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The Characteristics and Perceived Value of Mobile Word of Mouth

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Report Summary

Should firms encourage consumers to write real-time reviews of their products and services on mobile devices? Some marketers fear that, since mobile reviews are usually written in real time, consumers are more likely to affectively (and negatively) respond to their current experiences.

To understand whether this concern is justified, in this study Nicholas Lurie, Sam Ransbotham, and Hongju Liu investigate two questions: How does content created on mobile devices differ from content created on desktop platforms? Further, how does mobile word of mouth (WOM) differ in its perceived value to consumers from WOM created on desktop platforms?

To begin, they propose that the content of mobile word of mouth is likely to be distinguished from desktop WOM for three reasons: (1) mobile WOM tends to be written in real time or shortly after consumption; (2) mobile devices' small screen size and limited keyboard increase their accessibility but may impose physical and cognitive costs; and (3) devices used to create mobile WOM are more personal than those used to create desktop content. They develop a conceptual framework for how each of these factors should affect the characteristics and perceived value of mobile WOM, and test their ideas using a unique dataset from Urbanspoon.com, which distinguishes mobile from desktop reviews.

Findings

Text and regression analyses of 299,798 reviews (from 125,146 users on 144,227 restaurants) show, among other findings, that mobile WOM is less reflective, more focused on the present, less subject to retrospective biases, more affective, less cognitive, more one-sided, more negative, and less socially oriented. Some of these content characteristics increase the value of mobile WOM (measured as number of "likes") while other characteristics lower perceived value. For example, while negative reviews are more valued by other consumers than positive reviews, shorter, less extreme, and less social reviews are less valued. Contrary to predictions, the less cognitive, more affective, more one-sided, and current-concerns characteristics of WOM do not significantly affect review value. Overall, after controlling for observable differences in content, mobile WOM is less valued than traditional WOM.

Implications

This research provides important insights into the underlying processes whereby mobile platforms affect the content and influence of WOM. Overall, it suggests that marketers need to account for differences in content created by consumers on mobile devices versus desktop platforms.

For example, mobile WOM may provide fewer insights into consumer cognitions and long-term attitudes, since real-time (negative) reactions may not persist when consumers have time to reflect on experiences. On the other hand, mobile WOM may be useful for market research in which real-time responses are desired for products or services or where consumers are unlikely to invest substantial cognitive resources. Similarly, mobile content may provide greater insights into individual (vs. group) experiences.

At the same time, marketers should remember that, although real-time consumer attitudes may not persist, their word of mouth will. Although mobile reviews are less valued, some aspects of these reviews—such as greater negativity—raise concerns. Marketers might address these concerns by encouraging consumers to write reviews after, rather than during, consumption experiences and by responding proactively to service failures.

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Introduction

The exploding growth of online word of mouth (WOM) is enhanced by the increased ability of consumers to access and create this content wherever they are. New mobile devices have led to a proliferation of applications that provide consumers with location-dependent information to make choices and evaluate decisions during as well as after purchase. Examples include the ability to read and write reviews of restaurants in mobile versions of Urbanspoon, Yelp, and Citysearch and to send real-time thoughts in Twitter while watching a movie.

Growing evidence indicates that consumers are increasingly likely to rely on information from other consumers (Ransbotham and Kane 2011; Weiss, Lurie, and MacInnis 2008). Recent empirical research shows that the valence, dispersion, and volume of consumer reviews predict sales in traditional (i.e., desktop) online environments (Chevalier and Mayzlin 2006; Duan, Gu, and Whinston 2008; Godes and Mayzlin 2004). Other research suggests that the perceived value of consumer-created content depends on characteristics such as contribution length, contributors' prior posting behavior, contributor expertise, review valence, the presence of temporal contiguity cues that connect word-of-mouth to product experiences, as well as the perceived similarity of the creators and readers of consumer-created content (Chen and Lurie 2013; Forman, Ghose, and Wiesenfeld 2008; Weiss, Lurie, and MacInnis 2008). However little is known about differences in the characteristics and perceived value of mobile versus desktop word of mouth.

From a managerial standpoint, there is substantial debate over the pros and cons of encouraging consumers to write real time reviews with some fearing that mobile reviews will not benefit from reflection and that consumers will affectively (and negatively) respond to their current experiences. This led some review sites (e.g., Yelp) to allow people to start reviews on their mobile devices but required them to use a desktop computer to finish them (Miller 2009), a requirement that has since been discontinued (Moon 2013). However it is still unclear whether concerns about differences in mobile content are justified.

This paper addresses these issues by identifying factors that should lead to differences in the *content* of word of mouth created on mobile versus non-mobile devices and identifying how and when mobile word of mouth is likely to differ in its *perceived value* to consumers. We propose that the content of mobile word of mouth is likely to be distinguished from desktop WOM for three reasons: 1) mobile WOM tends to be written in real-time or shortly after consumption; 2) form factors such as small screen size and limited keyboard increase accessibility but also the physical and cognitive costs of using mobile devices; and 3) devices used to create mobile WOM are more personal than those used to create desktop content. Each of these factors should have important implications for the characteristics and value of mobile WOM. Our conceptual model is shown in Figure 1.

