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User Generated Information on Mobile Channels With More Concise Reviews and More Extreme Ratings

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ABSTRACT Online word of mouth is shifting from personal computer (PC)-based channels to mobile-based channels in this mobile marketing age, which leads to the question of whether mobile word of mouth is shorter and louder than the PC word of mouth? By investigating the 162 452 pieces of online word of mouth created by 19 496 users on a top-three online shopping website in China during a two-year period, this paper successfully discovered that mobile reviews are shorter than PC reviews and that mobile ratings are more extreme than the PC ratings. These findings lead to the managerial implications that on one hand, managers may direct reviewers to PC channels to generate longer and consequently higher-quality reviews. On the other hand, managers of higher/lower quality products may prefer mobile/PC channels such that there products' merits can be underlined whereas their products' shortcomings may be obscured.

INDEX TERMS Mobile word of mouth, channel, length, extremity, timeliness.

I. INTRODUCTION

Online word of mouth has won great attention from marketing scholars over the years [1]–[8]. Online word of mouth is defined as the positive or negative statement addressed by former consumers about a product or service, which is accessible by a large group of people and institutions on the internet [9]. Online word of mouth is believed to have impact on brand image [10], brand attitude [11], price perception [12], purchase intentions [13], repurchase intention [14], willingness to pay [15], decision-making process [16], and sales volume [17]. Therefore, researchers have been extremely interested to understand what makes online word of mouth more helpful and more persuasive, such that the reviewers, the online community, the readers, and the product/service providers can all benefit from increased browsing and purchasing.

Existing studies on online word of mouth have primarily focused on personal computer (PC)-based word of mouth, or PC word of mouth for short. In other words, the majority of the studied online word of mouth was generated on PC. In comparison, investigation of mobile word of mouth, i.e. online word of mouth generated on mobile devices [18], is much less prevalent. Considering the prediction that the worldwide mobile application market will reach $110 billion by the end of 2018 [19], it is of ever increasing significance to discover knowledge based on mobile word of mouth. Meanwhile, mobile word of mouth differs from PC word of mouth in terms of review linguistic style [20], perceived value and helpfulness [21], and reader adoption rate [22]. Hence, previous knowledge from PC word of mouth may not necessarily apply to mobile scenarios.

At this point, both online communities and product/service providers face the question of how to combine the advantages of PC and mobile word of mouth to further increase browsing and purchasing. For example, should an online community temporarily direct its users from posting word of mouth through the PC channel to posting through the mobile channel? Likewise, is there an occasion in which a product/service provider needs to encourage PC word of mouth

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while discouraging mobile word of mouth? A prerequisite for handling the above questions is the correct understanding of the differences in the attributes [23], [24] of PC and mobile word of mouth, as well as the ways to adjust these attributes, so as to achieve the best communication and persuasion results.

To this end, this paper first collected dataset from a top-three online shopping website in China during a two-year period and obtained 162,452 pieces of online word of mouth created by 19,496 users. It then uncovered the effect of word of mouth channel, i.e. PC channel and mobile channel, on the two attributes of word of mouth, namely review length and rating extremity. Finally, it explored the mediating effect of word of mouth timeliness, and the moderating effect of reviewers' word of mouth history and product type. The major findings of this study indicate that mobile reviews are shorter than PC reviews, and that mobile ratings are more extreme than PC ratings. In response to these findings, managerial implications regarding the optimal strategy of word of mouth management were proposed.

This study has several contributions to the academic and industrial society. To the best of the authors' knowledge, there has not been a previous research that systematically investigates the relationship between online word of mouth channel and attribute. Besides, the dataset of this study is composed of massive authentic user generated contents, which ensures the credibility of the findings. Moreover, this study contributes by offering practical suggestions on online word of mouth management to marketing practitioners.

