reviews of 156,000 businesses in 12 metropolitan areas from 4 countries (Yelp 2017b). One hundred thousand of these reviews were randomly selected for analysis. In this final dataset, there were 76,544 unique reviewers for 42,883 different businesses. For each review, the data included: review text, star rating (a 5-point rating system with 5 being the best), date posted, and number of people who voted the review as useful.[11] It did not include information on the total number of people who viewed the review.

Amazon reviews were obtained from a publically available repository (He and McAuley 2016; McAuley, Targett, Shi and van den Hengel 2015). The dataset contains 82.8 million product reviews from May 1996 to July 2014. Two hundred thousand of these reviews were randomly selected for analysis. In the final dataset, there were 190,240 unique reviewers for 161,092 different product categories across 24 product categories. See Table 1 for details on the frequency of product categories. For each review, the data included review text, star rating (a 5-point rating system with 5 being the best), date posted, number of people who voted the review as helpful, and number of people who voted the review as unhelpful.

There are a few key differences between the Yelp and Amazon datasets that make their analyses distinct yet complementary to one another. First, Yelp's guidelines state that swearwords are allowed in reviews, whereas Amazon's guidelines state that swearwords are not allowed. Reviews containing swearwords on Amazon's website may be removed or rejected. Consequently, Yelp's dataset may have more reviews containing swearwords. Second, Yelp allows readers to vote a review as useful, but it is unclear how many readers saw the review or did not find the review to be useful. Alternatively, Amazon allows readers to vote a review as

[11] Yelp also allows readers to vote a review as cool and/or funny. I focus only on useful votes for two reasons. First, from a theoretical perspective, these other voting categories are not central to the framework. Second, from an empirical perspective, it is unclear how votes might overlap (or not) across the three categories.

helpful *or* unhelpful, thereby enabling a dependent variable that is the number of helpful votes in proportion to the total number of votes. Third, the reviews on Yelp are written about services, such as restaurants, excursions, and repairs, whereas the reviews on Amazon are written about products, such as books, clothes, and pet supplies, so the effect of swearwords in reviews is tested in different contexts. Fourth, the maximum review length in the Yelp reviews is 1,016 words, whereas the maximum review length in the Amazon reviews is 5,013 words. Finally, the Yelp dataset includes reviews as recent as January 2017, whereas the Amazon dataset includes reviews as recent as July 2014. Overall, both the Yelp and Amazon datasets have limitations that are addressed with the other dataset, enabling a stronger test of the swearing effect than each dataset alone.

Table 1. Product Categories Represented in Amazon Dataset

Product Category	Frequency	Percent
Apps for Android	6,414	3.2
Automotive	3,301	1.7
Baby	2,360	1.2
Beauty	5,085	2.6
Books	56,088	28.0
CDs and Vinyl	9,367	4.7
Cell Phones and Accessories	8,467	4.2
Clothing, Shoes, and Jewelry	14,190	7.1
Digital Music	2,071	1.0
Electronics	19,499	9.7
Grocery and Gourmet Food	3,147	1.6
Health and Personal Care	7,309	3.7
Home and Kitchen	10,540	5.3
Instant Video	1,438	.7
Kindle Store	7,674	3.9
Movies and TV	11,550	5.8
Musical Instruments	1,188	.6
Office Products	3,090	1.5
Patio Lawn and Garden	2,344	1.2
Pet Supplies	3,099	1.5
Sports and Outdoors	8,218	4.1
Tools and Home Improvement	4,706	2.4
Toys and Games	5,549	2.8
Video Games	3,306	1.7
Total	**200,000**	**100%**

Independent Measure

Using Linguistic Inquiry and Word Count (LIWC) software (Pennebaker et al. 2015), I identified all the reviews that contained at least one swearword. LIWC categorizes words into validated, pre-existing dictionaries (Tausczik and Pennebaker 2010) and reports the proportion of words in a text that fall into each dictionary (e.g., positive emotion). I updated the swearword dictionary of 53 word stems so that it (1) excluded words that did not function as swearwords in the review context (e.g., the word *bloody* was excluded because it was used in the Yelp dataset primarily in reference to a Bloody Mary cocktail) and (2) included some swearwords not in the dictionary (the dictionary included some euphemistic swearwords such as *heck* and *arse*, but I added others that were not included, such as *fock* and *frig*, and censored swearwords.[12] The final updated dictionary contained 94 word stems. This binary variable was set to 1 when a review contained one or more swearwords and 0 otherwise. Of the 100,000 Yelp reviews, 8,348 (8.3%) reviews contained swearwords. Unsurprisingly, there were fewer swearwords in the Amazon reviews. Of the 200,000 Amazon reviews, 6,608 (3.3%) reviews contained swearwords.

Dependent Measure

Following prior research, the value of a Yelp review was operationalized as the number of "useful" votes it received (*M* = 1.01, SD = 2.44; Chen and Lurie 2013), and the value of an Amazon review was operationalized as the number of "helpful" votes it received (*M* = 2.12, SD = 16.90; Chen, Dhanasobhon, and Smith 2008). These votes reflect the reader's inferences that a review is informative because it helps reduce uncertainty, guide decision-making, and influence purchase decisions (Bakhshi, Kanuparthy, and Shamma 2015; Chen, Dhanasobhon, and Smith 2008; Moore 2015; Zhu, Yin, and He 2014). Since Amazon also allows readers to vote a review as "unhelpful," the dependent measure for the Amazon dataset was the number of helpful votes in proportion to the total number of votes (*M* = 32.82%, SD = 43.59%).