Mobile WOM Content

Real-time creation process

Mobile WOM is often created during or immediately following consumption (Miller 2009). In particular, consumers increasingly tweet their real-time evaluations of movies and TV shows and evaluate the food they are eating as they eat it (Garcia Esparza, O'Mahony, and Smyth 2010; Miller 2009). In contrast, desktop WOM is generally created after consumption, is retrospective and involves memory about the experience. The real-time nature of mobile WOM should have a number of important effects on the characteristics of its content.

The real-time creation process associated with mobile WOM should make it less reflective relative to desktop WOM. In other words, mobile consumers will spend less time thinking about and processing their experiences before engaging in WOM. Because it involves limited reflection, mobile WOM should involve more "hot" reasoning (Ariely and Loewenstein 2006; Loewenstein 2000) and therefore be more affective and less cognitive. In other words, mobile WOM should reflect more visceral responses than desktop word of mouth. Limited reflection, and less consideration of the totality of an experience, should also lead to WOM that is more likely to use one- versus two-sided arguments.

More generally, creating WOM during or shortly after consumer experiences should reduce the psychological distance between these experiences and the related WOM. Although work on temporal construal has traditionally examined the mental representation of future events (Trope and Liberman 2003), more recent research suggests that effects of psychological distance apply in similar ways to retrospective evaluations (Trope and Liberman 2010). This means that mobile WOM should reflect a lower construal level than desktop WOM, as shown by a greater focus on current (rather than past or future) concerns (Trope and Liberman 2010; Trope and Liberman 2003).

Finally, because it is more likely to be created in real time, mobile WOM should be less subject to retrospective biases than desktop WOM. One retrospective bias is the “rosy view,” where retrospective evaluations are generally more positive than evaluations that occur during experiences (Mitchell et al. 1997; Novemsky and Ratner 2003; Wirtz et al. 2003). If mobile WOM is less subject to the rosy view, mobile WOM should be more negative than desktop WOM.

This discussion leads to the following testable hypotheses:

H_1: Compared with desktop word of mouth, mobile word of mouth is:

a) more affective,
b) less cognitive,
c) more one-sided,
d) more focused on current concerns, and
e) more negative.

Form factor

Another important difference between mobile and traditional WOM is that the devices used to create mobile WOM tend to be smaller in size, with smaller keyboards and smaller screens. These factors increase the cognitive and physical costs associated with using these devices (Lurie, Song, and Narasimhan 2009). For example, small keyboards make it difficult to engage in extensive communication. This should reduce the length of mobile WOM.

At the same time, the same factors that make it harder to create WOM on mobile devices increase device accessibility since they allow consumers to carry mobile devices wherever they go. This greater accessibility should increase the use of mobile devices in low-motivation contexts. That is, although consumers will engage in WOM on both mobile and desktop platforms for experiences that are strongly positive or negative, they should be less likely to use desktop platforms for WOM about neutral—and less memorable—experiences for which the motivation to engage is WOM is lower (Anderson 1998; Godes and Mayzlin 2004). In contrast, because mobile devices are always available, they are likely to be used to generate word of mouth about less memorable experiences. This greater likelihood of providing neutral WOM suggests that mobile WOM will be less extreme, on average, than desktop WOM.

Together, this implies:

H_2: Compared with desktop word of mouth, mobile word of mouth is:

a) shorter in length, and

b) less extreme.

Personal relationship with device

Another factor that is likely to affect the content of mobile WOM is the stronger personal relationship between mobile devices and their users. Unlike desktop computers, mobile devices are almost always used by a single individual. More importantly, mobile devices are an extension of the self (Greenwood 2011; Sultan and Rohm 2005). In particular, the ability to customize apps, wallpaper, ringtones, cases, and other features make mobile devices reflections of ourselves and provide ways to express ourselves to others (Greenwood 2011; Sultan and Rohm 2005). The constant physical presence of mobile devices lead to strong emotional and psychological connections between devices and users (Turkle 2008). Sometimes the intimate relationship between users and devices leads them to be perceived as competitors by romantic partners (Czaja 2012). To the extent that mobile devices foster personal, and autobiographical thoughts, mobile WOM should involve less use of socially-focused language. This implies

H_3: Compared with desktop word of mouth, mobile word of mouth is less socially-focused.

Mobile WOM Value

We proposed that differences in the word-of-mouth creation process, in the ease of using the devices used to create WOM, and in consumer relationships with these devices will lead to differences in the content of mobile WOM. Some of these differences in content should increase the value of mobile WOM while others should lower its value.

Real-time creation process

We proposed that that creating WOM in real-time will lead to WOM that is more affective, less cognitive, more one-sided, more focused on current concerns, and more negative. These differences in content should increase the value of mobile WOM. For example, given that emotional content increases psychological arousal, and is more likely to be shared with others (Berger and Milkman 2012), WOM that is more affective—and less cognitive—should have higher perceived value. In addition, given that WOM receivers often have action goals such as "Which product should I choose?" WOM that reflects a more concrete (vs. abstract) construal level, where feasibility concerns such as "Where is the closest place to eat?" trump desirability concerns such as "Which is the best restaurant in this area?" (Trope and Liberman 2003), WOM that is more focused on current concerns should be more valued. Further, research on the "negativity bias" (Chen and Lurie 2013) shows that negative WOM is usually given greater weight in decision making than positive WOM. This suggests that negative WOM should be perceived as more valuable.