II. LITERATURE REVIEW

A. ONLINE WORD OF MOUTH CHANNEL: MOBILE CHANNEL VS. PC CHANNEL

Online word of mouth can be created on, delivered through, and received from two major channels, namely the PC channel (PC word of mouth) and the mobile channel (mobile word of mouth). While the motivation of mobile word of mouth generation is relatively clear, and is quite similar with that of PC word of mouth generation [25]–[28], existing studies that compare the attributes and helpfulness of online word of mouth delivered through the two channels have been surprisingly scarce and even contradictory in some ways. For example, Burtch and Hong [20] discovered that mobile review is more helpful than PC review, whereas März *et al.* [21] arrived at the opposite conclusion that consumers discount the helpfulness of mobile reviews. Thus it can be seen that much work needs to be done to fully uncover the effect of online word of mouth channel on its attributes, which further lead to helpfulness, persuasiveness, and eventual purchase.

B. ONLINE WORD OF MOUTH ATTRIBUTES

Online word of mouth takes two typical forms: review and rating [29]. Review is a piece of textual comment which describes the experience of a customer with a provider in a qualitative manner [30]. Rating, usually based on a five-point scale, quantitatively tells whether and to what extent a customer is satisfied with a provider [31]. Taken together, the three of the most important attributes of online word of mouth are review length, rating extremity, and timeliness [23], [24].

Review length is defined as the total number of typed characters in a review text [32]. The effect of review length on its persuasiveness is quite complicated [33]. On one hand, lengthy reviews are associated with more complete [34] and higher-quality [35] information. On the other hand, too long a review will introduce cognitive overload [24], [36], making consumers less willing to finish reading. Hence, there exists an optimal range of review length that can balance information richness and overload.

Rating extremity, sometimes also called polarity, is the second most important attribute [24], [35]. Rating extremity is defined as the deviation from the midpoint of an attitudinal scale [37]. For example, in a typical numerical star rating that ranges from one to five stars, both one star and five stars have the strongest extremity, whereas the relatively neutral three stars is regarded as having the least extremity. There have been competing arguments about rating extremity, with some researchers viewing high-extremity rating as more helpful because it is more pronounced and attracts greater attention [24], [38], and others advocating neutral ratings based on the reasons that exaggeration (i.e. high-extremity) may be discounted [39], and that neutral rating is associated with stronger diagnosticity [35].

Last but not least, timeliness, also referred to as temporal contiguity or immediacy, has been proved to positively influence online word of mouth readers' adoption of the information [18], [23], [40]. Timeliness measures the time gap between product purchase and online word of mouth posting. Normally, the time gap is not explicitly presented to online word of mouth readers. Instead, readers can judge the timeliness of a review by responding to temporal contiguity cues, i.e. words and phrases that indicate the temporal proximity between product consumption and review writing [40], such as 'this morning' or 'last month'. However, according to Chen and Lurie [40], over 83% of review does not contain any temporal contiguity cues, which may result in less convincing research findings. Therefore, alternative measurement of timeliness needs to be developed to generate better understanding of its impact on online word of mouth helpfulness and persuasiveness.

III. HYPOTHESIS DEVELOPMENT

A. EFFECT OF ONLINE WORD OF MOUTH CHANNEL ON ONLINE WORD OF MOUTH ATTRIBUTES

This study focuses on the effect of online word of mouth channel, i.e. mobile channel vs. PC channel, on online word of mouth attributes. One of the major consequences of online word of mouth channel, as has been reported by previous studies [20], [21], is review length. For example, Burtch and Hong [20] discovered that mobile reviews contain fewer words than PC reviews. They explained the finding by suggesting that submitting reviews from a mobile device is more difficult than from a PC, resulting in reduced length of mobile reviews. Similarly, März *et al.* [21] found that mobile reviews use fewer function words than PC reviews. They attributed the finding to the typing habit of mobile users who have learned to write short messages, abbreviations, and acronyms on mobile devices that once had limitation on the number of input word [41], [42]. Therefore, the following hypothesis is proposed to verify the impact of online word of mouth channel on review length.

H1: Mobile reviews are shorter than PC reviews.

Rating extremity, being another major attribute of online word of mouth, is also expected to be affected by online word of mouth channel. From linguistic style perspective, Burtch and Hong [20] detected more extreme and more emotional expressions in mobile reviews than in PC reviews. They interpreted the results by speculating that before the introduction of mobile technology, a consumer does not post a review until he/she has access to a computer, during which he/she becomes calmer and reflects his/her experience more objectively, resulting in a less extreme review. For similar reasons, the extremity of rating is also expected to be lower on a PC channel than on a mobile channel, which leads to the following hypothesis.