[12] I conducted a robustness check by testing the models using LIWC's original swearword dictionary (i.e., unmodified). The results are comparable to those using the modified dictionary. See the Appendix for the results of the robustness check.

Control Variables

Months posted. I controlled for the number of months between review posting and data extraction (January 21st, 2017 for Yelp; July 24th, 2014 for Amazon) because reviews posted later had less opportunity to receive useful votes (Yelp: $M = 32.01$, SD = 25.66; Amazon: $M = 28.59$, SD = 35.56; Zhu et al. 2014).

Review valence. The star rating accompanying each review served as a proxy for review valence (on a scale of 1-5, with 5 indicating a very positive review). I controlled for valence because prior research shows that negative reviews are considered more valuable than positive reviews (Bakhshi et al. 2015; Chen and Lurie 2013; Sen and Lerman 2007; Zhu et al. 2014). The average star rating in the Yelp sample was positive ($M = 3.73$, SD = 1.40); 21.6% of the reviews were negative (1 or 2 stars), 12.5% were neutral (3 stars), and 65.9% were positive (4 or 5 stars). The average star rating in the Amazon data was slightly more positive ($M = 4.17$, SD = 1.25); 13.03% of the reviews were negative (1 or 2 stars), 8.58% were neutral (3 stars), and 78.40% were positive (4 or 5 stars). Both spreads are consistent with prior analyses of Yelp reviews (Chen and Lurie 2013; Yelp 2009; Woolf 2014), Amazon reviews (Chevalier and Mayzlin 2006), and other online platforms (Fowler and De Avila 2009).

Review length. The number of words in the review (Yelp: $M = 117.64$, SD = 109.77; Amazon: $M = 92.01$, SD = 123.97) was used as a control variable because longer reviews may be perceived as more valuable than shorter reviews (Bakhshi et al. 2015; Zhu et al. 2014), but only up to a point (Schindler and Bickart 2012). The effect of review length on value is curvilinear (an inverted U shape) because particularly long reviews are difficult to absorb and therefore negatively affect value (Shindler and Bickart 2012). In line with prior research, for Yelp reviews, the quadratic regression line for review length significantly improved its prediction on the number of useful votes relative to the linear regression line (R^2 change = .003, F(1, 99,997) = 355.86, p < .001). Given that Amazon reviews are up to five times the length of the longest Yelp review (Yelp's longest review = 1,016 words; Amazon's longest review: 5,013 words), I expected the curvilinear effect of review length to be particularly prominent in Amazon reviews. Indeed, for the Amazon reviews, the quadratic regression line for review length significantly improved its prediction on the proportion of helpful votes compared to the linear regression line (R^2 change = .014, F(1, 199,997) = 3,081.12, p < .001). Thus, I applied a square transformation on the review length variable in order to include it as a control variable in both models (Yelp: M = 25,866.82, SD = 62,733.06; Amazon: M = 32,369.32, SD = 233,437.48).

Results

Most of the reviews in the sample received few useful/helpful votes and a small number received many useful/helpful votes. Given that the dependent variable value is a count variable and its variance exceeds its mean (Yelp: $M_{useful\ votes}$ = 1.01, Var = 5.94; Amazon: $M_{proportion\ helpful\ votes}$ = 32.82%, Var = 1899.12), I used negative binomial regression, which relies on the Wald test (Greene 2008). Indeed, the dispersion coefficients in both datasets were positive and significant (Yelp: β = 1.76; 95% CI, 1.73 to 1.79; Amazon: β = 9.83; 95% CI, 9.75 to 9.91), suggesting the negative binomial model was more appropriate than a Poisson model (Greene 2008; UCLA Statistical Consulting Group 2017).

Controlling for months posted, review valence, and review length, Yelp reviews with swearwords received more useful votes than Yelp reviews without swearwords (β = .309, Wald X^2 (1, n = 100,000) = 281.09, p < .001). Consistent results for the Yelp data were obtained when the number of swearwords in a review was modeled as a continuous variable (β = .175, Wald X^2

(1, n = 100,000) = 205.23, $p < .001$), and when star ratings were modeled as a three-level categorical variable (i.e., negative, neutral, positive; $\beta = .311$, Wald X^2 (1, n = 100,000) = 284.43, $p < .001$). Further, Amazon reviews with swearwords received a higher proportion of helpful votes than Amazon reviews without swearwords ($\beta = .150$, Wald X^2 (1, n = 200,000) = 14.26, $p < .001$). Consistent results for the Amazon data were obtained when swearwords were modeled as a continuous variable ($\beta = .090$, Wald X^2 (1, n = 200,000) = 10.51, $p = .001$), and when star ratings were modeled as a three-level categorical variable ($\beta = .145$, Wald X^2 (1, n = 200,000) = 13.31, $p < .001$). Descriptive statistics and results are presented in Tables 2-4.