We also proposed that mobile WOM is likely to be more one-sided. Prior research (Schlosser 2011) suggests that the value of one- versus two-sided arguments depends on the congruency between these arguments and WOM ratings. In particular, one-sided arguments are perceived as more helpful when they accompany strongly negative or strongly positive ratings. However, two-sided arguments are perceived as more helpful for moderate ratings. Given this, perceived value should not necessarily be greater for one-sided WOM. In summary:

H_4: Perceived value should be greater for word of mouth that is:

a) more affective,
b) less cognitive,
c) more focused on current concerns,
d) more negative, but not
e) more one-sided.

Form factor

We further proposed that that the small size of mobile devices will lead to WOM that is shorter and less extreme. A decrease in review length should lower the value of mobile WOM. In particular, more extensive word of mouth provides greater information and details that increase word of mouth diagnosticity, reduce uncertainty, and therefore enhance perceived value (Mudambi and Schuff 2010; Weiss, Lurie, and MacInnis 2008). In addition, to the extent that more extreme reviews provide a stronger case for choosing or not choosing a particular product and provide more diagnostic information (Forman, Ghose, and Wiesenfeld 2008), less extreme (i.e., neutral) reviews should be less valued, although this effect should depend on the extent to which consumers share similar tastes and product attributes are perceived as objective (Mudambi and Schuff 2010). In summary:

H_5: Perceived value will be lower for word of mouth that is:

a) shorter in length, and

b) less extreme.

Personal Relationship with Device

Finally, we proposed that that the stronger personal relationship of consumers with their mobile devices will lead to WOM that is more self- and less socially-focused. That is, the autobiographical nature of mobile word of mouth should involve fewer references to family and friends. More self-focused language should lower the perceived value of WOM since it is less inclusive and shows lower concern for others. Greater focus on social versus non-social aspects, and greater use of inclusive language, has been shown to increase participation in online communities; perhaps by enhancing feelings of group solidarity (Arguello et al. 2006; Ren et al. 2007). To the extent that word-of-mouth receivers value social and inclusive aspects in online word of mouth, this suggests:

H_6: Perceived value will be lower for word of mouth that is less socially-focused.

In summary, we predict that some aspects of mobile WOM should increase its value while other aspects should decrease it. In our empirical analysis we test these predictions and also examine differences in the value of mobile and desktop WOM after controlling for differences in content.

Empirical Analyses

Data

We use reviews from Urbanspoon.com, an online restaurant review website that, during our study period of October 2006 to November 2009, indicated which reviews were created using mobile devices. Our full dataset has a total of 299,798 reviews from 125,146 users on 144,227 restaurants. Among them 136,304 reviews (45%) were written on mobile phones, while 163,494 (55%) were written on desktops. We test our hypotheses on the subset of 48,610 reviews from the 4,499 users who wrote at least one mobile and one desktop review. This subsample controls for reviewer-specific effects that might explain differences in the characteristics of mobile and desktop reviews. For example, it might be that those who write mobile reviews are different from those who write desktop reviews and that this, rather than differences in the creation platform, explains differences in WOM content. For each review, we record the reviewer's name, restaurant, date, title, text, reviewer rating (dislikes, likes, really likes it, or neutral), and whether it was a mobile or desktop review. We use these variables to examine differences in the content of mobile WOM.

To assess differences in the perceived value of mobile and desktop WOM, we record the number of users that indicate they like each review. In this analysis, we supplement the Urbanspoon data with the restaurant's average price level from Factual.com. This allows us to control for price associated restaurant characteristics that could affect our results. Figure 2 shows examples of mobile and desktop reviews and identifies variables that were coded. Table 1 provides descriptive statistics for the focal variables.

Mobile WOM content

Language use. Following prior research (e.g., Berger and Milkman 2012; Ludwig et al. 2013), to test for differences in language use for mobile versus traditional WOM, we process the full text of reviews using the Linguistic Inquiry and Word Count (LIWC) software program (Pennebaker et al. 2007). LIWC measures the percentage of words in a given text that reflect particular linguistic or psychological processes, personal concerns, or spoken categories of language.

We compare the degree to which reviews are affective (vs. cognitive) using the LIWC category *Affective Processes*, which includes positive and negative emotion words; and the category *Cognitive Processes*, which includes words reflecting insight, causation, and discrepancy. To compare the use of one-sided arguments, we create the binary variable *One-Sided* and code it as 1 if the review text contains only positive emotion words or only negative emotion words; 0 otherwise. We identify a lower construal level in WOM through greater use of language reflecting *Current Concerns* (Trope and Liberman 2010; Trope and Liberman 2003), which includes words about work, achievement, leisure, home, and money. We examine the extent to which WOM reflects concern about others (vs. the self) through the category *Social*

Processes, which includes words related to family and friends. Beyond word of mouth language, we measure word of mouth length by counting the number of words in each review.