H2: Mobile ratings have higher extremity than PC ratings. In other words, mobile ratings have higher percentage of one star and five stars than PC ratings.

B. MEDIATING EFFECTS

Timeliness is explored as the potential mediating factor of the above two relationships. To study the mediating factor, one first needs to investigate the relationship between the potential mediating factor and the antecedent, which in this study is online word of mouth channel. Compared with the traditional PC channel, the mobile channel features ubiquity in terms of location and time [25]. Unlike computers, mobile devices can be accessed almost anywhere and anytime. A consumer does not have to keep his/her word of mouth in mind until he/she uses a computer; he/she can just take out his/her mobile phone, assign the rating, and type the review. Existing studies also reveal that more expressions of consumption recency [20] or immediacy [21] are found in mobile reviews, suggesting the timeliness of mobile word of mouth. Consequently, it is sensible to expect stronger timeliness in mobile word of mouth, as is proposed in the following hypothesis.

H3: Mobile word of mouth has stronger timeliness than PC word of mouth. To put it in another way, the time gap between product purchase and mobile word of mouth posting is smaller than the time gap between product purchase and PC word of mouth posting.

The ubiquitous mobile network is associated with additionally fragmented usage of user time compared with computer network [43]. To make it clear, while having instant access to a mobile device, a consumer is very likely to spend less time to create a piece of online word of mouth on the mobile device than he/she would do when using a computer [25]. Consequently, mobile reviews are expected to be shorter than PC reviews because of the shorter creation time. Moreover, the shortened creation time may subsequently induce the rating to be one-sided [44], i.e. focusing on either the merit or the defect (higher extremity), instead of two-sided, i.e. covering both the merit and the defect (lower extremity). Based on the above reasoning, the following two hypotheses both propose timeliness as a mediator.

H4: Timeliness mediates the relationship between online word of mouth channel and review length.

H5: Timeliness mediates the relationship between online word of mouth channel and rating extremity.

C. MODERATING EFFECTS

1) REVIEWERS' WORD OF MOUTH HISTORY

Reviewer plays an indirect but significant role in enhancing the helpfulness and persuasiveness of his/her online word of mouth [45]–[47]. Gottschalk and Mafael [45] discovered that a piece of online word of mouth is regarded as of higher quality when the reviewer chooses to reveal his/her personal information such as profile or preference. Similarly, Xu [48] addressed the positive role of displaying profile picture. Moreover, if a reviewer is perceived of as having expertise, his/her online word of mouth is also regarded as more helpful [46], [49]. Overall, online word of mouth readers are more easily persuaded by credible, attractive, and stylish authors [47]. A less studied indicator of reviewer is the activeness [50] or frequency [51] of his/her previous online word of mouth posting behavior, but this indicator seems to be closely related to the online word of mouth creation process [50] and consequent online word of mouth attributes [51]. Hence, it would be beneficial to incorporate reviewers' word of mouth history into this study.

More specifically, Topaloglu *et al.* [51] observed that reviewers who post online word of mouth more frequently in the past tend to post a new piece of online word of mouth later than less productive reviewers. Likewise, reviewers with larger number of history posts are expected to be less timely than reviewers with smaller number of history posts. According to previous inferences, reduced timeliness may lead to lengthier but less extreme online word of mouth. Therefore, the following hypotheses propose the potential moderating role of reviewers' word of mouth history.

H6: Reviewers' word of mouth history moderates the relationship between online word of mouth channel and review length. To be more specific, if a reviewer has a larger number of history posts, the effect of online word of mouth channel on review length is weakened.

H7: Reviewers' word of mouth history moderates the relationship between online word of mouth channel and rating extremity. To be more specific, if a reviewer has a larger number of history posts, the effect of online word of mouth channel on rating extremity is weakened.

