Selectively Emotional:
How Smartphone Use Changes User-Generated Content

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Abstract: [172 words]

Consumers regularly access user-generated content when making purchases, content that is increasingly generated on smartphones versus personal computers. The authors argue that because of its physically constrained nature, smartphone (vs. PC) use leads consumers to generate briefer content, which focuses them on the overall gist of their experiences. This focus on gist, in turn, tends to manifest as reviews that emphasize the emotional aspects of the experience in lieu of more specific details. Across five studies – two field studies and three controlled experiments – natural language processing tools and human-judged assessments were used to analyze the linguistic characteristics of user-generated content. The findings support the thesis that smartphone use results in the creation of content that is less specific and privileges positive affect and, to a lesser extent, negative affect relative to PC-generated content. The findings additionally show that differences in emotional content are driven by the tendency to generate briefer content on smartphones rather than user self-selection, differences in topical content, or timing of writing. Implications for research and practice are discussed.

Keywords: Mobile Marketing; User-Generated Content; Word of Mouth; Social Media; Emotion; Affect; Natural Language Processing; Computational Linguistics

Recent years have witnessed two major trends of enormous importance for marketers. The first is the explosion of user-generated content (UGC) in the marketplace (e.g., Tweets, Yelp restaurant reviews, Facebook posts, Amazon product reviews). Understanding UGC is critical for marketers, as most consumers—as many as 81% according to certain studies (Deloitte 2016)—now rely on UGC in forming their purchase decisions. The second trend is the so-called "mobile revolution," wherein consumers now spend a greater amount of time on their smartphone than any of their other devices (Think with Google 2016). These two trends have, in turn, engendered a third: UGC is now increasingly produced on consumers' smartphone devices. According to one Pew Research Center report (2015), 67% of smartphone owners now use their device to share content online. Taken together, these trends raise an important question for marketers: Are smartphones just an additional platform for creating UGC, or are these devices fundamentally changing the nature of the content being generated by consumers? The purpose of this research is to provide a partial answer to this question.

Extending the nascent stream of work on the effects of mobile use on online consumption activities (e.g., Ghose and Han 2011; Ransbotham, Lurie, and Liu 2018), our research shows through both field studies and controlled experiments that user-generated content produced on smartphones privileges the inclusion of emotional content relative to that produced on PCs. In addition, and importantly, our research clarifies the mechanism that underlies this phenomenon. Here, we use the term "emotionality" or "emotional content" to refer to language conveying affective information (e.g., Berger and Milkman 2012; Ludwig et al. 2013), such as "love," "disgust," "reassuring," and "embarrassed," independent of the valence of the emotionality, which we examine as well. We show that differences in emotional content are driven by a tendency for users to generate briefer content on their smartphones, which focuses them on the gist or essential elements of what they are trying to convey. This focus on gist manifests as content containing lower specificity and, critically, the privileged inclusion of emotional aspects of the experience.

We report five studies: two field studies leveraging data from a leading online travel and restaurant review forum (Study 1) and from a major social media network (Study 5); and three controlled experiments (Studies 2-4). Our findings show that the effect of device use on the revealed emotionality of content is robust. This effect is observed across a range of datasets as well as various methods of measuring linguistic characteristics, including different automated tools and human judgments. In addition, we provide convergent evidence for the underlying mechanism. Because smartphones promote the generation of content that is briefer (vs. PCs), they encourage users to focus on the overall essence or gist of what they wish to convey, which manifests as a selective emphasis on emotional aspects of the experience at the expense of specific details (Study 1). We also show that the effect cannot be explained by alternative mechanisms such as self-selection biases and the relative timing of the review vis-à-vis the experience (Studies 1-4).

FOCUS ON GIST AND THE EMOTIONALITY OF SMARTPHONE-GENERATED CONTENT

Recent work has shown that compared to larger devices such as PCs, the smaller keyboards and screens of smartphones increase the physical and cognitive effort required for using the device (e.g., Raptis et al. 2013). As a result, for example, compared to PC users, smartphone users tend to search through and consume less information when browsing on their devices (Ghose, Goldfarb, and Han 2013). It naturally follows that written content *generated* (as opposed to consumed) on smartphones would similarly be constrained. This constraint may alter not only how much is written on the device, but, more interestingly, *what* is written on the device.

We hypothesize that the inclination to generate shorter content on a smartphone steers writers to focus on the overall gist of their ideas, defined as a narrative that conveys the essential elements, as opposed to specific details, of their perceptions of an experience (e.g., Harding, Cooke, and Konig 2007; Oliva 2005; Pieters, Wedel, and Smith 2012). In the context of customer-generated reviews and other types of evaluative UGC—wherein consumers' assessments tend to be based on their feelings about a topic or experience—we argue that this focus on gist will manifest as content containing fewer details and, more importantly for the present work, the privileged inclusion of emotional information (e.g., Reyna 2012; Rivers, Reyna, and Mills 2008). As a consequence, the tendency to generate shorter content on the device will lead to the selective reporting of affective information, yielding content that is perceived to be more emotional by readers relative to content written on PCs. We provide a depiction of this conceptual model in Figure 1A.

[Insert Figures 1A & 1B]

Some initial evidence in support of this idea has been reported in a paper by Ransbotham, Lurie, and Liu (2018), who find that mobile-generated restaurant reviews posted on one online forum (formerly known as Urbanspoon) tended to contain a higher proportion of emotional words. Our own program of research extends this recent work by: (a) demonstrating the internal validity of the phenomenon through controlled experiments; (b) exploring the generality of the phenomenon across a range of data contexts and measurement tools; and (c) investigating the mechanisms that underlie the phenomenon. With respect to the last point, Ransbotham et al. (2018) speculate that the phenomenon is due to mobile devices (relative to PCs) being more likely to be used in "realtime" (e.g., writing a review while at a restaurant), when emotional reactions may be more salient. In our studies, we show that the phenomenon holds independent of the relative timing of the content generation, and that the explanation actually lies elsewhere: in the propensity of smartphone users to generate shorter content on the device and thus focus on the gist of what they want to share.

Our proposition that the brevity imposed by smartphone use encourages users to prioritize the most essential, emotional aspects of an experience is consistent with research on how people conceive of the "gist" of an idea or event. One such literature is the *fuzzy-trace theory* of processing (e.g., Reyna 2012; Rivers et al. 2008), which argues that people form multiple mental representations of a given stimulus that range in level of precision, from low-level details (e.g., exact numerical information) to a "gist" representation that focuses on the overall meaning or essence of a stimulus and omits its specific details. For example, if in a given choice "Option A can save 100 lives," whereas "Option B can save 1,000 lives," a gist representation of this choice might be that "Option A saves fewer lives than Option B."

Research further suggests that in addition to containing fewer specific details, the gist representation of an experience—that is, the overall meaning one ascribes to it—is more likely to reflect one's feelings during or about the experience (e.g., Brainerd and Reyna 1990). This should especially be the case in evaluative contexts such as reviews of service experiences or other opinion-based posts, where the content relates to consumers' feelings about a given topic. Indeed, classic work on dimensions of semantic meaning show that the primary dimension of meaning ascribed to stimuli is affective in nature (e.g., Osgood 1962). Other classic work on the "primacy of affect" suggests that affective responses are inescapable, fast, and thus primary in responses to stimuli (e.g., Zajonc 1980). Not only is a focus on gist more likely to involve affect, it has also been observed that a focus on affect tends to encourage gist-like representations in negotiations (Stephen and Pham 2008) and in assessment of value (Pham et al. 2015).

One would therefore predict that if users focus on the gist of their experience when writing on a smartphone (vs. PC), they would prioritize expressions of affective reactions (e.g., how restaurant patrons felt about a dining experience; how excited soccer fans are that their favorite team won) over purely descriptive information (e.g., how much the restaurant patrons paid for their meal; at what times in the game goals were scored). This prediction is conceptually consistent with the finding that pressure to reduce the complexity of one's mental representation of objects (i.e., to represent the gist of the objects) results in more emotionally polarized evaluations of these objects (Paulhus and Lim 1994), and with the finding that time pressure in realtime evaluation increases the likelihood that the evaluation is based on affect (Pham et al. 2001). In short, privileging the inclusion of emotional information will lead content generated on smartphones to appear to be more emotional than that written on PCs.

The Emotional Valence of Smartphone-Generated Content

If the tendency to create shorter content on smartphones indeed leads users to prioritize emotional information when writing on the device, one question that naturally follows is whether this applies to both positive and negative affect or is instead driven by one type of affect or the other. Intuitively, if smartphone use leads users to emphasize emotionality, then this effect should hold for *both* positive and negative emotions. For example, to the extent that a consumer had a mostly positive experience at a restaurant, the use of a smartphone to review this experience should result in the selective inclusion of positive emotional information relative to the use of a PC. Similarly, if the consumer had a mostly negative experience at the restaurant, the use of a smartphone to review this experience should result in the priviliging of negative emotional content relative to the use of a PC.