We model the effect of the mobile platform on WOM content and length using seemingly unrelated regressions (SUR), in which all models are estimated simultaneously and errors between models are allowed to correlate. We model the effect of the mobile platform on the variable *One-Sided* using a binary logit.

Rating valence. Along with the review text, reviewers rate restaurants on a four-level scale: dislike; neutral; like; and really like. Given the ordinal nature of the scale, we estimate an ordered logit model of rating valence on a set of review attributes as independent variables

$$y^* = x'\beta + \varepsilon;$$
$$y = \begin{cases} 1 \text{ if } & y^* \le \kappa_1, \\ 2 \text{ if } \kappa_1 < y^* \le \kappa_2, \\ 3 \text{ if } \kappa_2 < y^* \le \kappa_3, \\ 4 \text{ if } \kappa_3 < y^*. \end{cases} \tag{1}$$

Here y^* is a latent variable that depends on the set of independent variables x, while y is the observed ordinal recommendation. Assuming that the error term ε follows a logistic distribution, we can estimate the model parameters β and cutoffs κ by maximizing the likelihood of the observed recommendations. For robustness, we estimate four ordered logit models: Model 1 includes only the mobile dummy, Model 2 adds controls for review age and content attributes, Model 3 adds the restaurant price level (where available), and Model 4 controls for reviewer fixed effects.

Rating extremity. In addition to review valence, we characterize extreme ratings as those for which the rating is "doesn't like" and "really like." We model rating extremity using a binary logit model, in which extreme ratings are coded as 1; 0 otherwise.

Mobile WOM value

We proposed that the review platform affects how the reviews are written, which will in turn affect the perceived value of these reviews. Some content differences should increase the value of mobile WOM while others should decrease its value. To test our hypotheses, we empirically examine differences in the perceived value of mobile and desktop reviews and how characteristics of mobile WOM help explain such differences.

We measure the influence of a review by its number of likes. To account for the over-dispersion in this count variable, we employ a negative binomial regression to study how the influence is affected by various review attributes. The model is specified as

$$P(Z=z)=\left(\frac{r}{r+\lambda}\right)^{r}\frac{\Gamma(r+z)}{\Gamma(z+1)\Gamma(r)}\left(\frac{\lambda}{r+\lambda}\right)^{\lambda}\text{; where } \lambda = x'\beta+\varepsilon. \quad (2)$$

Here Z is a random variable representing the number of likes. *Γ* is the gamma function, and *r* is a dispersion parameter. The model parameters *β* and *r* are estimated through maximum likelihood. Model 1 includes only the mobile dummy; Model 2 adds controls for review age, rating, and content attributes; Model 3 adds the restaurant price level (where available); because some reviewers may be inherently more influential than others due to differences in number of followers or visibility, Model 4 includes fixed effects for each reviewer.

Results

Mobile WOM content

Table 2 reports the estimated coefficients for the joint seemingly unrelated regressions that examine the effects of using a mobile platform on WOM content as well as separate binary logit models examining whether using a mobile device increases the likelihood of one-sided and less extreme word-of-mouth. Table 3 presents results from the ordered logit models that examine the effects of the mobile platform on rating valence.

Real-time creation process. Hypothesis 1 proposed that the real-time creation of content on mobile devices will lead to word of mouth that is a) more affective, b) less cognitive, c) more one-sided, d) more focused on current concerns, and e) more negative. Consistent with these predictions, SUR results show that mobile WOM is more affective (β = 3.610, $p < .01$) but less cognitive (β = -.1.207, $p < .01$) and that mobile WOM has a greater focus on current concerns (β = 2.107, $p < .01$), suggesting a lower construal level. A binary logit shows that mobile WOM is more likely to be one-sided and contain only positive or only negative language (β = .481, p < .01).

In line with the idea that the real-time creation process associated with mobile WOM reduces retrospectively positive biases, ordered-logit results presented in Table 3 show that mobile ratings are more negative (β = -.282, $p < .01$). Consistent results are found in Model 2, which controls for review age and content attributes (β = -.387, $p < .01$); Model 3, which controls for restaurant price level (where available; β = -.368, $p < .01$); and Model 4, which controls for reviewer fixed effects (β = -.382, $p < .01$).

Form factor. Hypothesis 2 proposed that the greater physical and cognitive costs associated with using mobile devices will lead to WOM that is shorter in length. However, the greater availability of the mobile platform will also increase the likelihood of engaging in WOM in low-motivation contexts; this should lead to WOM that is less extreme on average. SUR results show that mobile reviews are much shorter, with an average word count of 32.62 versus an average of 70.20 for desktop reviews (β = -.376, $p < .01$). Supporting the idea that greater availability increases the likelihood that mobile WOM for neutral (i.e., non-extreme) experiences, binary logit results show that mobile reviews have a lower proportion of "doesn't like" and "really like" ratings (β = -.822, $p < .01$).

Personal relationship with device. Hypothesis 3 proposed that consumers have a more personal relationship with mobile devices and that this should lead to more self- versus social-focused WOM. Consistent with this hypothesis, SUR results show that mobile reviews contain less social language (β = -.602, $p < .01$).