2) PRODUCT TYPE

Online word of mouth study either focuses on individual product(s), or treats similar products as a collective type. Nel-

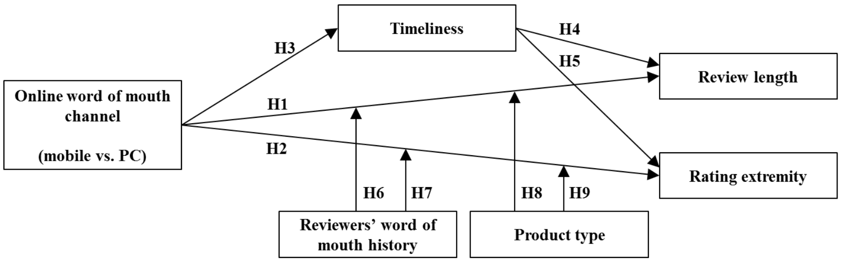

FIGURE 1. Conceptual framework.

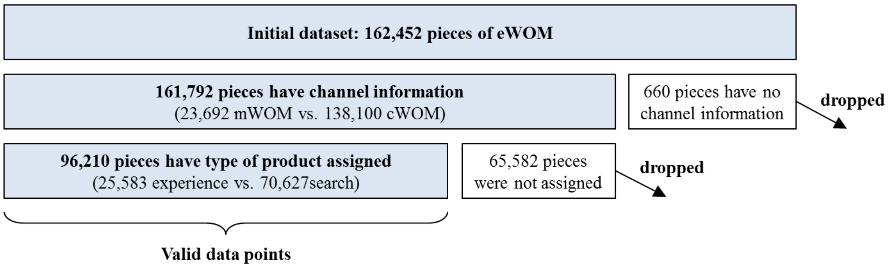

FIGURE 2. The data screening process.

son [52] divided products into two major categories. The first category, search products, features products having attributes can be acquired prior to purchase. In other words, by simply searching such products (e.g., on the internet nowadays), a consumer can obtain the complete or the majority of the product information. The second category, experience products, represents products the attributes of which cannot be known until after consumer using the product. Nelson's [52] classification method has been widely accepted and adopted in online word of mouth studies [53], [54].

It is worth noting that product category often plays a significant moderating role [35], [55], [56] in online word of mouth studies. More importantly, compared with search products, experience products are less tangible [53] and their evaluation involves higher subjectivity [57]. Such intangibility and subjectivity can prompt the timely creation of online word of mouth before the opinion blurs with time. In this sense, product type is very likely to be a moderating factor that can control the intensity of the effects of online word of mouth channel on online word of mouth attributes, as is proposed in the following hypotheses.

H8: Product type moderates the relationship between online word of mouth channel and review length. More specifically, for experience products, the effect of online word of mouth channel on review length is stronger than the effect for search products.

H9: Product type moderates the relationship between online word of mouth channel and rating extremity. More specifically, for experience products, the effect of online word of mouth channel on rating extremity is stronger than the effect for search products.

All the nine hypotheses together constitute the conceptual framework of this study, as is depicted in Figure 1.

IV. METHODS

A. DATA AND CONTEXT

The data of this study were obtained from a top-three online shopping website in China. The website has a full range of product portfolio and nearly 300 million active users who constantly access the website via mobile and PC devices. From the user library, 19,496 users were randomly selected, with the 162,452 pieces of online word of mouth they generated from January 1, 2012 to January 1, 2014 retrieved. Each piece of online word of mouth includes

- Product and purchase information: product name, product category (food & beverage, mobile phone electronics, et al.), and date of purchase;
- Product review information: date of posting, channel (mobile or PC), rating (from one star to five stars), and textual review comment;
- Author information: user ID, date of registration, and total history post counted on the day of purchase.

The dataset was screened to ensure each piece of online word of mouth has clear indication of channel (mobile or PC), as well as type of product (experience vs. search) according to Nelson (1974). The screening process is summarized in Figure 2. After screening, the number of valid data points reduced to 96,210.

B. ECONOMETRIC SPECIFICATION

From the dataset, six core variables were examined to validate the conceptual framework in Figure 1. The names and definitions of these variables are listed in Table 1.

Equations (1) and (2) were established to test the main effects (H1 & H2). In both equations, reviewers' word of mouth history and product type were incorporated for better goodness of fit. Ordinary least square (OLS) was applied to

TABLE 1. Definition of variables.