Although, conceptually, the use of smartphones should similarly affect the reporting of positive and negative emotions, *empirically* the effect may be more pronounced and easier to detect for positive emotionality given its greater prevalence in online word of mouth (e.g., Chevalier and Mayzlin 2006; Godes and Mayzlin 2004). For example, a meta-analysis by East, Hammond, and Wright (2007) found that positive WOM occurred three times more often than negative WOM, and occurred 3.7 times more often for restaurant reviews in particular. While there might be multiple reasons for the greater prevalence of positive WOM, one explanation proposed by Berger (2014) is that consumers seek opportunities to self-enhance by demonstrating the quality of their choices to others, which predisposes them to share more positive content (e.g., Chung and Darke 2006; Sundaram, Mitra, and Webster 1998). In summary, while we theorize that the use of smartphones (vs. PCs) will amplify the expression of both positive and negative affect, the amplification of negative emotionality may be more difficult to observe in light of consumers' general aversion to posting negative content online.

Predictions and Overview of the Studies

Our goal is to examine how smartphone (vs. PC) usage might alter the type of content generated by consumers, and to explore the mechanism that drives these differences. Our core hypothesis is that content generated on a smartphone (vs. PC) will be generally "more emotional" (i.e., selectively include emotional language and be perceived as more emotional by readers), and that this difference will be driven by the tendency to generate shorter content when writing on the device. We test this hypothesis in a series of five experimental and field studies.

In Study 1 we provide initial evidence for the basic phenomenon and the proposed mechanism by analyzing the sentiment of restautant reviews contained in a large online travel form (*TripAdvisor.com*). We then report the resuts of three laboratory experiments that test the proposed mechanism in settings that control the timing of the writing of the review (Study 2), the length of the review (Study 3), and the valence of the review (SStudy 3). In Study 5 we conclude by showing that the observed effects generalize across a very different context where emotional reactions are similarly likely to be at play: social media users Tweeting about topics such as movies, music, and celebrities.

STUDY 1

The purpose of the first study is to (a) establish the existence of the basic phenomenon in a marketplace context, and (b) test the hypothesis that the greater emotionality of smartphone-generated content is driven by a tendency to write more briefly on the device, such that users selectively convey the overall essence or gist of their experience. As a setting for testing our predictions, we analyze customer-generated restaurant reviews from TripAdvisor.com, a popular travel information and recommendation service. TripAdvisor provides a uniquely pertinent setting for our research because it contains a device label indicating whether reviews were written on mobile devices (vs. PCs), with traffic split roughly in half between mobile and web-based users.

We predicted that (a) smartphone-generated reviews would selectively include emotional content relative to PC-generated reviews; (b) this would be observed for both positive and, to a lesser extent, negative expressions of emotion; and (c) differences in emotional content would be driven by a heightened tendency for users to generate shorter content on their smartphones. In addition to testing our focal prediction about differences in emotionality, in Study 1 we tested the secondary proposition that the brevity of smartphone-generated content will also result in the creation of content that contains lower specificity relative to PC-generated content.

Dataset

We analyzed two replication datasets: one composed of 29,157 reviews for restaurants in Philadelphia, Pennsylvania, and a second composed of 32,485 reviews for restaurants in San Francisco, California. The reviews were posted from 2012 through 2017 and referenced a total of 593 restaurants listed on the TripAdvisor website. Of the 61,642 total reviews, 47,180 were written on PCs and 14,462 were written on smartphones (23.5%). Each post contains the title of the review, the text of the review, the name of the restaurant reviewed, the date on which it was posted, and the device from which it was posted (smartphone vs. PC).

Method

Measuring content emotionality and emotional valence. In order to test for differences in content emotionality, we measured content emotionality using two automated sentiment-analysis tools. (For a subset of the reviews we also conducted analyses of human judgments, which we discuss under "*Robustness of the Effects Using Human Judgments*" below.) One of the automated tools we utilized was Linguistic Inquiry and Word Count (LIWC; Pennebaker et al. 2015), which has been used to analyze many types of texts, including online blog posts, instant messages, and customer reviews (e.g., Ludwig et al. 2013; Slatcher and Pennebaker 2006). Since our research focuses on increased emotionality due to smartphone use, we test for cross-device differences in the "affective processes" linguistic category, which consists of 1,393 words classified by human coders as emotional (e.g., "love," "happy," "cried"). This linguistic category is divided into two subcategories: one for positive emotional words (620 words; e.g., "happy"), another for negative emotional words (744 words; e.g., "hurt"). We added a third subcategory: a remaining set of words in the affective category that were coded as neither positive nor negative that we categorized as "neutral emotional words" (e.g., "decent"). Our main dependent variable is the proportion of emotional words in the content (i.e., the sum across the three subcategories). Our other dependent variables of interest encompassed the emotional-valence subcategories: the proportions of positive, negative, and neutral emotional words.

Second, to test the robustness of our findings across operationalizations of emotional valence, in Study 1 we also utilized a text analysis tool called Hedonometer (Dodds and Danforth 2010). Hedonometer differs from LIWC in that it provides a continuous measure of positive versus negative emotionality of a text. The tool utilizes a dictionary of more than 10,000 common words that vary in the degree of happiness (vs. sadness) that is normally evoked by the word as judged by human coders (on a 1 to 9 scale), with higher scores indicating greater happiness and lower scores indicating greater sadness (see Web Appendix 1 for further details).

Measuring linguistic specificity. In addition to our central prediction about differences in content emotionality, we also test the secondary prediction that the tendency to focus on the gist of one's experience when writing on a smartphone will manifest as lower content specificity. To measure differences in linguistic specificity across devices, we use an algorithm called Speciteller by Li and Nenkova (2015) that analyzes a large number of lexical features to produce predictions of likelihood that sentences contained in a text would be judged by human judges as specific versus gist-like. Predictions are on a 0–1 continuous scale, such that a review with a greater emphasis on gist should exhibit *lower* specificity scores. In Web Appendix 1 we describe in greater detail the machine-learning approach used to derive the algorithm and provide examples of pairs of reviews that contain the same word count but vary in their degree of measured specificity. For example, below are two reviews each comprised of 25 words, the first with a low predicted specificity score, the second with a high score. While both are identical in length, the review with the lower specificity score describes the dining experience in less detail:

> **Specificity=.03***: We dined there twice while in SF and enjoyed everything! The service is great, the food is tasty and fresh and the atmosphere is wonderful!*
> **Specificity=.89:** *Great location down on fishermans wharf, seated quickly with daughter & stroller despite being in lunch hour rush, very attentive service, awesome Vietnamese food!! Love it*

Operationalizing the proposed brevity mediator. Recall that our core hypothesis is that smartphone (vs. PC) use drives the creation of shorter content, which leads users to privilege emotional information when writing on the device. Throughout the studies reported in this paper we use the word count of the reviews (i.e., review length) to operationalize the brevity of the content, and test for the mediating role of brevity on content emotionality across devices. To test the secondary prediction that the tendency to generate briefer content also yields less specific content, we also test for the mediating role of brevity on the degree of linguistic specificity across devices.

Content Emotionality and Emotional Valence Results

LIWC measures. To test for differences in content emotionality across devices, we first ran a mixed ANOVA with device (smartphone vs. PC) and replication city (Philadelphia vs. SF) as between-subjects factors, and type of emotion (positive, negative, and neutral) as a within-subject factor.[1] A main effect of type of emotion (F(2, 123276) = 95,304.261, $p < .001$) reveals that consumers used a greater proportion of positive emotional words (M = 7.52%) than negative emotional words (M = 0.72%; F(1, 61641) = 116,016.39, $p < .001$) and emotionally neutral words (M = 0.27%; F(1, 61641) = 155,001.93, $p < .001$; see Table 1). These findings are

[1] Across studies, we also conducted mixed ANOVAs after performing arcsine square-root transformations on the percentage dependent variables. The results were robust across analyses. The only differences were that the effect of device on negativity became nonsignificant in Study 1, and the effect of device type on positivity dropped from $p < .05$ to $p < .09$ in Study 2.

consistent with the greater incidence of positive content in online WOM observed in prior work (e.g., East et al. 2007). More importantly, the results reveal a main effect of device on the overall emotionality of the reviews, such that reviews written on smartphones contained a greater proportion of emotional words (M = 8.95%) than reviews written on PCs (M = 8.11%; $F(1, 61640) = 378.57$, $p < .001$). This finding supports our main thesis that relative to content generated on PCs, content written on smartphones privileges emotional information.

The results also show that while smartphone-generated content contained proportionately greater positive and negative emotionality, the effect was empirically larger for positive emotionality, which was much more pervasive in the reviews in general. This difference in effect sizes was reflected in significant device × type of emotion interaction ($F(2, 123280) = 202.49$, $p < .001$). Specifically, simple effect tests show that smartphone-generated content contained a greater proportion of positive emotional words (M = 7.90%) than did PC-generated content (M = 7.19%; $F(1, 61640) = 281.17$, $p < .001$), as well as a greater proportion of negative emotional words ($M_{\text{Smartphone}}$ = 0.75% vs. M_{PC} = 0.68%; $F(1, 61640) = 26.94$, $p < .001$), and neutral emotional words ($M_{\text{Smartphone}}$ = 0.31% vs. M_{PC} = 0.24%; $F(1, 61640) = 72.53$, $p < .001$). Finally, the device × type of emotion × replication city interaction is non-significant ($F(2, 123276) = 1.18$, *NS*), suggesting that the above-reported findings are robust across geographical markets.