Table 2. Yelp and Amazon Descriptive Statistics

	Yelp			*Amazon*		
Variable	*Total Mean (SD)*	*Swearwords Present Mean (SD)*	*Swearwords Absent Mean (SD)*	*Total Mean (SD)*	*Swearwords Present Mean (SD)*	*Swearwords Absent Mean (SD)*
Useful/ Helpful Votes	1.01 (2.44)	1.81 (4.03)	.94 (2.22)	2.12 (16.90)	4.95 (33.28)	2.03 (16.04)
Proportion Helpful Votes				32.82% (43.59%)	45.23% (43.59%)	32.39% (43.52%)
Review Length	117.49 (109.67)	200.99 (160.28)	110.04 (100.58)	92.01 (123.97)	231.83 (276.13)	87.23 (112.24)
Months Posted	32.01 (25.66)	38.56 (28.23)	31.41 (25.33)	28.59 (35.56)	40.12 (43.32)	28.19 (35.20)
Review Valence	3.73 (1.40)	3.20 (1.52)	3.77 (1.38)	4.17 (1.25)	3.69 (1.54)	4.18 (1.24)
Review Valence	*Total Count*	*Swearwords Present Count (%)*	*Swearwords Absent Count*	*Total Count*	*Swearwords Present Count (%)*	*Swearwords Absent Count*
N	100,000	8,348 (8.3%)	91,652	200,000	6,608 (3.3%)	193,392
Negative Reviews	21,583	2,954 (13.7%)	18,629	26,053	1,670 (6.4%)	24,383
Neutral Reviews	12,448	1,148 (9.2%)	11,300	17,154	625 (3.6%)	16,529
Positive Reviews	65,969	4,246 (6.4%)	61,723	156,793	4,313 (2.8%)	152,480

Table 3. Useful Votes as a Function of Swearwords in Yelp Reviews

	Discrete Model				Continuous Model	
	Star Ratings (Continuous)		Star Ratings (Categorical)		Star Ratings (Continuous)	
Variables	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*
Swearwords	.309***	(.017)	.311***	.018	.175***	(.012)
Controls						
Months Posted	.007***	(.0002)	.007***	(.0002)	.007***	(.0002)
Review Valence	-.082***	(.0038)			-.083***	(.004)
Review Length[1]	.00001***	(.0000001)	.00001***	(.0000001)	.00001***	(.0000001)
Negative Review			.190***	(.019)		
Positive Review			-.061***	(.017)		
Dispersion	1.76*	(.016)	1.76*	(.016)	1.76*	(.016)
Pearson X^2	193443.03		193306.99		194365.68	

[1] Square transformed, *$p \le .05$, **$p \le .01$, ***$p \le .001$, N = 100,000

Table 4. Proportion of Helpful Votes as a Function of Swearwords in Amazon Reviews

	Discrete Model				Continuous Model	
	Star Ratings (Continuous)		Star Ratings (Categorical)		Star Ratings (Continuous)	
Variables	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*
Swearwords	.150***	(.040)	.145***	.040	.09***	(.035)
Controls						
Months Posted	.011***	(.0002)	.0004***	(.00001)	.011***	(.0002)
Review Valence	-.025***	(.006)			-.025***	(.006)
Review Length[1]	.000001***	(.0000001)	.000001***	(.00000001)	.000001***	(.0000001)
Negative Review			.190***	(.031)		
Positive Review			.050*	(.025)		
Dispersion	9.83*	(.041)	9.83*	(.041)	9.94*	(.058)
Pearson X^2	44632.09		44779.03		44615.38	

[1] Square transformed, *$p \le .05$, **$p \le .01$, ***$p \le .001$, N = 200,000

Swearwords across review valence. Given their historically negative effects (Rassin and Muris 2005; Robbins et al. 2011; Stapleton 2010; Stephens, Atkins, and Kingston 2009), it is possible that swearwords only increase the value of negative reviews; however, consistent with my conceptual framework and with the results from study 4, I posit that swearwords should convey meaning and provide value regardless of review valence. To test this notion, I split the datasets into negative (1 or 2 stars), neutral (3 stars), and positive (4 or 5 stars) reviews and reran the negative binomial regression models (again controlling for months posted and review length). The analysis of Yelp data showed that reviews containing swearwords (vs. no swearword) were more valuable across all review valence categories, and were the most valuable for positive-valence reviews (Yelp: $\beta_{negative}$ = .220, Wald X^2 (1, n = 21,583) = 58.96, $p < .001$; $\beta_{neutral}$ = .249, Wald X^2 (1, n = 12,448) = 24.56, $p < .001$; $\beta_{positive}$ = .365, Wald X^2 (1, n = 65,969) = 193.03, $p < .001$). The analysis of the Amazon data showed directionally similar effects on the proportion of helpful votes, though it was only significant for positive reviews ($\beta_{negative}$ = .045, Wald X^2 (1, n = 26,053) = 0.52, $p = .472$; $\beta_{neutral}$ = .138, Wald X^2 (1, n = 17,154) = 1.18, $p = .28$; $\beta_{positive}$ = .184, Wald X^2 (1, n = 156,793) = 12.75, $p < .001$). These results are presented in Tables 5 and 6. Similar results were found when an interaction term for the presence of swearwords and star ratings was added to the original model (Yelp: β = .115, Wald X^2 (1, n = 100,000) = 92.81, $p < .001$; Amazon: β = .047, Wald X^2 (1, n = 200,000) = 3.36, $p = .067$).