Variable name (in model)	Variable name (in conceptual framework)	Definition
Channel	Online word of mouth channel	*Channel* = 1: mobile channel; *Channel* = 0: PC channel
Length	Review length	The number of characters in a review
Extremity	Rating extremity	The extremity of a rating; *Extremity* = 2: one star or five stars; *Extremity* = 1: two stars or four stars; *Extremity* = 0: three stars
Timeliness	Timeliness	The number of days from date of purchase to date of online word of mouth posting
History	Reviewers' word of mouth history	Total history post counted on the day of purchase
Type	Product type	*Type* = 1: experience product *Type* = 0: search product

estimate the coefficients in Equation (1). Meanwhile, because Extremity is a discrete variable (0, or 1, or 2), it was described using ordered probit model when studied as a dependent variable, as is in Equation (2).

$$Length = \beta_0 + \beta_1 * Channel + \beta_2 * History + \beta_3 * Type + \varepsilon \tag{1}$$

$$\begin{aligned} Extremity^* &= \beta_0 + \beta_1 * Channel + \beta_2 * History + \beta_3 * Type + \varepsilon, \\ &\quad and\ Extremity = j[k_{j-1} <= Extremity^* < k_j], \\ &\quad \text{where } k_j \text{ is the cut point for} Extremity^* \end{aligned} \tag{2}$$

Equations (3)–(5) were employed to study the mediating effects. Firstly, Equation (3) investigated the impact of online word of mouth channel on timeliness. Subsequently, Equations (4) and (5) validated the mediating effects of timeliness.

$$Timeliness = \beta_0 + \beta_1 * Channel + \varepsilon \tag{3}$$

$$\begin{aligned} Length &= \beta_0 + \beta_1 * Channel + \beta_2 * History + \beta_3 * Type \\ &\quad + \beta_4 * Timeliness + \varepsilon \end{aligned} \tag{4}$$

$$\begin{aligned} Extremity^* &= \beta_0 + \beta_1 * Channel + \beta_2 * History + \beta_3 * Type \\ &\quad + \beta_4 * Timeliness + \varepsilon,\ and\ Extremity = j[k_{j-1} \\ &\quad <= Extremity^* \\ &\quad < k_j], \quad \text{where } k_j \text{ is the cut point for} Extremity^* \end{aligned} \tag{5}$$

Equations (6) and (7) were established to study the moderating effect of reviewers' word of mouth history, with Equation (6) discussing review length and Equation (7) discussing rating extremity. Similarly, Equations (8) and (9) were dedicated to the verification of the moderating effect of product type.

$$\begin{aligned} Length &= \beta_0 + \beta_1 * Channel + \beta_2 * History \\ &\quad + \beta_3 * Type + \beta_4 * Channel * History + \varepsilon \end{aligned} \tag{6}$$

$$\begin{aligned} Extremity^* &= \beta_0 + \beta_1 * Channel + \beta_2 * History \\ &\quad + \beta_3 * Type + \beta_4 * Channel * History + \varepsilon, \\ &\quad and\ Extremity = j[k_{j-1} <= Extremity^* < k_j], \\ &\quad \text{where } k_j \text{ is the cut point for } Extremity^* \end{aligned} \tag{7}$$

$$\begin{aligned} Length &= \beta_0 + \beta_1 * Channel + \beta_2 * History \\ &\quad + \beta_3 * Type + \beta_4 * Channel * Type + \varepsilon \end{aligned} \tag{8}$$

$$\begin{aligned} Extremity^* &= \beta_0 + \beta_1 * Channel + \beta_2 * History \\ &\quad + \beta_3 * Type + \beta_4 * Channel * Type + \varepsilon, \\ &\quad and\ Extremity = j[k_{j-1} <= Extremity^* < k_j], \\ &\quad \text{where } k_j \text{ is the cut point for } Extremity^* \end{aligned} \tag{9}$$

V. EMPIRICAL RESULTS

A. SAMPLING

The descriptive statistics of the screened dataset ($N = 96,210$) are summarized in Table 2. The mean value of *Channel* is 0.096, indicating reviews from mobile channel takes up approximately 9.6% of all the reviews. The average review length is 37.75 characters, with a quite large variation of 34.00. Considering the fact that the maximum length reaches 239 whereas the minimum is as short as 2, such *Length* statistics are reasonable. Also scattered are the *Timeliness* statistics, with a mean value of 29.71 days and an even larger variation of 40.88. Indeed, some reviewers post online review on the same day of purchase ($Timeliness = 0$), while others wait until nearly six month later ($Timeliness = 181$). The mean *Extremity* is 1.737, a number very close to 2, suggesting the generally high extremity of the studied reviews. The average *History* is 22.69 posts, incorporating both veteran reviewers ($History = 2167$) and rookie ones ($History = 0$). Last but not least, around 26.6% of the reviews address experience products ($Type = 0.266$).