[Insert Table 1]

Hedonometer measures. Although LIWC is a well-established tool for linguistic analysis (e.g., Ludwig et al. 2013; Slatcher and Pennebaker 2006), to establish robustness we also tested for differences in emotional valence across devices using the continuous Hedonometer scores of positive versus negative emotionality. Specifically, we estimated a binary logit model in which we regressed type of device (smartphone coded as 1 and PC as 0) on the linear and quadratic effects of the continuous Hedonometer score (with lower scores pointing to more negative emotionality and higher scores pointing to more positive emotionality). Testing for the quadratic effect allowed us to model the likelihood that a highly negative *or* positive review would be written on a smartphone (vs. PC). The results reveal a significant linear effect of the Hedonometer score ($B = 4.69$, Wald $\chi 2 = 83.21$, $p < .001$; see Table 1 for means) such that the more positive the review, the more likely it was to have been written on a smartphone (vs. PC), thus replicating the finding of greater emotional positivity of smartphone-generated content using LIWC scores reported above. Importantly, as shown in Figure 2, the results also reveal a significant quadratic effect of the Hedonometer score ($B = -0.39$, Wald $\chi 2 = 92.2$, $p < .001$), confirming that reviews that contained greater positive *or* negative emotionality were more likely to have been generated on a smartphone than on a PC.

[Insert Figure 2]

Mediating Effects of Brevity

Our central hypothesis is that the tendency to generate shorter content on smartphones focuses users on the overall gist of their experience, which manifests in the privileging of emotional information and a reduction in linguistic specificity. Above we report evidence that indeed, smartphone-generated reviews were more emotional than PC-generated reviews on average. In addition, a similar ANOVA confirms an effect of device on specificity, showing that content written on smartphones indeed contained lower specificity ($M_{Smartphone} = .18$ vs. $M_{PC} = .2$; $F(1, 61641) = 153.4$, $p < .001$).

Next, to test our thesis that these effects are driven by differences in content brevity across devices, we estimated a structural path model depicted in Figure 1B. In this model, brevity was measured by the word count of a review, emotionality by the LIWC affect measure, and specificity by the Speciteller algorithm. The fit statistics, maximum-likelihood estimates of path coefficients, variances of the manifest variables, and indirect effects are reported in Table 2, which were estimated using SPSS' Amos (Arbuckle 2014). In Web Appendix 2 we also compare the fit of this model to two other plausible process accounts: a serial mediation model in which use of smartphone (vs. PC) leads to lower word counts, which leads to lower specificity which, in turn, leads to higher affect (i.e., Device→Word Count→Specificity→Affect), and a non-mediation mediation model in which device independently impacts word count, specificity, and affect (i.e., Device→[Word Count, Specificity, Affect]).

These analyses support our hypothesized causal model (Figure 1B) as a superior account of the data, as measured by having the best comparative fit (e.g., Bentler comparative fit index [CFI] of .995), with the standardized path coefficients supporting the predicted directionality: smartphone use produces reviews that have lower word counts (B = -.11, p < .001), and higher word counts result in both higher specificity (B = .18, p < .001) and lower emotionality (B = -.32, p < .001). As predicted, we also find a positive indirect effect of smartphone use on emotionality through word count (B = .04, 95% CI: [.0398, .0402]) as well as a negative indirect effect on specificity (B = -.02, 95% CI: [-.0202, -.0198]; see Table 2).

[Insert Table 2]

The results also indicate a negative covariance between specificity and affect (θ = .04; t = -13.60, p < .001), which is consistent with our prediction that a heightened focus on gist when writing on smartphones manifests in the reduction of specific details in lieu of more emotional information about the experience. In contrast, as shown in Web Appendix 2, both alternative process accounts provide an inferior statistical account of the covariance structure of the data, with both the serial mediation model and non-mediation model having low comparative fit indices (e.g., Bentler CFIs of less than .35 in both cases). Taken together, these results are consistent with our prediction that the tendency to generate briefer content on smartphones (vs. PCs) leads to decreased specificity and, more critically, privileged inclusion of emotional content.

Testing Alternative Accounts

The results of the above analyses support our predictions that (a) reviews produced on smartphones (vs. PCs) tend to contain greater emotionality, and (b) this effect is mediated in part by the tendency to generate shorter content on the device. It is possible, however, that differences in emotionality may have been more directly caused by other factors associated with smartphone use, such as the timing of when the review was written (as suggested by Ransbotham et al. [2018]) or individual differences in reviewers across devices. We test for these two alternative explanations below.

Temporal proximity. Ransbotham et al. (2018) speculate that consumers writing reviews on their smartphones (vs. PCs) use more emotional language simply because they tend to write their reviews shortly after their consumption experience, which would render their feelings more salient or “hot” (e.g., Metcalfe and Mischel 1999). To test this explanation, we extracted from each review two types of linguistic evidence about when the review was written: the degree to which a review uses present-focused vs. past-focused words (e.g., “is” vs. “was”), and explicit references to timing in the reviews (e.g., “tonight” vs. “last night”). Contrary to a temporal-proximity account, however, we find that smartphone-generated reviews included a *smaller* proportion of present-focused words, as well as a *larger* proportion of past-focused words, compared to PC-generated reviews (see Table 1). To provide a further test of this account we conducted a mixed ANCOVA using the same factors as in the main analysis while also controlling for temporal markers in the reviews: the proportions of present-focused, past-focused, and future-focused words. We find that the same pattern of effects hold for differences in valence and word count (see Table 1) and that smartphone-generated content continues to contain a greater proportion of emotional words (LS-means: $M_{Smartphone}$ = 8.95% vs. M_{PC} = 8.11%; $F(1, 61637) = 403.17$, $p < .001$).

As an additional analysis of the temporal proximity account, we analyzed only reviews that made specific types of references to the time elapsed between the dining experience and the creation of the review (see Table 1). For example, we only analyzed posts that contained the phrase "last night" (N = 688), which were presumably written the day after the experience (see Table 1). The results confirm that smartphone-generated content contain a greater proportion of emotional words than PC-generated content for reviews presumably written the day after the experience ($M_{Smartphone}$ = 7.88% vs. M_{PC} = 6.98%; $F(1, 686) = 10.38$, $p = .001$).

Self-selection. Another alternative explanation is that the observed difference in emotionality is driven by a selection bias. Users who are generally more prone to writing emotional reviews may tend to use their smartphones (vs. PCs); or the types of experiences reviewed on smartphones may systematically differ from those reviewed on PCs. To test these possibilities, we conducted repeated-measures t-tests on the 1,103 unique users who had used both their mobile and PC devices at least once to post reviews on TripAdvisor. The results confirm that effectively holding the person constant, smartphone-generated content still convey greater emotionality than PC-generated content ($M_{Smartphone}$ = 8.58% vs. M_{PC} = 8.05%; $t(1,102) = 3.05$, $p = .002$).

Robustness of the Effects Using Human Judgments

Above we used two text-analysis tools (LIWC and Hedonometer) to compute objective linguistic metrics of content emotionality and emotional valence, as well as an automated measure of text specificity (Speciteller). Although these tools were developed based on human judgments of lexical features, one may wonder whether the observed content differences are subjectively perceptible to readers of the reviews. To test this, we conducted the same analyses reported above, this time using human judgments of the content.

Overview and design. Five-thousand reviews written on smartphones and five-thousand reviews written on PCs from the TripAdvisor data were randomly selected for assessment by a separate group of human judges.[2] To collect assessments of the reviews, participants from the Amazon Mechanical Turk (MTurk) panel were asked to read one randomly selected review and judge its emotional content and specificity along eleven dimensions (described below). Each participant was asked to assess up to ten such reviews. Participants were blind to whether the reviews had been written on smartphones or PCs, thereby ensuring that participants' assessments of the reviews would not be biased by knowledge of the originating device. After removing incomplete responses and those with implausibly short survey completion times (less than one second per response-item) the final dataset contained human assessments of 9,373 reviews.[3]

To measure perceptions of content emotionality, we asked participants to indicate the extent to which seven different attributes came across prominently in the review (on a 1: "Not prominent" to 7: "Very prominent" scale): "Happiness"; "Delight"; "Positive emotions"; "Anger"; "Disappointment"; "Negative emotions"; and "Emotions—EITHER positive OR

[2] Because of the strong positivity of the reviews observed using automated measures, an *a priori* power analysis based on the effect sizes observed (d = .18) suggested that a sample size of at least 2,600 would be needed to obtain an 90% chance a true device difference at $p < .01$. A sample of 5,000 per condition was gathered to provide additional power and to allow for sample attrition.

[3] An analysis of the full dataset yields similar results to those reported in the main text except for the main effect of device on perceived specificity, which drops from $p < .001$ to $p = .297$.

negative." Because the three positive-emotion items had a strong negative correlation with the three negative-emotion items (e.g., low negative affect was strongly associated with high positive affect), the six items were averaged to create a single index of "perceived sentiment" ($\alpha = .87$), with lower scores pointing to greater negative affect and higher scores pointing to greater positive affect. This index is therefore analogous to the Hedonometer positive-affect scale analyzed earlier. The perceived sentiment index was positively correlated with LIWC's overall affect score ($r = .17$, $p < .001$), positively correlated with LIWC's positive affect score ($r = .22$, $p < .001$) and negatively correlated with LIWC's negative affect score ($r = -.21$, $p < .001$). These results suggest that the emotional content detected by automated measures were also perceptible to human judges reading the reviews.