Table 5. Yelp: Useful Votes by Review Valence

	Discrete Model					
	Negative Reviews (1 or 2 Stars)		Neutral Reviews (3 Stars)		Positive Reviews (4 or 5 Stars)	
Variables	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*
Swearwords	.220***	(.029)	.249***	(.050)	.365***	(.027)
Months Posted	.009***	(.0004)	.002***	(.0005)	.008***	(.0003)
Review Length[1]	.000003***	(.0000001)	.00001***	(.0000003)	.00001***	(.0000002)
Dispersion	1.34*	(.025)	1.79*	(.044)	1.89*	(.022)

[1]Square transformed, $*p \leq .05$, $**p \leq .01$, $***p \leq .001$

Table 6. Amazon: Proportion of Helpful Votes by Review Valence

	Discrete Model					
	Negative Reviews (1 or 2 Stars)		Neutral Reviews (3 Stars)		Positive Reviews (4 or 5 Stars)	
Variables	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*
Swearwords	.045	(.062)	.138	(.127)	.184***	(.051)
Months Posted	.008***	(.0005)	.011***	(.0008)	.011***	(.0003)
Review Length[1]	.000001***	(.0000002)	.000001***	(.0000003)	.000002***	(.0000001)
Dispersion	5.90*	(.060)	9.46*	(.132)	10.81*	(.052)

[1]Square transformed, $*p \leq .05$, $**p \leq .01$, $***p \leq .001$

Multiple swearwords. Similar to study 6, I tested whether there was a point at which increasing numbers of swearwords in a review negatively affected useful/helpful votes. I changed the number of swearwords from a continuous to a categorical variable, to compare reviews at each number of swearwords (1, 2, 3, etc.) to reviews containing no swearwords (0; the control condition).

For Yelp reviews, the results of a negative binomial regression (controlling for months posted, review valence, and review length) showed that Yelp reviews containing one swearword received significantly more useful votes than those with no swearwords ($n_{1\ swearwords}$ = 6,560, β = .287, Wald X^2 (1, n = 100,000) = 195.01, $p < .001$). Reviews containing two swearwords also received significantly more useful votes relative to reviews with no swearwords ($n_{2\ swearwords}$ = 1,229, β = .368, Wald X^2 (1, n = 100,000) = 68.71, $p < .001$). Yelp reviews containing three swearwords evoked the largest positive effect on useful votes relative to reviews with no swearwords ($n_{3\ swearwords}$ = 332, β = .542, Wald X^2 (1, n = 100,000) = 42.88, $p < .001$). The effect began to dissipate at four swearwords ($n_{4\ swearwords}$ = 134, β = .260, Wald X^2 (1, n = 100,000) = 3.96, $p = .048$) and became insignificant at five or more swearwords ($n_{5\ swearwords}$ = 93, β = .107, Wald X^2 (1, n = 100,000) = .46, $p = .497$).

Similarly for Amazon reviews, the results of a negative binomial regression (controlling for months posted, review valence, and review length) showed that Amazon reviews containing one swearword received a higher proportion of helpful votes than those with no swearwords ($n_{1\ swearword}$ = 5,424, β = .148, Wald X^2 (1, n = 200,000) = 11.55, $p = .001$). Amazon reviews containing two swearwords evoked a larger, but only marginally significant effect relative to reviews with no swearwords ($n_{2\ swearwords}$ = 843, β = .165, Wald X^2 (1, n = 200,000) = 2.29, p = .130). The effect of swearwords on the proportion of helpful votes was insignificant at three swearwords ($n_{3\ swearwords}$ = 221, β = .174, Wald X^2 (1, n = 200,000) = .675, $p = .411$), four swearwords ($n_{4\ swearwords}$ = 57, β = -.033, Wald X^2 (1, n = 200,000) = .006, $p = .937$), and five or more swearwords ($n_{5+\ swearwords}$ = 63, β = .213, Wald X^2 (1, n = 200,000) = .289, $p = .591$). These results are presented in Table 7.

Table 7. The Effect of Increasing the Number of Swearwords in Reviews

	Yelp (DV = Useful Votes)		Amazon (DV = Proportion of Helpful Votes)	
Variables	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*
1 Swearword	.287***	(.021)	.148***	(.062)
2 Swearwords	.368***	(.044)	.165^	(.158)
3 Swearwords	.542***	(.083)	.174	(.308)
4 Swearwords	.260*	(.131)	-.033	(.417)
5+ Swearwords	.107	(.158)	.213	(.396)
Months Posted	.007***	(.0002)	.011***	(.0002)
Review Valence	-.082***	(.004)	-.025***	(.006)
Review Length[1]	.00001***	(.0000001)	.000001***	(.0000001)
Dispersion	1.76	(.016)	9.83*	(.041)
Pearson X^2	193106.56		44632.05	

[1]Square transformed, ^p = .13, *$p \le .05$, **$p \le .01$, ***$p \le .001$

Uncensored, euphemistic, and censored swearwords. Given that the swearword dictionary contains uncensored (e.g., *fuck*), euphemistic (e.g., *frick*), and censored (e.g., *f*ck*) swearwords, it is possible that the swearing effect observed in the field data is driven by censored and euphemistic swearwords. However, consistent with the results from the experiments, I posit that uncensored swearwords should provide value. To test this notion, I categorized the words in the swearword dictionary into three new independent variables: uncensored, euphemistic, and censored swearwords (see appendix for details). Of the 100,000 Yelp reviews, 5,227 reviews contained uncensored swearwords, 577 contained euphemistic swearwords, and 252 contained censored swearwords. Of the 200,000 Amazon reviews, 5,480 reviews contained uncensored swearwords, 955 contained euphemistic swearwords, and 389 contained censored swearwords. I used these three swearword variables, along with the control variables, to predict review value in the Yelp and Amazon datasets. As a robustness check, the three independent variables were first modeled as categorical variables (0 = absent; 1 = present) and then modeled as continuous variables (i.e., the number of uncensored/censored/euphemistic swearwords in a review).

