The influence of launching mobile channels on online customer reviews

The Influence of Launching Mobile Channels on Online Customer Reviews

Abstract

We explore the effect of launching mobile channels on online customer reviews. We show that the launch of mobile channels does not significantly influence online review generation, contrary to the general expectation that the accessibility of mobile channels stimulates online review generation intention. Using a Difference-In-Difference (DID) approach to analyzing review data from online travel websites, we find that the launch of a mobile channel does not affect the volume and the average rating of the generated reviews. However, we discover that reviewers with extreme experiences tend to use mobile devices to post their online reviews, providing evidence that the new channel introduction influences only the device chosen to post online reviews. Based on our findings, we extend extant literature and research on electronic Word of Mouth (eWOM) and develop business implications for online review platform managers on a mobile channel strategy that could improve business value.

Keywords: *mobile channel, Difference-In-Difference approach, review volume, review rating, review distribution channel choice, eWOM*

1. Introduction

The widespread usage of the Internet and digital platforms in everyday life has made consumer decision-making increasingly dependent on online customer reviews. Online reviews generated by other customers can assist prospective customers to quickly search for products and services that match their needs or preferences (Dellarocas, 2003), and make more informed and thus less risky decisions (Cheung and Lee, 2012). On the other hand, customers can also post their own reviews and share their experiences with other customers to help them during their decision-making processes (Hennig-Thurau et al., 2004) in a way that helps co-creation of meaningful marketing information (Zwick et al., 2008). In other words, online review platforms provide customers with digital environments where they can generate, share, and exchange information eventually critical for making purchase decisions (Ek Styven and Mariani, 2020). More recently, firms have been seeking ways to effectively deploy and manage online review channels because their financial performance is closely tied to the decisions made by customers (Chevalier and Mayzlin, 2006) across different channels (Chevalier et al., 2018; Chu et al., 2010; Dwivedi et al., 2020). For example, many e-commerce websites, such as Dianping.com in China, use coupons or price discounts to motivate their users to generate high-quality reviews and provide better information to those customers who make decisions based on these reviews (Wu et al., 2015; Zhu et al., 2019).

The emergence of mobile technologies has significantly modified how consumers share and exchange information online, with a detectable shift from non-mobile to mobile devices and platforms. Because mobile devices enable users to access and generate information anywhere and anytime (Dwivedi et al., 2021), the breadth and intensity of impacts that online reviews have on both customers and firms are growing (Burtch and Hong, 2014; Ransbotham et al., 2019). Consequently, firms are making efforts to incorporate mobile platforms into their business models, leading to rapid growth in the mobile platform market. Online review websites, including TripAdvisor.com and Yelp.com, are leading the shift towards incorporating mobile platforms into their online services (Schonfeld, 2011). Given the growing importance of mobile channels in businesses (Akter et al., 2019; Baabdullah et al., 2019; Dwivedi et al., 2020), academic researchers are increasingly investigating the impacts that mobile platforms have on customers' word of mouth (WOM) behaviors (Burtch and Hong, 2014; Kim and Hyun, 2021; Ransbotham et al., 2019). Despite the emergence of a nascent research stream investigating the influence of the launch of mobile platforms on the volume, valence, and variance of the generated online reviews (e.g., Kim et al., 2020), to date, literature examining the causal effects of mobile channels on online customer reviews is still rather limited. Thus, in this research, we try to address these two inter-related research questions: Is consumers' online review generation shifted by the introduction of mobile channels? In what directions and to what degrees does the shift occur?

Specifically, we investigate how the launch of a mobile channel can generate systematically different online reviews, by analyzing online customer review data collected from Booking.com and TripAdvisor.com. To achieve this aim, first we collected a large sample of 677,013 customer reviews for London-based hotels from Booking.com and 117,994 for London-based hotels from TripAdvisor.com. Using the matched 348 hotels from the two platforms, we subsequently deployed a Difference-In-Difference (DID) model to examine the direct causal relationship between the launch of a mobile channel and the volume, valence, and variance of online reviews, while controlling for the time-varying impact of adding a mobile channel.