To measure our secondary prediction about the perceived specificity of the reviews, participants were also asked to indicate the degree to which they agreed with each of three statements about the review (on a 1: "Not true at all" to 7: "Very true" scale): "The review focuses on the overall essence of the dining experience rather than its specific details"; "The writer describes the experience in general rather than specific terms"; and "The writer focuses on the main takeaway of the experience rather than details about the restaurant." These three items were reverse-coded and averaged to create an index of "perceived specificity," with lower scores indicating less specificity in the reviews ($\alpha = .82$).

Results using human judgments. We first conducted ANOVAs of the perceived sentiment index as well as the "Emotions--EITHER positive or negative" item with originating device as the between-subjects factor. The results reveal a main effect of originating device for both measures (Perceived sentiment: $F(1, 9156) = 78.81$, $p < .001$; "Either emotion": $F(1, 9336) = 182.09$, $p < .001$). Consistent with the results using automated measures, relative to PC-generated reviews, smartphone-generated reviews were perceived as conveying more prominent use of emotions in general, either positive or negative ($M_{Smartphone}$ = 5.52 vs. M_{PC} = 5.11) as well as higher positive affect in particular ($M_{Smartphone}$ = 5.26 vs. M_{PC} = 4.98). In addition, the results of a similar ANOVA confirm that smartphone-generated reviews were perceived as less specific than PC-generated reviews ($M_{Smartphone}$ = 3.41 vs. M_{PC} = 3.54; $F(1, 9316) = 14.99$, $p < .001$).

Second, mirroring the analysis of the Hedonometer scores reported earlier, we estimated the likelihood that a given review was generated on smartphone versus PC as a logistic function of linear and quadratic trends in the perceived sentiment index. Consistent with the findings using Hedonometer, we observe a significant increasing linear effect of device on perceived sentiment ($B = 0.31$, Wald $\chi 2 = 13.62$, $p < .001$), and, more importantly, a significant negative quadratic effect ($B = -.05$, Wald $\chi 2 = 27.07$, $p < .001$), such that reviews that contained highly positive *or* highly negative emotional content were more likely to have been generated on a smartphone than on a PC. In Web Appendix 3 we plot the functional form of this relationship which shows that the quadratic effect of device on the perceived sentiment index was driven primarily by increasing positivity, with a smaller effect of increasing negativity.

To test the hypothesized mechanism underlying the results, mirroring the analysis for the automated measures we estimated the single mediator path model shown in Figure 1B which predicted that smartphones would lead to greater brevity (lower word count), and that this greater brevity would drive two related aspects of heightened focus on gist: the privileging of emotional content and lower specificity. The dependent measures in this model were the indices of perceived sentiment and perceived specificity. The results replicate the findings observed using automated measures (maximum likelihood estimates of the path coefficients for the hypothesized model, as well as variances and fit statistics, are reported in Web Appendix 4). Specifically, the hypothesized structure illustrated in Figure 1B provides a good account for the human-judged measures (e.g., Bentler CFI=.99), revealing significant indirect effects of device through word count on both perceived sentiment (B_{Human} = .02, 95% CI: [.016, .024]) as well as on perceived specificity (B_{Human} = -.04, 95% CI: [-.046, -.034]). These results provide convergent support for the hypothesis that the use of smartphones (vs. PCs) leads to greater brevity, which results in both lower specificity and, more importantly, the privileged inclusion of emotional information.

Finally, to further test for the uniqueness of this process specification with human judgments, as we did for the automated measures, we estimated the serial path model (i.e., Device→Word Count→ Specificity→Affect) and a non-mediation mediation model (i.e., Device→[Word Count, Specificity, Affect]). Again, these models provided inferior fits to the data (Bentler CFIs = .93 and .78 respectively). In Web Appendix 5 we report the statistics for these models as well as those for the main structural model with alternative measures of affect, which provide similar results to those reported here.

Discussion

The results of Study 1 provide initial marketplace evidence consistent with our prediction that smartphone use promotes the creation of more emotional content relative to the use of a PC, and lend support for the proposed explanation for the effect. Specifically, the data support the hypothesis that the brevity of reviews written on smartphones (vs. PCs) results in lower linguistic specificity and, more importantly, privileged inclusion of emotional information. This pattern of results is robust across (a) two geographical American markets and (b) objective linguistic measures as well as as a set of subjective human ratings. Moreover, these findings suggest that smartphone (vs. PC) use amplifies the expression of both positive affect and, to a lesser extent, negative affect.

It is also notable that the observed effects of Study 1 hold after controlling for potential differences in temporal proximity between the writing of the review and the consumption experience, which mitigates the possibility that smartphone-generated content is more emotional simply because of the "real-time" nature of smartphones (vs. PCs). Moreover, the predicted pattern of results still holds among the subset of users who had used both their mobile and PC devices to post reviews, which makes a selection-bias interpretation of the findings unlikely.

STUDY 2

While the findings of the TripAdvisor data in Study 1 offer initial support for our thesis, the correlational nature of the data limits the degree to which causal inferences about the effects can be drawn. We cannot rule out the possibility, for example, that writing on a smartphone (vs. PC) might lead people to recall different types of experiences altogether, or that the effects are driven by unmeasured individual differences that are correlated with the tendency to generate reviews on one device versus the other. To address these concerns, in Study 2 we examine whether the observed effects hold in a controlled experimental setting. Participants in Study 2 were randomly assigned to write a review of the same type of experience (their most recent meal at the on-campus dining hall) on either their smartphone or their PC. The experimental control afforded by this procedure allows us to (a) address potential issues of self-selection that might have arisen in the first field study, (b) hold the target (the restaurant) under review constant across conditions, and (c) randomize the recency of the experience, which further addresses potential differences in temporal proximity.

Method

Under the guise of a study on students' opinions of university services, 71 undergraduate students at a large urban university recruited from a behavioral research pool were asked to write a review of their most recent dining experience at the university's main undergraduate dining hall. Participants were randomly assigned to one of two conditions: a treatment condition in which they were asked to use their smartphone to write the review, or a control condition in which they were asked to use their PC to write the review.

Since we were specifying the topic of their review, to preserve ecological validity we sent the survey to participants via email so that they could complete the review at their preferred location and time (within a window of a few hours). Participants received two sequential emails before beginning the study. The first email provided the cover story for asking participants to use their randomly assigned device and contained the following information:

> We are interested in students' experiences with various services offered by the university. In particular, in this study we are interested in your consumption experiences at [the main campus] dining hall. In order to ensure that our surveys are optimized for mobile devices (*personal computing devices*), we ask that you complete this study on your smartphone (*PC*). In a few minutes you will be receiving an email from the experimenter that contains a link to this survey. We ask that you open this link on your smartphone (*PC*). If you do not complete this survey on your smartphone (*PC*), you cannot be compensated.

The second email contained the survey link, which led participants to an external page where they were instructed to write a review of their most recent experience at the campus dining hall. They were also asked to indicate approximately when the experience occurred on an eight-point scale (1 = "Today" to 8 = "4 or more weeks ago"), which allowed us to further control for temporal proximity of the experience across conditions. To confirm that participants were using the devices to which they were assigned, an unobservable check was embedded throughout the survey that recorded the brand and model of the device being used to complete the study. One participant was excluded for not having used the assigned device. In addition, two participants were excluded for having failed an attention check. After removing these reviews from the dataset, 68 responses remained for analysis (75% women). Finally, after completing their review participants were asked to indicate where they had completed the study so that we could control for potential location effects, and were then asked to answer a series of demographic questions.

Results

Preliminary analyses. There were no differences across conditions in terms of any of the demographic measures or the location in which the study was completed (largest $F(1, 66) = 2.32$, *NS*). Participants in the PC condition unexpectedly reported that their experience at the dining hall was more recent than that of participants in the smartphone condition ($M_{\text{Smartphone}} = 4.68$ vs. $M_{\text{PC}} = 3.53$; $F(1, 66) = 3.97$, $p = .05$). Nevertheless, additional analyses confirm that the results reported below persist after controlling for the timing of the experience.

Content emotionality and emotional valence. A mixed ANOVA of the proportion of emotional words with device as a between-subjects factor and type of emotionality (positive, neutral, or negative) as a within-subject factor reveals a main effect of type of emotion ($F(2, 132) = 67.51$, $p < .001$). As in Study 1, on average participants used a greater proportion of positive emotional words (M = 6.94%) than negative emotional words (M = 0.91%; $F(1, 66) = 63.76$, $p < .001$) and neutral emotional words (M = 0.27%; $F(1, 66) = 87.32$, $p < .001$). More importantly, as in Study 1 there is a main effect of device. Participants who wrote a review on their smartphone used a greater proportion of emotional words (M = 10.12%) than did participants who wrote on their PC (M = 6.13%; $F(1, 66) = 5.95$, $p < .02$). Additional analyses show that this effect persists after controlling for the recency of the experience reviewed ($F(1, 65) = 6.05$, $p < .02$). This pattern of results replicates the findings of the first field study and demonstrates that smartphone (vs. PC) use indeed has a causal impact on the selective inclusion of emotional content.

In regard to differences in emotional valence, the results reveal a marginally significant device × type of emotion interaction ($F(2, 132) = 2.53$, $p < .085$). Smartphone-generated content contained a significantly greater proportion of positive emotional words (M = 8.43%) than PC-generated reviews (M = 5.45%; $F(1, 66) = 4.36$, $p < .05$), as in Study 1. However, smartphone-generated reviews were not significantly more negatively emotional (M = 1.15%) than reviews generated on PCs (M = 0.68%; $F(1, 66) = 1.24$, *NS*), unlike in Study 1. This is likely due to insufficient statistical power in light of the low rate of negative emotional words across devices (M = .91%). Additional analyses show that after controlling for the recency of the experience, the device × type of emotion interaction becomes significant ($F(1, 65) = 3.1$, $p < .05$).