For Yelp reviews, the results of a negative binomial regression (controlling for months posted, review valence, and review length) showed that Yelp reviews containing uncensored swearwords received more useful votes than reviews with no uncensored swearwords (β = .264, Wald X^2 (1, n = 100,000) = 131.54, p < .001). Reviews containing euphemistic swearwords also received more useful votes than reviews with no euphemistic swearwords (β = .244, Wald X^2 (1, n = 100,000) = 13.02, p < .001). There was no difference in effect between reviews with censored swearwords or no censored swearwords (β = .165, Wald X^2 (1, n = 100,000) = 2.59, p = .11). These results are presented in Table 7. Similar results were obtained when the number of censored, uncensored, and euphemistic swearwords in a review was coded as three continuous variables ($\beta_{uncensored}$ = .172, Wald X^2 (1, n = 100,000) = 174.57, p < .001; $\beta_{euphemistic}$ = .325, Wald X^2 (1, n = 100,000) = 47.93, p < .001; $\beta_{censored}$ = .065, Wald X^2 (1, n = 100,000) = 1.02, p = .31).

Similarly for Amazon reviews, the results of a negative binomial regression (controlling for months posted, review valence, and review length) showed that Amazon reviews containing uncensored swearwords received a higher proportion of helpful votes than those without uncensored swearwords (β = .136, Wald X^2 (1, n = 200,000) = 9.80, p = .002). Reviews containing euphemistic swearwords also received a higher proportion of helpful votes compared to those without euphemistic swearwords (β = .200, Wald X^2 (1, n = 200,000) = 3.85, p = .050). There was no significant difference between reviews with or without censored swearwords on the proportion of helpful votes (β = .083, Wald X^2 (1, n = 200,000) = .27, p = .604). These results are presented in Table 8. Similar results were obtained when the number of censored, uncensored, and euphemistic swearwords in a review was modeled as three continuous variables

($\beta_{uncensored}$ = .084, Wald X^2 (1, n = 200,000) = 7.48, p = .006; $\beta_{euphemistic}$ = .173, Wald X^2 (1, n = 200,000) = 3.38, p = .066; $\beta_{censored}$ = .041, Wald X^2 (1, n = 200,000) = .11, p = .737).

Table 8. Uncensored, Euphemistic, and Censored Swearwords

	Discrete Model			
	Yelp (DV = Useful Votes)		Amazon (DV = Proportion of Helpful Votes)	
Variables	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*
Uncensored Swearwords	.264***	(.023)	.136**	(.044)
Euphemistic Swearwords	.244***	(.068)	.200*	(.102)
Censored Swearwords	.165	(.112)	.083	(.160)
Months Posted	.007***	(.0002)	.011***	(.0002)
Review Valence	-.083***	(.004)	-.025***	(.006)
Review Length[1]	.00001***	(.0000001)	.000001***	(.0000001)
Dispersion	1.77	(.016)	9.83*	(.041)
Pearson X^2	197691.36		22071.43	

[1] Square transformed, *$p \leq .05$, **$p \leq .01$, ***$p \leq .001$

Discussion

An analysis of reviews from Yelp and Amazon showed that the presence of swearwords in reviews, particularly uncensored and euphemistic swearwords, increased the value of reviews regardless of their valence. Censored swearwords did not affect the value of reviews. Further, consistent with Hair and Ozcan's recent findings (2018), swearwords were most valuable in positive reviews. Finally, corroborating study 5, these results showed that 1 to 3 swearwords (vs. no swearwords) in a review increased the number of useful votes received. However, this effect was attenuated when the review contained four swearwords and insignificant when the review contained 5 or more swearwords. Overall, consistent with the experiments, these findings support the conjecture that swearwords – particularly uncensored or euphemistic swearwords – provide value and can positively and negatively affect readers.

While both of these datasets supported the basic prediction, it is possible that unobserved variables or selection issues drove the results, despite the inclusion of control variables. Fortunately, both the Yelp and Amazon datasets have limitations that are addressed with the other dataset, enabling a stronger test of the swearing effect than each dataset alone. For example, given that the Yelp data does not specify the total number of review readers, it could be that the number of consumers who value vulgar reviews is smaller than the number of customers who do not. Yet, the results from Yelp appear consistent with those from the Amazon dataset, which uses the proportion of helpful votes as the dependent variable. Furthermore, the experiments address these issues by providing causal evidence that swearwords in reviews affect product attitudes, which prior research has shown to be related to review helpfulness ratings (Chen, Dhanasobhon, and Smith 2008; Moore 2015).

GENERAL DISCUSSION

While swearwords are used more often than ever before (Jay and Janschewitz 2008; Stapleton 2010), it is not clear what role they play in online WOM. The current research fills this gap by addressing how, why, and when swearwords affect review readers. I show that swearwords can affect readers positively or negatively. Specifically, a reviewer can use a swearword to qualify desirable [undesirable] product attributes, which increases [decreases] readers' attitudes towards and willingness-to-pay for the reviewed product. These results hold relative to reviews containing no swearwords, and relative to reviews containing non-swearword intensifiers. I find that inferred meaning about the reviewer's feelings and the product's attributes function as independent, parallel mediators of this effect. Finally, I demonstrate that swearwords do not affect readers when their meaning is not diagnostic. I tested the model across six experiments that used different swearword intensifiers and products, and established the external validity of these results with an analysis of Yelp and Amazon data.