Mobile WOM value

Table 4 shows the results of analysis of the effect of the mobile platform and WOM content on *Review Value*. Model 1 includes only the mobile dummy; Model 2 adds controls for review age, rating, and content attributes; Model 3 adds the restaurant price level (where available); and Model 4 includes fixed effects for each reviewer.

Real-time creation process. Hypothesis 4 proposed that perceived value should be greater for word-of-mouth that is a) more affective, b) less cognitive, c) more focused on current concerns, d) more negative, but not e) more one-sided. As expected, one-sided word of mouth was not perceived as significantly more valuable than two-sided word of mouth. Contrary to our predictions, we do not find significant effects of affective processes, cognitive processes, or current concerns. Coding "dislike" and "neutral" ratings as negative, and "like" and "really like" as positive, we find that support for the prediction that negative reviews are more valued. (Using a dummy variable to code "dislike" ratings as negative and others as positive leads to similar results.)

Form factor. Hypothesis 5 proposes that word of mouth that is a) shorter and b) less extreme will be less valued. Results in Table 4 (Model 4) show that perceived value increases with review length (β = .353, $p < .01$) and is lower for less extreme reviews (β = .188, $p < .01$).

Personal relationship with device. Hypothesis 6 proposed that perceived value will be lower for word of mouth that is less socially-focused. Consistent with this proposal, Our results (Table 4, Model 4) show that an word of mouth value is greater as the proportion of social (i.e., less self-focused) increases (β = .007, $p < .01$).

Mobile effect. We proposed and find that the mobile platform leads to WOM content that has both positive and negative effects on WOM value. This makes it difficult to predict a-priori whether mobile WOM will be more or less valuable than desktop WOM. Our empirical analysis finds, across a variety of specifications, that mobile WOM is less valuable. Model 1 includes only the mobile dummy and finds that mobile reviews have lower value (β = -.561, $p < .01$). Model 2 adds controls for review age, rating, and content attributes and also finds lower value for mobile WOM (β = -.269, $p < .01$). Model 3 adds the restaurant price level (where available) and continues to find lower value for mobile (β = -.351, $p < .01$). Because some reviewers may inherently provide more valuable reviews than others, due to differences in number of followers or visibility, Model 4 includes fixed effects for each reviewer and continues to find lower (but reduced) value for mobile WOM (β = -.192, $p < .01$). Across all these models, mobile reviews have lower value than desktop reviews even after controlling for other review attributes and user fixed effects.

Conclusion

Summary of findings

Constant access to mobile technology has become the norm for many consumers. In addition to using mobile devices to gather product information, make purchases, watch video, and get news, consumers increasingly use mobile devices to share their product and service experiences with others. Although some are excited about these developments, others are concerned about the potential negative implications of real-time word of mouth. More generally, there is an interest in understanding how the growing use of mobile technology will change the content and impact of consumer word of mouth. This research is an initial attempt to address these issues.

We propose that differences in the way in which mobile and desktop word of mouth are created will lead to differences in the content of mobile and desktop word of mouth. Our conceptual model identifies three factors that should lead to content differences: 1) A real-time creation process that affects the likelihood that consumers reflect on their experiences, the construal level at which word of mouth is written, and the likelihood of engaging retrospective biases; 2) a smaller form factor that makes it more difficult to create extensive word of mouth yet increases accessibility and therefore the likelihood of engaging in word of mouth; and 3) a more personal relationship between the consumer and device that changes the type of language used in word of mouth. Based on these three factors, we develop a set of hypotheses that we test on a unique set of data that identifies whether reviews were created on mobile versus desktop platforms.

Our results show a number of important differences in the characteristics of mobile and desktop word of mouth. In support of the idea that the real-time creation process reduces reflection, we find that content created on mobile devices is more affective, less cognitive, and more one-sided. In support of the idea that the real-time creation process and greater temporal proximity of experiences and word of mouth engages a lower construal level, we find that mobile word of mouth reflects greater current (vs. past or future) concerns. In support of the idea that real-time word of mouth should be less subject to retrospective biases, we find that mobile word of mouth is more negative than desktop word of mouth.

In addition to differences in the creation process, the devices used to create mobile content differ in important ways. Is support of the idea that small keyboards and screens make it more difficult to create content on mobile devices, we find that mobile content is shorter in length. In support of the idea that the constant accessibility of mobile devices increases the likelihood that consumers engage in word of mouth about neutral, as well as very positive and very negative experiences, we find that mobile word of mouth is less extreme. Finally, in support of the idea that consumers have a more personal relationship with mobile devices, we find lower use of social language in mobile word of mouth.

Some of these content differences should increase the value of mobile word of mouth while others should lower its perceived value relative to desktop word of mouth. Our empirical results provide evidence for these mixed effects on value. For example, negative reviews are more valued whereas shorter, less extreme, and less social reviews are less valued. Contrary to our predictions, review value is not significantly affected by differences in extent to which word of mouth is cognitive, affective, one-sided, or reflects greater current concerns. Even after controlling for differences in the content of mobile and desktop word of mouth, we find that mobile word of mouth is less valued.