Mediating effects of brevity. We next test our thesis that the propensity to write shorter content on a smartphone (vs. PC) leads users to privilege the inclusion of emotional content. As in Study 1, smartphone-generated content contained fewer words (was briefer) than PC-generated content on average ($M_{Smartphone}$ = 23.44 words vs. M_{PC} = 39.82 words; $F(1, 66) = 11.2$, $p = .001$). We then conducted a mediation analysis with 5,000 bootstrapped samples using model 4 of the PROCESS macro for SPSS (Preacher and Hayes 2004). The results reveal an indirect effect on the proportion of emotional words ($B = 2.06$ with a bias-corrected 95% confidence interval that does not include 0 [.5, 1.96]). These results indicate that the effect of device on content emotionality is fully mediated by the length of the reviews, which supports our proposed explanation. The results also provide directional support for our secondary prediction that smartphone (vs. PC) use decreases the degree of content specificity ($M_{PC} = .19$ vs. $M_{Smartphone} = .1$, $F(1, 66) = 3.40$, $p = .07$), and confirms that this effect is significantly mediated by the brevity of the content (Indirect effect: $B = -.03$; 95% CI: [-.06, -.01]).

Discussion

Consistent with the results of the first study, Study 2 shows that participants who were randomly assigned to write a review on their smartphone priviledged the inclusion of emotional content—in particular, content that was more positively emotional—than did those who were assigned to write a review on their PC. This finding further supports our main thesis that smartphone use actually changes the nature of user-generated content in the direction of greater expressed emotionality. Whereas the field-data evidence presented in the first study was only correlational, the results of this second study were experimental, allowing for causal inferences and bypassing potential issues of self-selection. Moreover, because all participants were asked to review their most recent experience at the same dining hall, the results of Study 2 minimize the concern that the observed effects are driven by differences in the types of dining experiences reviewed across devices. Additional results indicate that, consistent with our thesis, the greater observed emotionality of smartphone-generated content was mediated by the greater brevity of reviews written on the device. In Study 3 we provide further experimental evidence for our proposed explanation.

STUDY 3

The purpose of Study 3 was to more directly test our proposed explanation for the privileging of affect in smartphone-generated content. In addition to randomly assigning participants to a device, in Study 3 we randomly assigned them to write either a short review or a long review. If smartphone-generated content is more selectively emotional because users generate shorter content on the device, then (1) constraining participants to shorter reviews on their PC than they typically would write should *increase* the relative emotionality of PC-generated content, whereas (2) forcing participants to write longer reviews than they usually do on their smartphone should *decrease* the relative emotionality of smartphone-generated content.

Method

Overview and design. One hundred and thirty-four participants from the MTurk panel (62.4% women) were randomly assigned to the conditions of a 2 (device: smartphone vs. PC) × 2 (review length: short vs. long) between-subjects design. Similar to Study 2, participants were asked to write a review of their most recent experience at a restaurant, and they were randomly assigned to do so either on their smartphone or PC. To determine the particular number of words to be written in each review-length condition, we referenced the average word count of the smartphone-generated (M = 23.44 words) and PC-generated reviews (M = 39.82 words) written by participants in Study 2. Based on this, participants in Study 3 were randomly assigned to write a review that contained either exactly 20 words (as was typical of a smartphone-generated review in Study 2) or exactly 40 words (as was typical of a PC-generated review in Study 2).

We predicted that participants using their smartphone to write a "standard" short review would use a greater proportion of emotional words than those using their PCs to write a "standard" long review, thereby replicating our prior findings. More importantly, we predicted that participants using their PC to write a short review would use (1) a *greater* proportion of emotional words than participants writing a "standard" long review on their PC, and (2) a *similar* proportion of emotional words as participants writing a "standard" short review on their smartphone. Similarly, participants using their smartphone to write a long review would use (1) a *lower* proportion of emotional words than participants writing a "standard" short review on their smartphone, and (2) a *similar* proportion of emotional words as participants writing a "standard" long review on their PC.

Procedure and measures. As in Study 2, Study 3 was conducted in two sequential parts in order to provide participants the opportunity to prepare their assigned devices. To administer the device manipulation, the first email notified participants that they would shortly be receiving the survey link and that they must prepare their smartphone (vs. PC) to complete the survey. To ensure that participants used their assigned device, we again embedded an unobservable check that recorded the brand and model of the device being used. The survey link was sent in the second email, at which point participants used their assigned device to begin the "Restaurant Experiences Survey." To manipulate review length, we presented the following instructions to participants in the short (vs. *long*) condition:

> In this market research, we are interested in consumers' experiences with various services. Please take a moment to recall your most recent experience at a sit-down restaurant. In the space below, please write a review of the restaurant in light of this experience. Your review must contain exactly 20 (*40*) words. A word counter (below the text box) will indicate how many words you have written. You will not be able to submit your review unless it contains 20 (*40*) words.

To enforce the assigned word count, we programmed a webpage that displayed a counter indicating how many words had been written, and restricted reviews from being submitted until they contained the assigned word count.

Results

To test our proposed explanation for the privileging of emotional information in smartphone-generated content, we ran a mixed ANOVA with device and review length as between-subjects factors and type of emotion as a within-subject factor.[4] A planned contrast showed that short reviews written on smartphones contained a greater proportion of emotional words (M = 11.07%) than long reviews written on PCs (M = 8.14%; $F(1, 129) = 7.3$, $p < .01$), thereby replicating the findings in the first two studies.[5] However, unlike in the previous studies,

[4] The results of a preliminary analysis confirm that participants did not differ across conditions in terms of general online review behavior, propensity to eat at restaurants, or any of the demographic variables (largest $F(1, 129) = 3.55$, *NS*).

[5] An analysis of specificity scores showed that, as expected, long (40-word) reviews contained greater specificity than short (20-word) reviews, although this difference did not reach statistical significance ($M_{Short} = .07$ vs. $M_{Long} = .08$; $F(1, 129) = 2.39$, $p = .125$).

there was no longer a main effect of device (F < 1). Instead, there was a main effect of review length showing that relative to long reviews, short reviews contained a greater proportion of emotional words (M_{Short}= 11.48% vs. M_{Long} = 7.95%; F(1, 129) = 21.18, *p* < .001). Finally, there was no device × review length interaction (F < 1).

Importantly, among PC-generated reviews, short reviews contained a greater proportion of emotional words (M = 11.89%) relative to long reviews (M = 8.14%; F(1, 129) = 13.93, *p* < .001). Similarly, among smartphone-generated reviews, short reviews contained a greater proportion of emotional words (M = 11.07%) relative to long reviews (M = 7.76%; F(1, 129) = 8.15, *p* = .005). Viewed from a different perspective, among the short reviews, the results indicate no differences between smartphone-generated and PC-generated content in the proportion of emotional words ($M_{Smartphone}$= 11.07% vs. M_{PC} = 11.89%; F < 1). Similarly, among the long reviews, smartphone-generated content and PC-generated content contained a comparable proportion of emotional words ($M_{Smartphone}$ = 7.76% vs. M_{PC} = 8.14%; F < 1; see Table 3). Taken together, these results provide further support for our proposition that the tendency to generate shorter content on a smartphone inclines users to selectively describe the more emotional aspects of their experience.

[Insert Table 3]

Additional analyses show that differences in the proportion of emotional words were again mostly driven by differences in positive affect. Relative to long reviews written on PCs, short reviews written on smartphones contained a significantly greater proportion of positive emotional words ($M_{Smartphone}$ = 9.29% vs. M_{PC} = 6.92%; F(1, 129) = 4.71, *p* < .035), providing a conceptual replication of the results in our previous studies. Further examination showed that this difference was driven by the length of the reviews. For example, short reviews written on PCs contained a greater proportion of positive emotional words than long reviews written on smartphones ($M_{Smartphone}$ = 6.12% vs. M_{PC} = 10.95%; $F(1, 129) = 19.61$, $p < .001$). Similar analyses for negative emotionality show no differences across conditions, which is consistent with our earlier suggestion that while the effect of device may be symmetric for positive and negative affect, the latter result may be less visible due to the low incidence of negative emotionality in WOM.

Discussion

Study 3 shows that constraining users to shorter reviews than they normally would write on their PC drives the inclusion of more emotional content, while leading users to write longer reviews than they typically would on their smartphone drives the inclusion of *less* emotional content. In other words, the observed differences in content can be attenuated by holding constant the length of the reviews across devices. In combination with the results of the mediation analyses across our prior studies, these findings support our thesis that the privileging of emotions in smartphone-generated content is driven by the tendency of smartphone users to concisely report the gist of their experience. Next, in Study 4 we investigate differences in emotional valence more directly.