A single-paper meta-analysis (SMP; McShane and Böckenholt 2017) confirmed the effect of swearwords on reader's attitudes. Across the relevant studies (1-4 and 6), the presence of swearword intensifiers (versus absence or non-swearword intensifier) in reviews increased readers' attitudes towards the reviewed product. The SPM estimates the effect at 0.34 (95% CI: .23 to .45). I^2 was estimated at 26.10% (95% CI: 0% to 65.43%), suggesting that heterogeneity is low, but the width of the interval suggests that this estimate may not be precise (McShane and Böckenholt 2017).

Theoretical Contribution

This research makes several theoretical contributions to marketing and linguistics. First, despite the frequency with which swearwords are used in our daily lives, on social media, and in online reviews, it is not clear how swearwords might affect consumers. Prior work shows that swearwords are impolite (Jay and Janschewitz 2008) and impolite reviews could negatively affect review readers (e.g., Hamilton, Vohs, McGill 2014). However, swearwords do not always have negative effects (e.g., Brown and Schau 2001); for example, Hair and Ozcan (2018) demonstrate that swearwords are valuable in positive reviews. The current work builds on this recent work to provide a novel demonstration that although swearwords are offensive, they can affect consumers both positively and negatively. Further, the present research demonstrates when each effect occurs. Specifically, swearwords that qualify desirable product attributes increase readers' attitudes and willingness-to-pay, while the opposite is true for swearwords that qualify undesirable product attributes.

Second, this research contributes by examining *why* swearwords affect listeners. Though Löbner (2013) theorized that swearwords as nouns may function as mixed-meaning expressions, this research is the first to empirically test whether swearwords do so. The data shows that swearwords convey meaning more effectively than non-swearword synonyms (e.g., *super*) and negative synonyms (e.g., *insanely*). As such, this research suggests that swearwords are a particularly useful communication tool for consumers. Furthermore, this research is novel because it investigates the relationship between meanings. While prior work in linguistics has theorized about mixed-meaning expressions (e.g., Gutzmann and Turgay 2012), it remains unclear how these dual meanings relate to one another. Likewise, while prior research in marketing (e.g., WOM, product design) shows that consumers make inferences about the speaker (e.g., Hamilton, Vohs and McGill 2014) and the product (e.g., Kivetz and Simonson 2000; Bloch 1995) with implications for judgment and choice, much of this work has explored these inferences separately. The current research demonstrates that a single word can simultaneously communicate information about different entities. The resulting inferences function as parallel mediators that can independently affect product attitudes. Perhaps even more relevant to consumer research is that the current data show that inferences about the reviewer and the product affect reader's attitudes equally. This equivalence is perhaps surprising, given the relatively impoverished social and relational context of reviews (Naylor, Lamberton, and Norton 2011), and suggests that academics and marketers should consider both product and reviewer inferences in future models on WOM.

Finally, the current research introduces a moderator (i.e., diagnosticity) that has not been previously examined in the swearwords context. Previous work suggests that swearwords may be more conversationally normative for hedonic products (e.g., Anderson and Carnagey 2009) and that adherence to conversational norms may positively influence consumer attitudes (e.g., Kronrod and Danziger 2013). Examining diagnosticity as a moderator differs from prior theorizing because it explains when swearwords—even if they are conversationally normative for certain products—will not influence review readers. Further, it explains why increasing the number of swearwords in a review does not necessarily increase the review's usefulness.

Practical Implications

This research has practical implications for review and seller websites because it demonstrates how swearwords in reviews affect the readers, positively and negatively. Presently, the guidelines for swearwords in reviews vary, but the majority of high-traffic websites (e.g., Amazon, TripAdvisor, Google) do not allow swearwords in reviews. Reviews that violate this rule may be flagged for removal. The exception is Yelp, which allows swearing in reviews, so long as the word(s) is not a threat, harassment, or hate speech. The findings of this research suggest that website moderators may be wise not to ban swearwords in reviews because they are useful to readers, and can increase their attitudes towards the reviewed product. However, I also demonstrate that these effects depend on the product category or the number of swearwords in a particular review, allowing website moderators to predict when reviews with swearwords may be more or less useful.

Although the data show that swearwords in reviews help consumers update their attitudes toward reviewed products, it is possible that swearwords in reviews could diminish the reader's attitudes towards the seller's website. To test this notion, I measured participant attitudes towards the seller's website in study 5, but found that the presence of a swearword in a review had a positive effect on attitudes towards the seller's website, suggesting that swearing in online reviews should not negatively affect perceptions of the host website.