Through this research, we contribute to the extant electronic Word-of-Mouth (eWOM) literature and specifically the nascent research stream revolving around mobile eWOM (Grewal and Stephen, 2019; Kim et al., 2020; Mariani et al., 2019; Ransbotham et al., 2019; Zhu et al., 2020) by examining the impact of mobile channels on online review generation. We also offer important business and managerial implications for online review platform managers regarding how to design and manage their online platforms encompassing mobile channels to create and maximize business value. The remainder of the paper is organized as follows. In section 2 we review the relevant literature. Section 3 illustrates the empirical approach, while section 4 presents the data and methods. The fifth section elucidates the main findings. The sixth section describes the theoretical contributions and implications, the managerial implications, and offers a reflection on the study's limitations and future research. The last section succinctly draws the conclusions.

2. Related Literature

2.1 Online Reviews and Electronic Word of Mouth (eWOM)

Online customer reviews shared through online communication channels like blogs, online review sites, online discussion forums, or SNS are the most commonly shared form of information within eWOM (Cheung and Lee, 2012; Hennig-Thurau et al., 2004). Word of mouth (WOM), by definition, is a form of marketing communication through which information about goods or services is communicated among consumers (De Matos and Rossi, 2008), and it is also a process and an outcome of a customer journey and customer decision-making (Rosario et al., 2020). The Internet, based on its real-time nature, enables users to communicate and share in real time information regardless of where they are. Consequently, the effects that eWOM has on consumer decisions and behaviors, as well as their satisfaction, are more immediate and widespread (Chevalier and Mayzlin, 2006).

Prior literature on eWOM has focused on investigating the impacts of eWOM on both customers (Fan and Miao, 2012; See-To and Ho, 2014) and firm performance (Mariani and Visani, 2019; Rosario et al., 2016). In particular, the volume (Zhu and Zhang, 2010), valence (Chevalier and Mayzlin, 2006), and variance (Martin et al., 2007) of the online reviews have been investigated as the key dimensions that drive the influences of eWOM on customers and firms (Rosario et al., 2020). The volume of customer reviews represents the number of reviews generated, while the valence (i.e., the level of review ratings) and variance (i.e., the degree to which review ratings are spread out) of reviews jointly describe the distribution of review ratings generated by review posters.

Regarding the effect of the volume of online reviews, prior research has shown that the review volume has a positive influence on product or service sales, thus creating business value. For example, Zhu and Zhang (2010) showed that consumers tend to perceive the number of online reviews as an indicator of review credibility because they are more likely to trust the reviews when the volume is large. This is because an increase in the number of reviews implies that more people have used the product or service and therefore the product or service reviewed is more popular online. Consequently, consumers are more likely to purchase a product with a greater number of reviews, positively influencing firms' sales (Dhar and Chang, 2009).

The valence and variance of online reviews also influences firms' sales. Specifically, past studies have shown that an increase in the level of online review ratings (i.e., valence) has a positive influence on sales, because consumers tend to consider products or services with higher review ratings to be superior in quality (Chevalier and Mayzlin, 2006; Dellarocas et al., 2007; Mariani and Borghi, 2018). Consequently, positive online reviews are more likely to increase product sales by motivating consumer purchases. However, the evidence is mixed regarding the actual direction of the impact that review rating variance has on production evaluation as well as sales. One stream of research has shown that an increase in the variance of customer review ratings leads to a drop in consumers' perceived helpfulness for the reviews (Lee et al., 2021) and also in sales (Ye et al., 2009), while there are also studies showing that consumers are more likely to prefer products with greater dispersion in review ratings (Martin et al., 2007).

In sum, the volume, valence, and variance of online customer reviews significantly influence consumer purchase decisions, and ultimately firm performance. Consequently, exploring the factors that influence the volume, valence, and variance of online reviews has been a major topical area of work among both business practitioners and academic researchers. For example, Sridhar and Srinivasan (2012) showed that triggering reviewers' motivation to post reviews that are consistent with others' can increase their intention to post reviews. Similar findings regarding the influence of social norms are found in various contexts, including retirement fund decisions (Duflo and Saez, 2002), restaurant selection (Cai et al., 2009), and music downloads (Salganik et al., 2006). In addition, providing financial incentives in exchange for posting online reviews can also directly motivate the intention to generate reviews (Cabral and Li, 2015). Another source of influence can be the type of communication channels, such as the channels utilizing mobile devices including smartphones or tablet PC versus those using PC which is relatively more static. In this study, we innovatively examine the impact that the mobile channels have on online review generation by building on mobile eWOM literature which is critically reviewed to elucidate a relevant research gap (see ensuing section 2.2).