STUDY 4

A consistent finding of the first three studies is that content generated on smartphones contained greater expressions of positive affect than content generated on PCs. The evidence for whether there was a comparable effect for negative affect, however, was more equivocal. Whereas we observed an effect of device on negative emotionality in the large-scale field data (Study 1), there was less statistical support in the smaller-sample lab studies (Studies 2 and 3). While it is possible that this reflects a systematic asymmetry in how device use affects expressions of positive versus negative emotion, a more straightforward explanation is that because WOM tends to be much more positive in general (e.g., Chevalier and Mayzlin 2006; East et al. 2007), amplification of negative emotions may simply be more difficult to uncover. To further explore this asymmetry, in Study 4 in addition to being randomly assigned to a device type, participants were randomly assigned to review a positive dining experience, a negative dining experience, or their most recent dining experience. If smartphones enhance both positive and negative emotionality indiscriminately, we should find that the effect of device on selective emotionality is not contingent on the valence of the emotion.

Method

Under the guise of a study on customer opinions on restaurant experiences, 119 participants (72.3% women) from the behavioral research lab of a large urban university were randomly assigned to the conditions of a 2 (device: smartphone vs. PC) × 3 (experience valence: negative vs. positive vs. control) between-subjects design. For the device manipulation, participants were randomly assigned to write a review either on their smartphone or their PC. To manipulate the valence of the experience, we randomly assigned participants to write a review of a negative restaurant experience in one condition, a positive restaurant experience in a second condition, or their most recent dining experience in a third condition.

We followed a similar procedure as in Studies 2 and 3, implementing the study in two sequential parts and providing the cover story that we were interested in consumers' opinions of restaurant experiences. Upon opening the survey link, participants in the positive-experience (negative-experience) condition received the following instructions:

> Please take a moment to think about a sit-down restaurant at which you have had a positive (*negative*) experience. In the space below, please write a review of this restaurant in light of this positive (*negative*) experience.

Participants in the control condition were told to recall their most recent experience at a sit-down restaurant and to write a review in light of this experience (as in Study 3). As a check of the experience-valence manipulation, participants were also asked to rate the restaurant on a scale of 1 to 5 stars. After completing their reviews, participants indicated how often they eat at restaurants in general (1 = "Less than once a week" to 5 = "2-3 times a day, every day") and responded to the same online review activity ($\alpha = .73$) and demographic questions as in Study 2.

Results

Emotional valence. To test for differences in emotional valence, we ran a mixed ANOVA with device and experience-valence as between-subjects factors, and type of emotion as a within-subject factor.[6] Confirming the predicted differences in general emotionality, the results show that reviews written on smartphones contained a greater proportion of emotional words on average (M = 12.23%) relative to reviews written on PCs (M = 8.45%; $F(1, 113) = 7.67$, $p = .007$).[7] This effect was not qualified by a device × experience-valence interaction ($F < 1$; see Table 4), showing that the selective emotionality of smartphone-generated content did not vary according to the particular valence of the experience assigned.[8]

[Insert Table 4]

[6] A first check of the valence manipulation confirms that reviews in the positive condition elicited higher numerical ratings than in the negative ($F(1, 112) = 129.60$, $p < .001$) and control conditions ($F(1, 112) = 10.90$, $p < .001$). A second check confirms that reviews in the positive condition contained a greater proportion of positive words than in the negative, and a comparable proportion to the control conditions, and reviews in the negative condition contained a greater proportion of negative words than in the other conditions ($F(4, 226) = 9.09$, $p < .001$).

[7] Mediation analyses confirm that brevity mediated the effect of device on both emotionality ($B = .98$, 95% CI: [.42, 1.65]) and specificity ($B = -.02$, 95% CI: [-.04, -.01]), although there was no direct effect on specificity ($F < 1$).

[8] A preliminary analysis confirms no differences across conditions in terms of general online review activity or any of the demographic measures (largest $F(2, 113) = 2.44$). The results show a main effect of valence on the general tendency to dine at restaurants ($F(2, 113) = 3.13$, $p < .05$), but an analysis confirms that the main results still hold after controlling for general dining tendency.

The device × type of emotion interaction was not significant (F(1, 113) = 2.56, *NS*), suggesting that the effect of device on the proportion of emotional words holds equally for positive and negative affect, even in a setting where the expression of both positive and negative emotions was explicitly encouraged. It is worth noting, however, that the mean difference between devices was directionally larger for positive emotions within the positive-experience condition ($M_{\text{Smartphone}}$ = 13.41% vs. M_{PC} = 8.97%; F(1, 113) = 4.06, $p < .05$) than for negative emotions within the negative-experience condition ($M_{\text{Smartphone}}$ = 4.19% vs. M_{PC} = 2.74%; F(1, 113) = 1.92, *NS*), which is consistent with the results of the previous studies.

Discussion

The findings of Study 4 provide further insight into differences in emotional valence across devices. Consistent with our previous studies, the results show that content written on smartphones (vs. PCs) contained a greater proportion of emotional words—regardless of whether participants were instructed to write about a positive experience, a negative experience, or a recent experience. Our results also provide further support for the notion that smartphone (vs. PC) use enhances both positive and negative affect. We find that even when participants were explicitly instructed to review a positive experience, smartphone use still increased positive emotionality relative to PC use. With respect to negative emotionality, the effect was similar but statistically weaker. When participants were instructed to write about a negative experience, smartphone use directionally increased negative emotionality relative to PC use, but not significantly. It is worth noting, though, that the percentage increase in negative emotionality due to smartphone use within the negative-experience condition (52.92%) was in fact similar to the percentage increase in positive emotionality due to smartphone use within the positive-experience condition (49.5%). Therefore, the results of this study align with our previous finding that while smartphone use tends to increase both the positive and negative emotionality of user-generated content, the latter effect may be more difficult to observe due to relatively low incidence rate of negative emotionality in the types of reviews examined.

STUDY 5

Given that the first four studies were conducted in the context of restaurant reviews, one may wonder whether the findings are specific to this particular domain or if they generalize to other domains of user-generated content. To examine this issue, in this final field study we test for the phenomenon with content posted on a substantively different platform: Twitter. Twitter provides a particularly interesting forum for testing our thesis for three reasons. First, it is one of the largest and most popular online social networks. Second, from political opinions to celebrity gossip, Twitter allows for the sampling of a broad range of topics. We examined Tweets referencing a variety of pop-culture-related "trending hashtags," thereby extending our investigation well beyond restaurant reviews. We chose Tweets about pop-culture-related topics because, while removed from the domain of restaurants, this context is still an evaluative one—that is, one in which affective reactions are likely to be an essential part of one's response to the content (e.g., expressing love or contempt for a TV show). In other words, Tweets about pop culture should lead users to selectively privilege emotional reactions to the topic when pressed for space. Finally, at this time Tweets were constrained to a maximum of 140 characters, whereas in most of our previous studies (except Study 3) the content was not restricted in length. The length restriction imposed on Twitter thus provides a conservative test of our thesis.

Dataset

To indicate that they are referencing a particular topic, users on Twitter accompany their posts with a "hashtag" (e.g., "#NFLprotest"), and the most popular hashtags within a given location and time period are identified by Twitter as "trending hashtags." To construct our dataset we selected thirty-two pop-culture-related hashtags that were "trending" at a particular period of time and covered a broad range of entertainment topics (e.g., "#SNLChristmas"; "WomenInMusic"; "#WorseWaysToBecomeFamous"). Any Tweets containing one of the thirty-two hashtags that were trending between December 1 and 11, 2015, and between January 19 and 29, 2016, were scraped, resulting in 70,027 unique Tweets. The final dataset included 27,671 Tweets that had been posted from PCs and 42,356 posted from smartphones (60.5%). To obtain measures of the degree of emotionality expressed in the Tweets, as in the prior studies the text bodies we subjected analysis by LIWC. This yielded for each Tweet a measure of the percentage of affective words, posiive emotional words, and negative emotional words.

Results

Content emotionality and emotional valence. To test for differences in emotionality, we again ran a mixed ANOVA with device as a between-subjects factor and type of emotion as a within-subject factor.[9] Once again, the results revealed a main effect of device (F(1, 70025) = 310.66, $p < .001$), indicating that Tweets posted from smartphones contained a greater proportion of emotional words (M = 12.35%) relative to Tweets posted from PCs (M = 11.32%). This finding suggests that the greater emotionality of smartphone-generated content observed among restaurant reviews in our prior studies generalizes to the context of social media.

The results additionally revealed a main effect of type of emotion (F(2, 140050) = 31153.15, $p < .001$), such that Tweets contained a greater proportion of positive emotional words on average (M = 8.44%) than negative emotional words (3.34%) and neutral emotional words (M

[9] A Levene's test for equality of variances found that the homogeneity of variance assumption was violated. However, the results of an independent samples t-test confirm that even when equal variances are not assumed, the same pattern of results holds for emotionality (t(61463.6) = 17.84, $p < .001$), positive emotionality (t(61067.3) = 9.86, $p < .001$), and negative emotionality (t(66310.4) = 10.19, $p < .001$).

= .05%). This effect was qualified by a device × type of emotion interaction ($F(2, 140050)$ = 42.25, $p < .001$). Simple effects tests show that similar to the results of the previous studies, smartphone-generated Tweets contained a greater proportion of positive emotional words (M = 8.74%) than PC-generated Tweets (M = 8.15%; $F(1, 70025) = 95.43$, $p < .001$). Interestingly, smartphone-generated Tweets also contained a greater proportion of negative emotional words than PC-generated Tweets ($M_{\text{Smartphone}}$ = 3.56% vs. M_{PC} = 3.12%; $F(1, 70025) = 95.89$, $p < .001$), although as in Study 1 the means were rather low. We note that these results hold when controlling for the particular hashtag mentioned in the Tweet. Overall, these findings converge with those of the previous studies in showing that smartphone use tends to increase the expression of both positive and negative emotionality, even in the context of social media.