In a related vein, I compared Amazon and Yelp reviews with uncensored (e.g., "the sound is *fucking* clear."), censored (e.g., "the sound is *f**king* clear."), or euphemistic swearwords (e.g., "the sound is *fricking* clear.") to reviews without any swearwords; I found uncensored and euphemistic swearwords to evoke a positive effect on useful/helpful votes compared to no swearwords. There was no difference in effect between censored swearwords and no swearwords. These results suggest that website moderators might not benefit from removing or censoring swearwords in the reviews. However, further research is needed on censorship in WOM because the lack of effect may depend on how readers attribute the censorship. Censored reviews may only be less impactful if readers attribute the censorship to the reviewer's weak feelings (i.e., the reviewer did not feel strong enough about the product to break the taboo), rather than to the website (i.e., the website chose to censor the reviewer). It is therefore not clear if website moderators should encourage reviewers to censor their own language, if the moderator should do the censoring on behalf of the reviewer, or if no censorship is optimal. Overall, the current data suggests that seller and review websites may benefit from tolerating swearwords because of their potential to positively influence readers.

Limitations and Future Research

As this research is the first to empirically explore the meaning of swearwords, there are a number of areas for future research. First, future research should consider the effect of swearwords in different marketing contexts. For example, it is not clear whether this model would hold for swearwords in advertising. Kronrad and Danziger (2013) point out that consumers apply different conversational norms to advertising and WOM. In particular, advertising content, compared to WOM, is typically exaggerated and emotionally intensified. Consequently, the meanings conveyed by swearwords may not be diagnostic in advertising, but other characteristics of swearwords may be (e.g., in-group/out-group effects, offensiveness, etc.).

In a similar vein, while I do not find support for alternative explanations such as arousal, believability, interpersonal closeness, or conversational norms, prior research has found support for these processes in other swearing contexts (e.g., Feldman et al. 2017; Janschewitz 2008). It is possible that the lack of evidence for these explanations is due to the online WOM context, where swearwords are prevalent (e.g., over 8% of Yelp reviews contained at least one swearword). It is therefore imperative that researchers continue to test these explanations as they explore the value of swearwords in new areas, such as face-to-face interactions and advertising.

Finally, while this research considers diagnosticity as a moderating variable, other variables are likely to moderate the effect of swearwords on purchase decisions—for example, other variables related to the reviewer. Prior research shows that the frequency of swearing depends on demographic characteristics, such as age, gender, social class, and level of education (see Dewaele 2015 for a review). Thus, the effect of swearwords in WOM may be diminished if readers know that the reviewer is young, for example. In this case, readers may attribute the swearword to the reviewer rather than the product, thereby mitigating the positive effect of the swearword on product attitudes. These questions and others await future investigation.

Overall, the current research shows that although swearwords are taboo and can cause offense, they are useful to review readers because they efficiently convey two meanings. These findings suggest that website moderators may benefit from tolerating swearwords in WOM, and that marketers could consider new opportunities that maximize the value of swearwords as a communication tool.

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APPENDIX

This appendix includes the swearword dictionary used to identify reviews containing swearwords in the field study (Appendix A), a robustness check for the Yelp data (Appendix B), and a robustness check for the Amazon data (Appendix C).

Appendix A: Swearword Dictionary for Coding Reviews

The table of swearwords in the modified swearword dictionary is organized by uncensored, censored, and euphemistic swearwords (table 9). A diamond (◆) denotes the acceptance of all letters, hyphens or numbers following its appearance. For example the dictionary includes the word shit◆, which allows for any word that matches the first four letters to be counted as a swearword (including shithead, shitty, shits). The phrase of an acronym is in brackets.

Table 9. Modified Swearword Dictionary

Uncensored	*Euphemistic*	*Censored*
assh◆	arse◆	@$$◆
assl◆	dang	a**◆
assp◆	darn	bullsh*t◆
asses	effin◆	b*tch◆
ass	eff	b**ch◆
assf◆	fock	b***h◆
bastard	faak	b****
bullshit◆	fark	b**b◆
bitch◆	fcuk	bs (bullshit)
bombass	fawk	c*ck
boob◆	frig◆	c*nt◆
butt	frick◆	c**t◆
butts	heck	c***
cock◆		d*mn◆
crap		d*ck◆
crappy		d**k◆
cunt◆		d***
damn◆		fml (fuck my life)
dammit		f*ck◆

dick◆ douche◆ dumbass dumbf◆ fuck◆ goddam◆ hell hella kickass kissass jackass◆ jerk lameass◆ motherf◆ mothaf◆ nigger◆ piss◆ prick◆ pussy◆ soneofa◆ suck◆ shit◆ tit tits titties titty twat wanker◆		f**k◆ f***◆ h*ll◆ h*** mofo n*gger◆ p*ssy◆ p***y◆ p**** sh*t◆ s**t s*** sh**◆ sol (shit outta luck)

Appendix B: Robustness Check of Yelp Field Data

I conducted a robustness check to see if the results of the Yelp field data would hold if swearwords were identified using the original (i.e., unmodified) swearword dictionary from LIWC (Tausczik and Pennebaker 2010). The dependent variable (number of useful votes) and the control variables (review length, review valence, and months posted) remained the same. Of the 100,000 randomly selected reviews, the unmodified dictionary identified 7771 (7.7%) reviews containing at least one swearword (the modified dictionary identified 8,348 reviews containing at least one swearword). Descriptive statistics using the unmodified dictionary are presented in Table 10.