2.2 Electronic Word-of-Mouth through Mobile Channels

Many online review websites now provide customers with the option to communicate via mobile channels. Popular online travel agencies (OTAs) like TripAdvisor.com, Expedia.com, and Booking.com all provide users with the option of posting reviews using their mobile devices. Consequently, academic researchers are shifting their attention to the investigation of consumers' perceptions of the mobile review channels (Wang et al., 2016) as well as the understanding of the differences between mobile versus non-mobile review channels (e.g., Mariani et al., 2019). However, there is still a very limited number of studies that have explored the impact of the launch of mobile channels on eWOM generation (Burtch and Hong, 2014; Ransbotham et al., 2019).

One of the key characteristics of mobile channels is that they are highly accessible and portable, making it easier for users to share and communicate information (Ghose and Han, 2011; Okazaki, 2009). Because mobile devices are small in size to assure portability, users can carry their devices and communicate from anywhere, anytime they want (Lurie et al., 2018; Ransbotham et al., 2019). The portability and accessibility of mobile devices allow users to post reviews about their experiences right away, without having to find a PC to post from.

Based on such characteristics, prior literature has explored how online review generation is influenced when mobile channels are adopted. With regard to the volume of online reviews, the accessibility and portability of mobile devices are likely to motivate their potential reviewers to post reviews (Gruen et al., 2006). Kim et al. (2020) further found that the potential reviewers' perception of cost on posting reviews tends to be lower for mobile devices, as the latter ones remove the psychological barriers to posting reviews. Such findings suggest that it is more likely that a greater number of reviews can be generated through mobile channels. For instance, Mariani et al. (2019) showed that the share of online reviews posted via mobile increased over time. When the mobile platforms are not available, reviewers must find a desktop or laptop PC to post from, making them unable to give feedback right away.

Regarding the impact on the valence and variance of the generated reviews, past studies have shown that the review ratings generated on mobile devices are more likely to shift toward each end of the extremes because the time between the actual experience and review posting is shorter (Burtch and Hong, 2014; Mariani et al., 2019). In related research, Ransbotham et al. (2019) showed that mobile-generated customer reviews tend to be more concrete and emotional because of the accessibility of mobile devices. A shorter time lapse between the consumption experience and the review posting indicates that the reviews are likely to be posted before the intensity and vividness of the experience fade out with time (Mazursky and Geva, 1989). Subsequently, the average of the overall review ratings would be less likely to shift with the launch of the mobile channels because individual review ratings would be dispersed in the direction of the positive or negative extreme.

In sum, based on the accessibility and portability afforded by mobile devices, the launch of a mobile channel would likely increase the volume of online customer reviews while simultaneously increasing the extremity of review valence and the dispersion of review ratings. We term this perspective *"the accessibility argument"*.

However, another stream of research suggests that accessibility is not the only characteristic of mobile channels that influences review posting. While mobile devices reduce the hassle of finding a PC or other non-mobile device to compose a review on, it can add physical inconveniences to the review posting process (De Haan et al., 2018). Mobile devices, such as smartphones, are typically compact with relatively smaller displays that usually range from 4 to 7 inches. Due to the limited screen size, the amount of information that can be displayed is also limited, making it more difficult for the users to fully comprehend and process all of the information at once (Adipat et al., 2011; Chae and Kim, 2004; Shankar et al., 2010). Furthermore, they are not typically accompanied by separate input devices (i.e., keyboard devices), causing reviewers to type using the display keyboard to compose their reviews. Prior literature has shown that such inconvenience in acquiring and sharing information using mobile devices increases the perceived risk in decision-making because individuals cannot sufficiently process the necessary information (Chin et al., 2012). Thus, individuals switching to non-mobile devices when they are making purchase decisions would further influence the decision-making process (De Haan et al., 2018).