From Table 2, the differences between mobile and PC word of mouth can already be preliminarily observed. For example, averagely mobile reviews are approximately 10 characters shorter in *Length* than PC reviews ($p < 0.001$); mobile word of mouth is posted 5 days earlier than PC word of mouth ($p < 0.001$); mobile rating extremity is more than 0.1 star higher than PC rating extremity ($p < 0.001$). These descriptive results are consistent with the regression results to be reported later.

TABLE 2. Descriptive statistics.

Variable	Online word of mouth (mobile and PC)				Mobile word of mouth		PC word of mouth		T test
	Mean	St. Dev.	Min.	Max.	Mean	St. Dev.	Mean	St. Dev.	
Channel	0.096	0.294	0	1	—	—	—	—	—
Length	37.75	34.00	2	239	28.42	27.31	38.74	34.48	27.80†
Timeliness	29.71	40.88	0	181	25.54	36.96	30.15	41.25	10.29†
Extremity	1.737	0.522	0	2	1.856	0.425	1.724	0.529	-23.05†
History	22.69	45.33	0	2167	23.78	46.06	22.58	45.25	-2.44†
Type	0.266	0.442	0	1	0.253	0.435	0.267	0.443	2.86†
Observations	96,210				9,203		87,007		—

†: $p < 0.001$

TABLE 3. Regression results of main and moderating effects.

Variable	*Length*	*Extremity*	*Length*	*Extremity*	*Length*	*Extremity*
Channel	-10.249***	0.429***	-9.574***	0.497***	-10.545***	0.468***
	(0.660)	(0.047)	(0.698)	(0.043)	(0.701)	(0.046)
History	-0.022**	0.003**	-0.019*	0.003**	-0.022**	0.003**
	(0.010)	(0.001)	(0.011)	(0.001)	(0.010)	(0.001)
Type	-3.714***	0.098***	-3.725***	0.097***	-3.822***	0.109***
	(0.620)	(0.032)	(0.621)	(0.032)	(0.670)	(0.034)
*Channel * History*	—	—	-0.028*	-0.003***	—	—
			(0.015)	(0.001)		
*Channel * Type*	—	—	—	—	1.164	-0.158*
					(1.349)	(0.086)
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Seasonality	Yes	Yes	Yes	Yes	Yes	Yes
Observations	96,210	96,210	96,210	96,210	96,210	96,210
Adjusted R^2	0.013	—	0.013	—	0.013	—
Pseudo R^2	—	0.013	—	0.014	—	0.013

Standard errors in parentheses
***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

B. MAIN AND MODERATING EFFECTS

The regression results of the main and moderating effects are reported in Table 3. According to Table 3, mobile reviews are 10.249 characters shorter than those PC reviews ($p < 0.01$), which supports H1. Meanwhile, on an all other things equal basis, mobile ratings have higher probability to be in high extremity (88.5% as opposed to 76.5%), and about less than half as likely to be in low extremity (1.5% versus 4.2%), which supports H2.

As for the moderating effects, according to Table 3, *History* can negatively moderate the effect of *Channel* on *Length* (-0.028, $p < 0.1$) and *Extremity* (88.7% vs. 76.4%, $p < 0.01$), thus supporting H6 and H7. In addition, H8 is not supported because of the insignificant coefficient (1.164, $p > 0.1$), whereas H9 is supported, but in the opposite direction, because of the negative coefficient (88.2% vs. 76.5%, $p < 0.1$). In other words, product type moderates the relationship between online word of mouth channel and rating extremity, but more specifically, for experience products, the effect of online word of mouth channel on rating extremity is weaker than the effect for search products.