Managerial Implications

For managers, this research provides important insights into how increased use of mobile platforms is likely to lead to differences in the characteristics and influence of consumer created content. Our conceptual model suggests that it is important to understand how concurrent creation, small form factor, and more personal user-device relations are likely to change the content and value of mobile word of mouth. Understanding these differences is important to marketers who seek insights from mobile word of mouth and who wish to determine how to best respond to mobile consumers.

Our results support the idea that mobile word of mouth is created in real-time using devices that are both harder to use than traditional desktop or laptop computers; yet more accessible; and more personal. Marketers who seek to understand and capitalize on this new content need to account for these differences. For example, real-time (negative) reactions may not persist when consumers are contacted later—and have more time to reflect on their experiences. In this way, mobile word of mouth may provide fewer insights into consumer cognitions and long-term attitudes. On the other hand, mining mobile word of mouth and using mobile devices for market research may be better for products and services in which real-time responses are desired or for which consumers are unlikely to invest substantial cognitive resources. Similarly, mobile content may provide greater insights into individual (vs. group) experiences.

Although real-time consumer attitudes may not persist, their word of mouth will. Although mobile reviews are less valued, and many aspects of mobile content lower or have non-significant effects on value, some aspects of these reviews—such as greater negativity—raise concerns. Marketers may seek to address these concerns by 1) encouraging review writing sufficiently after (as opposed to during) service experiences and 2) responding proactively to service failures.

Limitations and future fesearch

This research is an initial attempt to conceptually identify and empirically test differences in the content and value of mobile word of mouth. There are a number of opportunities to expand this work empirically and conceptually. To test our hypotheses, we take advantage of a unique dataset that identifies whether word of mouth is created on mobile devices and includes consumers who use both mobile and non-mobile platforms to create content. Our dataset uses word of mouth for restaurants, a product category that involves both search and experience attributes. Future research could test these ideas on more purely experience or search products using secondary data, lab, or field experiments.

In our conceptual model, we focus on the use of mobile platforms to generate word of mouth. Future research could expand these ideas to examine how word of mouth may be evaluated differently when using mobile devices, how mobile devices are likely to affect information search and decision making, what types of communication are likely to be most successful, which products are most likely to be evaluated and purchased on mobile devices, and how individual and contextual factors—including location—are likely to moderate these effects. Other research could examine how the use of mobile platforms for information creation information consumption can be best combined with other platforms and how this may depend on market factors such as product lifecycle and where the consumer is in the path to purchase.

Other research opportunities may be created by continuing changes in consumer technologies. For example, Google Glass offers opportunities to examine how augmented reality affects consumer decision making; future wearable devices should provide consumers with additional information that will be combined with information from the physical environment. Devices like Google Glass also allow consumers to share the entirety of their product experiences with others. Future research could examine how such immersive word of mouth has different effects on receivers than text-based and reflective word of mouth. As new technologies continue to change the consumer experience, and the ways in which consumers communicate these experiences to others, marketers will face new opportunities to gain insights as well as challenges to meet consumer needs.

References

Anderson, Eugene W (1998), “Customer Satisfaction and Word of Mouth,” *Journal of Service Research*, 1 (1), 5-17.

Arguello, Jaime, et al. (2006), “Talk to Me: Foundations for Successful Individual-Group Interactions in Online Communities,” in *Proceedings of the SIGCHI conference on Human Factors in computing systems*, ACM, 959-68.

Ariely, Dan and George Loewenstein (2006), “The Heat of the Moment: The Effect of Sexual Arousal on Sexual Decision Making,” *Journal of Behavioral Decision Making*, 19 (2), 87-98.

Berger, Jonah and Katherine L. Milkman (2012), “What Makes Online Content Viral?,” *Journal of Marketing Research*, 49 (2), 192-205.

Chen, Zoey and Nicholas H. Lurie (2013), “Temporal Contiguity and Negativity Bias in the Impact of Online Word-of-Mouth,” *Journal of Marketing Research*, 50 (August), 463-76.

Chevalier, Judith A. and Dina Mayzlin (2006), “The Effect of Word of Mouth on Sales: Online Book Reviews,” *Journal of Marketing Research*, 43 (August), 345-54.

Czaja, Julia (2012), “Intimate Telepresence: Perpetual Contact and the Channels of Presence in Mobile Communication,” in *ISPR 2012*. Philadelphia

Duan, Wenjing, Bin Gu, and Andrew B. Whinston (2008), “The Dynamics of Online Word-of-Mouth and Product Sales—an Empirical Investigation of the Movie Industry,” *Journal of Retailing*, 84 (2), 233-42.

Forman, Chris, Anindya Ghose, and Batia Wiesenfeld (2008), “Examining the Relationship between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets,” *Information Systems Research*, 19 (3), 291-313.

Garcia Esparza, Sandra, Michael P O'Mahony, and Barry Smyth (2010), “On the Real-Time Web as a Source of Recommendation Knowledge,” in *Proceedings of the Fourth ACM conference on Recommender Systems*, ACM, 305-08.