Mediating effects of brevity. First, an ANOVA on the word count of the content confirmed that the smartphone-generated Tweets contained fewer words (M = 14.97 words) than PC-generated Tweets (M = 17.2 words; $F(1, 70025) = 1897.21$, $p < .001$). To test whether word count mediated the effect of device on the proportion of emotional words, we then conducted a mediation analysis with 5,000 bootstrapped samples using model 4 of the PROCESS macro for SPSS (Preacher and Hayes 2004). The results showed that, as hypothesized, word count partially mediated the effect of device on the emotionality of the Tweeted content (Indirect effect: B = .69, with a bias-corrected 95% confidence interval that does not include 0 [0.66, 0.72]). The results also support our secondary prediction, showing a significant direct effect on specificity ($M_{\text{Smartphone}}$ = .47 vs. M_{PC} = .60; $F(1, 66032) = 3091.05$, $p < .001$)[10], and an indirect effect of device on specificity through word count (Indirect effect: B = -.0155; 95% CI: [-.016, -.015]).

[10] Because some Tweets were unreadable by the Speciteller algorithm, the specificity analysis was based on 3,993 fewer observations.

Discussion

The results of this final field study show that the selective inclusion of emotions in smartphone-generated content—both for positive emotionality and, to a lesser extent, stronger negative emotionality—extends to other domains of user-generated content, in this case, Twitter posts about pop-culture topics. Again, the phenomenon was driven by the tendency to generate shorter content on smartphones, which is consistent with our proposed explanation. It is noteworthy that the phenomenon replicates on Twitter where the length of the content was tightly constrained. These results suggest that the phenomenon is not platform- or topic-specific and is likely to generalize across a broad range of platforms and topics.

GENERAL DISCUSSION

Our research employed a multi-method approach—including two field studies and three controlled experiments—to investigate the unique consequences of smartphone use for content generation. Across our studies, a key finding emerges: relative to content generated on PCs, content generated on smartphones reveals the privileged inclusion of emotions. This phenomenon was found to apply to both positive and negative emotions, although it was more pronounced and observable among the former due to the relatively low incidence of negative affect in the data. This effect was also found to be quite robust, arising in a field study examining TripAdvisor restaurant reviews (Study 1), among restaurant reviews written by participants in several experimental settings (Studies 2–4), and in an additional Twitter field study examining a variety of entertainment-related social media topics (Study 5). Moreover, these linguistic differences were observed using measures from multiple natural language processing tools as well as human judgments (Study 1).

Our results also yield insight into the mechanism that underlies the selective emotionality of smartphone-generated content. Our central thesis was that, because of its physical constraints, consumers tend to generate shorter content on their smartphone (vs. PC), which focuses them on the overall gist of their ideas when writing on the device. This focus on gist, in turn, tends to be manifested by two linguistic features: (1) the exclusion of specific details and, more importantly for the present work, (2) the privileging of emotional information related to the experience or topic. We offer evidence in support of this process explanation by demonstrating the mediating role of brevity (Studies 1, 2 and 5), and by showing that differences in emotionality dissipate when the length of the review is held constant across devices (Study 3).

Theoretical and Practical Implications

The substantial body of work on the topic of online WOM has largely focused on the "impact" of WOM, such as its perceived helpfulness (e.g., Ghose and Ipeirotis 2011), virality (e.g., Berger and Milkman 2012), and effect on sales (e.g., Godes and Mayzlin 2009). However, much less work exists on the factors that influence the *type* of content shared in WOM. One such paper argues that the type of content shared in WOM is determined by the motivation to share the content in the first place, and that when people generate WOM as a means of emotional regulation, this drives them to share more emotionally laden content (Berger 2014). Berger and Iyengar (2013) examine how the medium through which WOM is transmitted—in their case, oral vs. written WOM—impacts the type of content shared. They argue that because written WOM is more asynchronous, people can take time to edit and refine their WOM, which leads them to share more interesting content with others. Our work extends these findings by showing that even within the mode of written communication, the use of different media can change the type of content shared. We show that because using the device encourages users to generate shorter content, smartphones (vs. PCs) result in WOM that is relatively more emotional in nature.

The differences in content generated on smartphones vs. PCs also bear implications for marketers concerned with the effects of online word of mouth (WOM). Prior work on online WOM has shown that its impact or persuasiveness depends on factors such as the characteristics of the reviewer (e.g., Godes and Mayzlin 2009) and the characteristics of the review itself, such as its linguistic characteristics (e.g., Schellekens, Verlegh, and Smidts 2010). While some of these findings would imply that smartphone-generated WOM might be less impactful or persuasive than PC-generated content (e.g., Banerjee and Chua 2014; Wang et al. 2015), other findings suggest that smartphone-generated content would actually be more impactful. For example, Ludwig et al. (2013) find that increasing the proportion of positive emotional language in Amazon reviews led to higher customer conversion rates. Other work has shown that more emotional content is more likely to be shared and discussed by others online (e.g., Berger and Milkman 2012; Luminet et al. 2000), and findings outside the WOM literature show that consumers' opinions are especially influenced by texts containing more emotional language (Lau-Gesk and Meyers-Levy 2009).

Combined with our findings, these earlier results would suggest that smartphone-generated content might be more impactful. Indeed, some of our own preliminary results, not reported here, show that participants were more interested in trying restaurants described in reviews written on smartphones (M = 5.21) than PCs (M = 4.80; $B = .48$, $p < .001$). Although more research into this issue is needed, these findings suggest that firms could benefit from marketing efforts that encourage customers to generate content on their smartphones, such as offering customers mobile apps that facilitate posting from the device. Our results also imply that attaining data on which device was used to generate WOM may be critical in helping firms identify the content that will be most influential—namely, smartphone-generated content.

Limitations and Directions for Future Research

While our research offers evidence that supports one explanation for why smartphone-generated content tends to be more selectively emotional (greater brevity due to physical constraints), the fact that in our large field studies the measure of brevity that we analyzed (word count) did not completely mediate the effect of device on emotionality suggests that there may be other, more subtle psychological drivers of the effect that were not measured here. For example, since consumers often form stronger emotional attachments to their smartphones than their other devices (e.g., Bianchi and Phillips 2005; Melumad and Pham 2018), it might be the case that engaging with their smartphone puts consumers in a more emotional mindset, thus increasing the emotionality—and especially the positive emotionality—of content generated on the device. An important area for future research would be to uncover what this "mobile mindset" might be, and how it might influence content beyond that fostered by a focus on gist.

Additionally, while across all of our studies we showed that smartphone-generated content contained significantly greater positive affect, in our field data we found that it also contained significantly greater negative affect (Studies 1 and 5). Recent findings show that whereas WOM tends to be positive for distant others, it tends to be more negative for close others (Dubois, Bonezzi and De Angelis 2016). Although users posting on TripAdvisor and Twitter might have varied in the degree to which they felt they were posting to close others—which could partly account for the perceived differences in proportions of negative emotions observed in Studies 1 and 5—in our lab studies we made no mention of the type of audience to which participants should write their reviews. Future research could thus examine whether the cross-device differences we observe still hold when the interpersonal closeness of the audience is manipulated. Another question worthy of future investigation is whether there are substantive differences across devices not just in terms of valence, but also in terms of the discrete emotions expressed (e.g., Raghunathan and Pham 1999). Finally, future work could identify boundary conditions under which focusing on the overall essence of an experience does *not* increase content emotionality, such as reviews of utilitarian products that presumably engage less affect (Pham 1998).

Many firms are struggling with how to sift through the explosion of user-generated content. Our findings help direct some of these efforts by assisting firms in identifying the user-generated content that might be most influential—that is, smartphone-generated content. The finding that smartphone use drives the creation of more emotional and mostly positive WOM also suggests that firms may want to encourage customers to post more content from their *smartphones* in particular. Our research thus provides guidance for firms' digital insights and analytics, and ideally will encourage other researchers to focus on this game-changing context.