C. MEDIATING EFFECTS

The mediating effects of *Timeliness* are not supported, judging from the regression results in Table 4. To be more specific, although mobile word of mouth has been estimated to be 4.464 days ahead of PC word of mouth ($p < 0.01$), it can hardly explain the variation of either *Length* or *Extremity*. Therefore, H3 is supported, whereas H4 and H5 are not.

VI. DISCUSSION

Mobile reviews have been found to be shorter than PC reviews, which is consistent with the observations by Burtch and Hong [20], and März et al. [21]. Considering the fact that the mean length of a mobile review is around 38 characters, the approximately 10-character difference is quite significant. Managers can take advantage of this channel-induced length difference. More specifically, merchants may encourage

TABLE 4. Regression results of mediating effects.

Variable	*Timeliness*	*Length*	*Length*	*Extremity*	*Extremity*
Channel	-4.464***	-10.249***	-10.560***	0.429***	0.432***
	(1.112)	(0.660)	(0.665)	(0.047)	(0.047)
History	—	-0.022**	-0.029***	0.003**	0.003**
		(0.010)	(0.010)	(0.001)	(0.001)
Type	—	-3.714***	-3.794***	0.098***	0.099***
		(0.620)	(0.611)	(0.032)	(0.032)
Timeliness	—	—	-0.070***	—	0.001**
			(0.005)		(0.000)
Observations	96,210	96,210	96,210	96,210	96,210
Adjusted R^2	0.015	0.013	0.020	—	—
Pseudo R^2	—	—	—	0.013	0.014

Standard errors in parentheses
***: $p < 0.01$, **: $p < 0.05$

potential online reviewers to keep their reviews untold until they reach a computer, for example by means of e-coupon delivery through computer channels, such that the reviewers can write longer reviews with more detailed description of the purchased products. After all, the currently 38-character online review is yet too short to arouse information overload [25], [36].

Mobile ratings have been proved to be more extreme, or, figuratively speaking, louder, than PC ratings. The managerial implication regarding this finding would be quite tricky. For managers who are relatively confident with their products, they may encourage reviewers to express their opinions through the mobile channel, such that the merits of their products can be emphasized owing to the enhanced positive extremity, i.e., more five-star ratings. On the contrary, for managers who happen to have some defects in products unresolved for the moment, they may try directing the reviewers to the PC channel where criticism is less sharp than it would otherwise be in the mobile channel.

Because the effects of online word of mouth channel on review length and rating extremity are moderated by reviewers' word of mouth history as well as product type, managers are further advised that the mobile-longer and mobile-more-extreme effects are more pronounced for quieter reviewers, i.e. reviewers with smaller number of history posts. Additionally, the mobile-more-extreme effect is stronger for search products. Last but not least, neither the mobile-longer nor the mobile-more-extreme effect is moderated by timeliness. In other words, the mechanism of the effect of online word of mouth channel on online word of mouth attributes remains unknown, leaving follow-up scholars to investigate into other potential mediators.

VII. CONCLUSIONS

Understanding the mechanism of mobile word of mouth creation is of both academic and industrial importance in this mobile marketing age. This study reveals the effects of online word of mouth channel on online word of mouth attributes by investigating the 162,452 pieces of online word of mouth created by 19,496 users on a top-three online shopping website in China during a two-year period. Findings suggest that mobile word of mouth is shorter and louder than PC word of mouth. Managers are thus encouraged to direct reviewers to corresponding channels to optimize online word of mouth marketing results.

The contributions of this study are two-fold. Theoretically, this study consolidates the relationship between online word of mouth channel and online word of mouth attributes. It not only validates the mobile-longer and mobile-more-extreme effects, which have been observed in only a limited number of previous studies, but also verifies the moderating effect of reviewers' word of mouth history, a variable that has never been sufficiently quantified in any existing study. Managerially, this study provides detailed advices to managers regarding the selection of online word of mouth channel depending on product status, which is also a pioneering report to the authors' knowledge.

Despite the above merits, this study has several limitations. Firstly, the dataset has been limited to one website in China. Future studies may consider incorporating more websites and more countries to obtain greater generality. Secondly, the R2 values have been very low in all models, suggesting the limited explanatory power of existing models. Future studies may introduce more variables to better account for the variation of the online word of mouth attributes. Finally, future studies may also be dedicated to the hypothesis and testing of the currently unknown moderating variable.

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