Godes, David and Dina Mayzlin (2004), “Using Online Conversations to Measure Word of Mouth Communication,” *Marketing Science*, 23 (4), 545–60.

Greenwood, Jess (2011), “The Mobile Metamorphosis,” *Think Quarterly: The People Issue*, (accessed March 15, 2014), [available at http://www.thinkwithgoogle.com/articles/the-mobile-metamorphosis.html].

Loewenstein, George (2000), “Emotions in Economic Theory and Economic Behavior,” *The American Economic Review*, 90 (2), 426-32.

Ludwig, Stephan, et al. (2013), “More Than Words: The Influence of Affective Content and Linguistic Style Matches in Online Reviews on Conversion Rates,” *Journal of Marketing*, 77 (1), 87-103.

Lurie, Nicholas, Doe-Hyun Song, and Sridhar Narasimhan (2009), “Decision Making on the Small Screen: Adaptive Behavior in Constrained Information Environments,” *Advances in Consumer Research*, [available at http://www.acrwebsite.org/volumes/v37/finalpapers/504487_101067_v1.doc].

Miller, Claire (2009), “The Review Site Yelp Draws Some Outcries of Its Own,” *New York Times*, (March 2), B1.

Mitchell, Terence R., et al. (1997), “Temporal Adjustments in the Evaluation of Events: The 'Rosy View',” *Journal of Experimental Social Psychology*, 33 (4), 421-48.

Mudambi, Susan M. and David Schuff (2010), “What Makes a Helpful Online Review? A Study of Customer Reviews on Amazon.Com,” *MIS Quarterly*, 34 (1), 185-200.

Novemsky, Nathan and Rebecca K. Ratner (2003), “The Time Course and Impact of Consumers' Erroneous Beliefs About Hedonic Contrast Effects,” *Journal of Consumer Research*, 29 (4), 507-16.

Pennebaker, James W., et al. (2007), “The Development and Psychometric Properties of LIWC2007,” [available at http://homepage.psy.utexas.edu/homepage/faculty/pennebaker/reprints/LIWC2007_LanguageManual.pdf].

Ransbotham, Sam and Gerald C. Kane (2011), “Membership Turnover and Collaboration Success in Online Communities: Explaining Rises and Falls from Grace in Wikipedia,” *MIS Quarterly*, 35 (September), 613-28

Ren, Yuqing, et al. (2007), “Talk Amongst Yourselves: Inviting Users to Participate in Online Conversations,” in *Proceedings of the 12th international conference on Intelligent user interfaces*, ACM, 62-71.

Schlosser, Ann E. (2011), “Can Including Pros and Cons Increase the Helpfulness and Persuasiveness of Online Reviews? The Interactive Effects of Ratings and Arguments,” *Journal of Consumer Psychology*, 21 (3), 226-39.

Sultan, Fareena and Andrew Rohm (2005), “The Coming Era of” Brand in the Hand” Marketing,” *MIT Sloan Management Review*, 47 (1), 83.

Trope, Yaacov and Nira Liberman (2010), “Construal-Level Theory of Psychological Distance,” *Psychological Review*, 117 (2), 440-63.

---- (2003), “Temporal Construal,” *Psychological Review*, 110 (3), 403-21.

Turkle, Sherry (2008), “Always-on/Always-on-You: The Tethered Self,” in *Handbook of Mobile Communication Studies*, James E. Katz, ed. Cambridge, MA: MIT Press, 121-37.

Weiss, Allen M., Nicholas H. Lurie, and Deborah J. MacInnis (2008), “Listening to Strangers: Whose Responses Are Valuable, How Valuable Are They, and Why?,” *Journal of Marketing Research*, 45 (August), 425-36.

Wirtz, Derrick, et al. (2003), “What to Do on Spring Break? The Role of Predicted, on-Line, and Remembered Experience in Future Choice,” *Psychological Science*, 14 (5), 520-24.

Table 1: Descriptive Statistics

	Mobile Reviews		Desktop Reviews	
	Mean	Std. Dev.	Mean	Std. Dev.
Affective processes (%)	11.543	9.993	7.934	6.039
Cognitive processes (%)	13.215	8.064	14.422	6.170
One-sided	.699	.459	.590	.492
Current concerns (%)	9.118	9.754	7.011	6.120
Word count	32.623	32.354	70.201	70.155
Rating extremity	.278	.448	.305	.461
Social processes (%)	5.023	5.753	5.625	4.698
Number of likes	.380	1.229	.666	1.620
Days since the review	152.046	81.754	188.925	132.294
Restaurant price level	1.722	.704	1.729	.738

Table 2: Content of Mobile versus Desktop Reviews

	Intercept	Mobile
Joint SUR model		
Affective processes (%)	7.934**	3.610**
Cognitive processes (%)	14.422**	-1.207**
Current concerns (%)	7.011**	2.107**
Word count (/ 100)	.702**	-.376**
Social processes (%)	5.625**	-.602**
Separate binary logit models		
One-sided	.363**	.481**
Rating extremity	-.822**	-.132**
# of observations	48,610	