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TABLES

Table 1
STUDY 1: REPLICATION SETS AND TEMPORAL CONDITION RESULTS: CONTENT CHARACTERISTIC MEANS (AND STANDARD ERRORS) ACROSS DEVICES (N=61,642)

Dependent Measure	Replication 1 (Philadelphia) (N=29,158)		Replication 2 (San Francisco) (N=32,485)		Controlling for Temporal Markers (Past-, Present- and Future-Focused Words)		Temporal Condition 1: "Last Night" (N=688)		Temporal Condition 2: "Tonight" (N=232)	
Type of Emotion:	Mobile	PC	Mobile	PC	Mobile	PC	Mobile	PC	Mobile	PC
Proportion of Emotional Words	8.52% (SE=.06)	7.81% (SE=.03)	9.29% (SE=.06)	8.39% (SE=.03)	8.95% (SE=.04)	8.11% (SE=.02)	7.88% (SE=.28)	6.98% (SE=.13)	7.88% (SE=.33)	6.94% (SE=.24)
Proportion of Positive Emotional Words	7.50% (SE=.05)	6.88% (SE=.03)	8.22% (SE=.06)	7.47% (SE=.03)	7.90% (SE=.04)	7.18% (SE=.02)	6.81% (SE=.27)	6.07% (SE=.14)	6.69% (SE=.32)	5.85% (SE=.25)
Proportion of Negative Emotional Words	0.76% (SE=.02)	0.70% (SE=.01)	0.73% (SE=.02)	0.66% (SE=.01)	0.75% (SE=.01)	0.68% (SE=.01)	0.73% (SE=.09)	0.72% (SE=.05)	1.05% (SE=.13)	0.95% (SE=.11)
Proportion of Neutral Emotional Words	0.26% (SE=.01)	0.23% (SE=.00)	0.34% (SE=.01)	0.26% (SE=.01)	0.31% (SE=.01)	0.24% (SE=.01)	0.34% (SE=.05)	0.19% (SE=.02)	0.15% (SE=.05)	0.15% (SE=.03)
Hedonometer	6.50 (SE=.00)	6.47 (SE=.00)	6.52 (SE=.00)	6.50 (SE=.00)	6.51 (SE=.003)	6.48 (SE=.002)	6.38 (SE=.02)	6.33 (SE=.01)	6.40 (SE=.04)	6.34 (SE=.03)
Other content characteristics:	Mobile	PC	Mobile	PC	Mobile	PC	Mobile	PC	Mobile	PC
Word Count	78.83 (SE=.78)	101.71 (SE=.60)	63.19 (SE=.59)	82.24 (SE=.50)	69.85 (SE=.65)	91.55 (SE=.36)	112.16 (SE=7.43)	155.73 (SE=5.78)	103.41 (SE=8.31)	176.8 (SE=13.08)
Proportion of Past-Focused Words	6.87% (SE=.05)	6.61% (SE=.03)	6.62% (SE=.05)	6.37% (SE=.03)			8.37% (SE=.23)	8.03% (SE=.14)	7.66% (SE=.40)	7.46% (SE=.26)
Proportion of Present-Focused Words	6.57% (SE=.06)	6.72% (SE=.03)	6.16% (SE=.05)	6.47% (SE=.03)			4.76% (SE=.22)	5.20% (SE=.13)	6.38% (SE=.37)	5.86% (SE=.27)
Proportion of Future-Focused Words	0.83% (SE=.02)	0.79% (SE=.01)	0.69% (SE=.01)	0.69% (SE=.01)			0.72% (SE=.09)	0.77% (SE=.04)	2.47% (SE=.15)	1.86% (SE=.11)

Table 2

STUDY 1: STRUCTURAL PATH COEFFICIENTS AND VARIANCES (N=61,642)

Standardized Path Model Estimates				
Path	**Estimate**	**Std Error**	**t Value**	**Pr>|t|**
Device-->Word Count (WC)	-0.11	0.004	-28.32	<.001
WC-->LIWC Affect	-0.32	0.004	-89.15	<.001
WC-->Speciteller Specificity	0.18	0.004	45.54	<.001
Device--> LIWC Affect	0.04	0.004	10.52	<.001
Indirect Effects				
Device-->WC--> LIWC Affect	0.04	0.001	26.89	<.0001
Device-->WC--> Speciteller Specificity	-0.02	0.001	-23.94	<.0001
Standardized Covariance Estimates				
Speciteller Specificity<--> LIWC Affect	-0.05	0.004	-13.78	<.001
Model Fit				
Model Chi Square	57.40			
Bentler Comparative fit	0.99			

Table 3
STUDY 3: MEANS (AND STANDARD ERRORS) AS A FUNCTION OF REVIEW LENGTH AND DEVICE (N=133)

Dependent Measure	Short Reviews (N=65)		Long Reviews (N=68)	
	Smartphone	PC	Smartphone	PC
Proportion of Emotional Words	11.07%$_a$ (SE=0.83)	11.89%$_a$ (SE=0.72)	7.76%$_b$ (SE=0.81)	8.14%$_b$ (SE=0.70)
Proportion of Positive Emotional Words	9.29%$_a$ (SE=0.83)	10.95%$_a$ (SE=0.72)	6.12%$_b$ (SE=0.82)	6.92%$_b$ (SE=0.70)
Proportion of Negative Emotional Words	0.71%$_a$ (SE=0.35)	0.41%$_a$ (SE=0.30)	1.29%$_a$ (SE=0.34)	0.77%$_a$ (SE=0.30)
Proportion of Neutral Emotional Words	1.07%$_a$ (SE=0.30)	0.54%$_a$ (SE=0.26)	0.35%$_a$ (SE=0.29)	0.45%$_a$ (SE=0.25)

Note: Different subscripts within a given row indicate significant mean differences at $p < .001$.

Table 4
STUDY 4: MEANS (AND STANDARD ERRORS) AS A FUNCTION OF EXPERIENCE-VALENCE AND DEVICE (N=119)

Dependent Measure	Positive Experience (N=32)		Negative Experience (N=41)		Control Condition (N=46)	
Type of Emotion:	Smartphone	PC	Smartphone	PC	Smartphone	PC
Proportion of Emotional Words	14.65%$_a$ (SE=1.69)	9.54%$_c$ (SE=1.57)	9.36%$_a$ (SE=1.84)	7.94%$_a$ (SE=1.84)	12.66%$_a$ (SE=1.57)	7.86%$_c$ (SE=1.50)
Proportion of Positive Emotional Words	13.41%$_a$ (SE=1.61)	8.97%$_b$ (SE=1.50)	5.17%$_a$ (SE=1.76)	5.20%$_a$ (SE=1.76)	10.69%$_a$ (SE=1.50)	6.33%$_b$ (SE=1.44)
Proportion of Negative Emotional Words	0.39%$_a$ (SE=0.68)	0.33%$_a$ (SE=0.63)	4.19%$_a$ (SE=0.74)	2.74%$_a$ (SE=0.74)	1.58%$_a$ (SE=0.63)	1.27%$_b$ (SE=0.61)
Proportion of Neutral Emotional Words	0.86%$_a$ (SE=0.26)	0.24%$_a$ (SE=0.24)	0.00%$_a$ (SE=0.28)	0.00%$_a$ (SE=0.28)	0.39%$_a$ (SE=0.24)	0.26%$_a$ (SE=0.23)

Note: Comparisons are within experience-valence.
$_{aa}$: Non-significant
$_{ab}$: $p < .05$
$_{ac}$: $p < .03$

Figure 1

Hypothesized Model of the Effects of Smartphone Usage on Content

Figure 1A: Conceptual Model

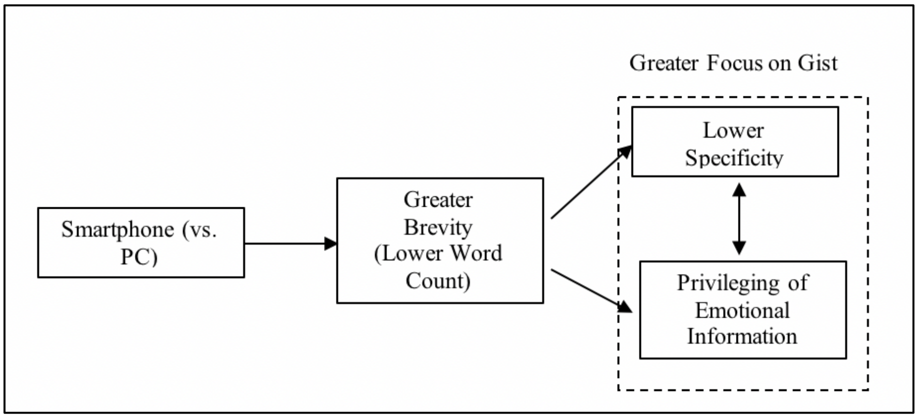

Figure 1B: Empirical Analog

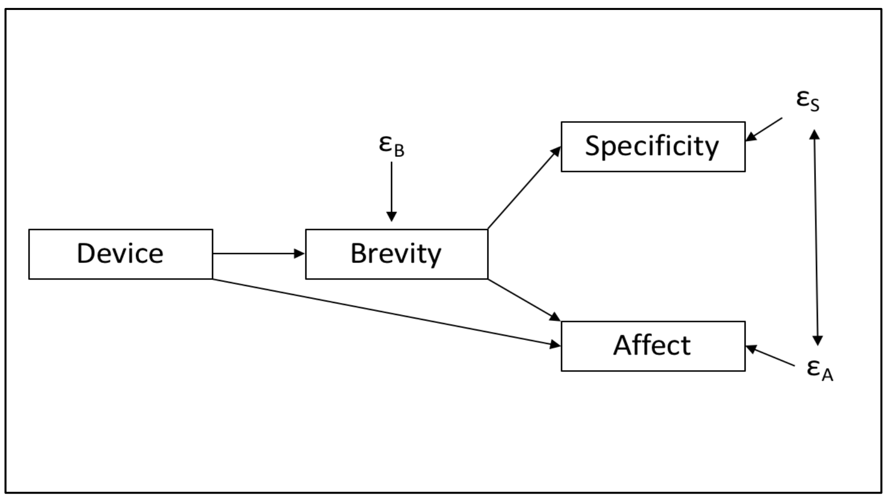

Figure 2

STUDY 1: Fitted relationship between Hedonometer rating and probability that a review was created on a smartphone (vs. PC). Bars display actual relative frequencies of smartphone use for Hedonometer scale intervals.