Table 10. Yelp Descriptive Statistics (Unmodified Dictionary)

Variable	*Total* *Mean (SD)*	*Swearwords Present* *Mean (SD)*	*Swearwords Absent* *Mean (SD)*
Useful Votes	1.01 (2.44)	1.87 (4.14)	.94 (2.22)
Review Length	117.37 (109.53)	202.17 (159.24)	110.23 (101.08)
Months Posted	32.01 (25.66)	39.34 (28.65)	31.39 (25.29)
Review Valence	3.73 (1.40)	3.02 (1.56)	3.79 (1.37)
	Total *Count*	*Swearwords Present* *Count*	*Swearwords Absent* *Count*
N	100,000	7,771	92,229
Negative Reviews	21,583	3,172	18,411
Neutral Reviews	12,448	1,035	11,413
Positive Reviews	65,969	3,564	62,405

I modeled the value of the review using negative binomial regression (M = 1.01, Var = 5.94, dispersion coefficient = 1.76, CI 1.73 to 1.79). Controlling for review length, months posted, and review valence, I found similar results to those using the modified swearword dictionary. Specifically, reviews containing swearwords received more useful votes than reviews without swearwords (β = .332, Wald X^2 (1, n = 100,000) = 308.09, p < .001). Consistent results were obtained when swearwords were modeled as a continuous variable using the number of swearwords as a proportion of review length (β = .192, Wald X^2 (1, n = 100,000) = 233.16, p < .001) and when star ratings were modeled as a categorical variable (β = .335, Wald X^2 (1, n = 100,000) = 311.66, p < .001). The results are summarized in table 11.

Table 11. Presence of Swearwords on Yelp Useful Votes (Unmodified Dictionary)

	Discrete Model				Continuous Model	
	Star Ratings (Continuous)		Star Ratings (Categorical)		Star Ratings (Continuous)	
Variables	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*
Swearwords	.332***	(.019)	.335***	(.019)	.192***	(.013)
Controls						
Review Length[1]	.00001***	(.0000001)	.00001***	(.0000001)	.00001***	(.0000001)
Months Posted	.007***	(.0002)	.007***	(.0002)	.007***	(.0002)
Review Valence	-.080***	(.004)			-.080***	(.004)
Negative Review			.181***	(.019)		
Positive Review			-.060***	(.016)		
Dispersion	1.75*	(.016)	1.76*	(.016)	1.76*	(.016)
Pearson X^2	192467.38		192324.30		189760.82	

[1] Square transformed, *$p < 0.05$, **$p < .01$, ***$p < .001$, N = 100,000

Appendix C: Robustness Check of Amazon Field Data

I conducted another robustness check to see if the results of the Amazon field data would hold if swearwords were identified using the original (i.e., unmodified) swearword dictionary from LIWC (Tausczik and Pennebaker 2010). The dependent variable (proportion of helpful votes) and the control variables (review length, review valence, and months posted) remained the same. Of the 200,000 randomly selected reviews, the unmodified dictionary identified 8,805 (4.4%) reviews containing at least one swearword (the modified dictionary identified 6,608 reviews containing at least one swearword). Descriptive statistics using the unmodified dictionary are presented in Table 12.

Table 12. Amazon Descriptive Statistics (Unmodified Dictionary)

Variable	*Total* *Mean (SD)*	*Swearwords Present* *Mean (SD)*	*Swearwords Absent* *Mean (SD)*
Proportion of Helpful Votes	32.82 (43.58)	45.26 (43.83)	32.24 (43.49)
Review Length	91.94 (123.85)	224.41 (257.83)	85.84 (110.17)
Months Posted	28.59 (35.56)	38.44 (41.58)	28.13 (35.19)
Review Valence	4.17 (1.25)	3.70 (1.51)	4.19 (1.24)
	Total *Count*	*Swearwords Present* *Count*	*Swearwords Absent* *Count*
N	200,000	8,805	191,195
Negative Reviews	26,053	2,159	23,894
Neutral Reviews	17,154	882	16,272
Positive Reviews	156,793	5,764	151,029

I modeled the value of the review using negative binomial regression (M = 32.82, Var = 1,899.82, dispersion coefficient = 9.83, CI: 9.75 to 9.91). Controlling for review length, months posted, and review valence, I found similar results to those using the modified swearword dictionary. Specifically, reviews containing swearwords received a higher proportion of helpful votes than reviews without swearwords (β = .180, Wald X^2 (1, n = 200,000) = 26.80, $p < .001$). Consistent results were obtained when swearwords were modeled as a continuous variable using the number of swearwords (β = .097, Wald X^2 (1, n = 200,000) = 17.98, $p < .001$) and when star ratings were modeled as a categorical variable (β = .176, Wald X^2 (1, n = 200,000) = 25.65, $p < .001$). The results are summarized in Table 13.

Table 13. Presence of Swearwords on Amazon Helpful Votes (Unmodified Dictionary)

	Discrete Model				Continuous Model	
	Star Ratings (Continuous)		Star Ratings (Categorical)		Star Ratings (Continuous)	
Variables	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*	*Coefficient*	*(SE)*
Swearwords	.180***	(.035)	.097***	(.023)	.097***	(.012)
Controls						
Review Length[1]	.000001***	(.0000001)	.000001***	(.0000001)	.000001***	(.0000001)
Months Posted	.011***	(.0002)	.011***	(.0002)	.011***	(.0002)
Review Valence	-.024***	(.006)			-.025***	(.006)
Negative Review			.188***	(.031)		
Positive Review			.051*	(.025)		
Dispersion	9.83*	(.041)	9.83*	(.041)	9.83*	(.041)
Pearson X^2	44683.27		44830.04		44645.19	

[1]Square transformed, $*p < 0.05$, $**p < .01$, $***p < .001$, N = 200,000