** $p < .01$

Table 3: Valence of Mobile versus Desktop Reviews

	Model 1	Model 2	Model 3	Model 4
Mobile	-.282**	-.387**	-.368**	-.382**
Affective processes		.025**	.023**	.030**
Cognitive processes		-.014**	-.015**	-.017**
One-sided		.816**	.754**	.758**
Current concerns		.000	-.002	-.000
Word count (/100)		.211**	.200**	.201**
Social processes		.009**	.011**	.017**
Log(days since the review)		.109**	.140**	.220**
Restaurant price level			.064**	.062**
Reviewer fixed effects				Included
# of observations	48,610	48,610	26,741	26,741

** $p < .01$

Table 4: Value of Mobile versus Desktop Reviews (Negative binomial regression)

	Model 1	Model 2	Model 3	Model 4
Intercept	-.407**	-3.986**	-4.114**	-4.672**
Mobile	-.561**	-0.269**	-0.351**	-.192**
Affective processes		-.003	-.001	-.002
Cognitive processes		-.002	-.004	-.003
Negative rating		.002	.109**	.075**
One-sided		-.034	-.024	-.003
Current concerns		.001	.001	.002
Word count (/100)		.368**	.274**	.353**
Rating extremity		.233**	.185**	.188**
Social processes		.005*	.009**	.007**
Log (days since review)		.629**	.611**	.513**
Restaurant price level			.151**	.188**
Reviewer fixed effects				Included
# of observations	48,610	48,610	26,741	26,741

* $p < .05$, ** $p < .01$

Figure 1: Characteristics of Mobile Word-of-Mouth and Implication for Perceived Value

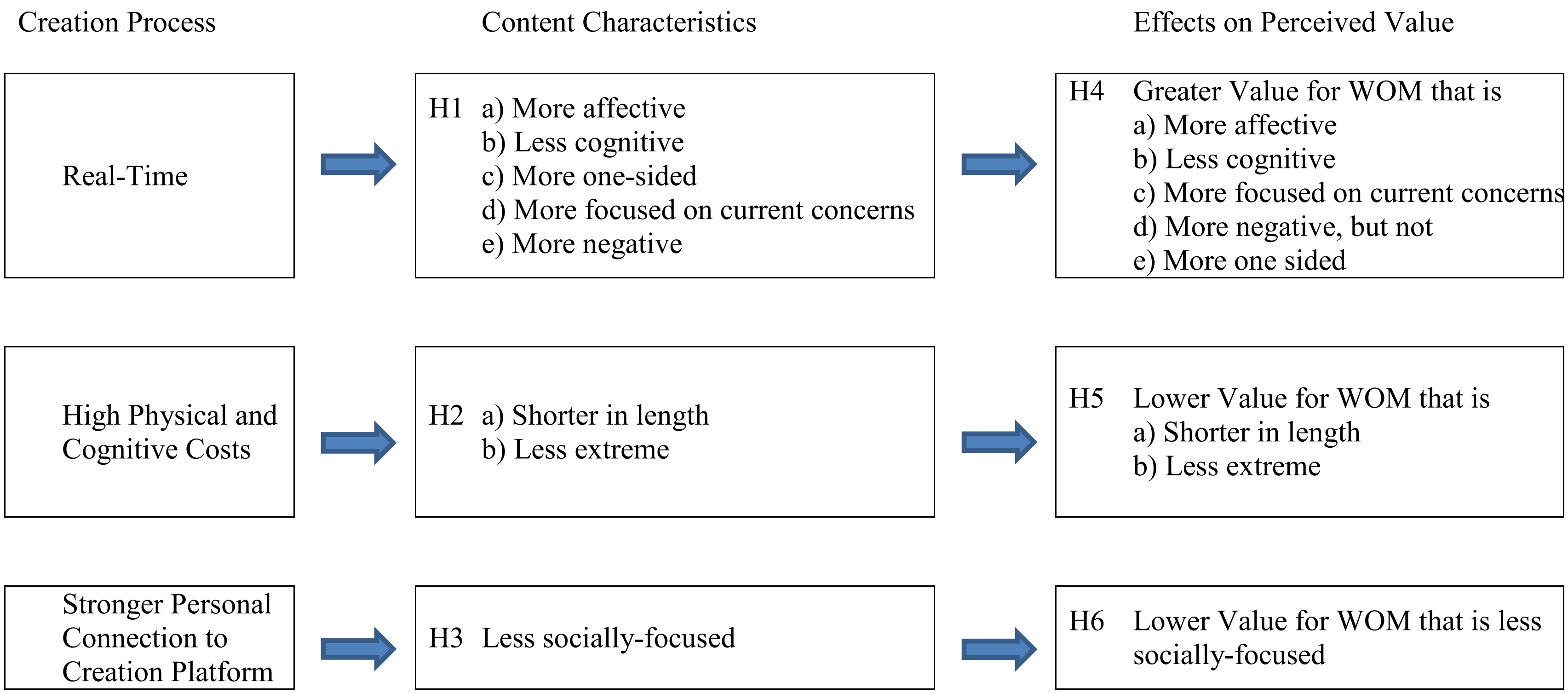

Figure 2: Sample Mobile and Desktop Reviews