Added inconveniences in using mobile devices for posting reviews would also influence individuals' online review generation. Specifically, the inconvenience of a smaller display could make potential reviewers less willing to post reviews. Consequently, the motivating effect of mobile channels, driven by the accessibility and portability of mobile devices, can be mitigated so that the shift in the volume of generated reviews would be diminished. We further infer that the potential reviewers would be less likely to post reviews using the mobile channels (Kim et al., 2020), therefore the shift in the dispersion of the review ratings and review rating averages would be limited. We term this alternative approach *"the usability argument"*.

Based on the literature reviewed so far, it appears that no prior study has examined empirically the causal effects of the introduction of mobile channels on online customer review generation. To bridge this relevant research gap, we build on two contrasting arguments – the *"accessibility argument"* (Ghose and Han, 2011; Okazaki, 2009) vs. the *"usability argument"* (De Haan et al., 2018) – to assess which of the two arguments prevails when analyzing the impact of the launch of mobile channels on online review production. Accordingly, within the emerging research stream on mobile eWOM (Grewal and Stephen, 2019; Kim et al., 2020; Ransbotham et al., 2019; Zhu et al., 2020), this study is to the best of our knowledge the first to develop theoretically backed causal explanations of the effect of the introduction of mobile channels on online customer review generation.

3. Empirical Approach

3.1 Research Setting

Our primary empirical approach is based on the online customer review data collected from TripAdvisor.com and Booking.com and related to hotel services, hotels being just an illustrative empirical setting. The two platforms were selected because they represent good examples of different types of platforms: TripAdvisor.com is a community-based platform while Booking.com is a transaction-based platform (Gligorijevic, 2016; Mariani and Borghi, 2020, 2021a). Moreover, the two platforms differ because they enforce different online review policies (Mayzlin et al., 2014). Conducting a multi-platform study therefore enhances the generalizability of our findings in line with other recent research examining customer reviews from a multi-platform perspective (Mariani and Borghi, 2021a, 2021b).

Our key independent variable is the availability of a mobile channel, which is provided by most OTAs. Both TripAdvisor.com and Booking.com provide mobile channels. Figure 1 shows a screenshot of customer reviews for a Holiday Inn Express in London, collected from TripAdvisor.com. Each review consists of a review rating along with the customer's accompanying comments. Whether the review was posted using a mobile device is indicated by the notation, *"via mobile"*.

[Insert Figure 1 About here]

Figure 2 provides a screenshot of an online customer review for Top Night Hotel, collected from Booking.com. Similar to the review in Figure 1, this review includes a review rating with a comment provided by the reviewer. The review also provides additional information about the trip that the reviewer was on, including information on the purpose of the trip (e.g., for leisure or business), room type, and the number of days the reviewer stayed at the hotel. The key independent variable, whether the review was posted using a mobile device, is indicated by the text, *"Submitted from a mobile device"*.

[Insert Figure 2 About here]

However, the initial launch date for the mobile channels differs across the two websites. Tripadvisor.com initiated its mobile channel late in 2010, but customers began to use it regularly from 2011, while Booking.com started providing the service in December 2014. The difference in their launch dates presents an opportunity to capture empirically the influence of the mobile channel launch on online review generation.

3.2 Identification Strategy

The main aim of this research is to identify if and how the launch of a mobile channel influences review posting behavior, by comparing review characteristics such as volume, valence, and variance of reviews from before and after the launch. However, there are critical challenges in pursuing this goal. The influence generated by the launch of the mobile channel could be confounded by many factors, one of which being positive momentum in the reviewers' review posting tendency (time trend). Because the Internet continues to become more user-friendly, the potential for review posting has been gradually going up over time. This positive momentum (time trend) would affect review posting tendency measured by review volume. In addition, unobservable hotel-level differences in services would also affect review posting behavior. Considering that consumers tend to leave reviews to either punish or reward a hotel for the services provided (Chevalier et al. 2018; Mariani, Borghi and Okumus, 2020), unobservable hotel-level differences could affect the review characteristics through a mobile channel. Thus, it is necessary to isolate the causal influences of the mobile device launch from the impacts of the time trend and unobservable hotel-level differences when estimating the influences of a mobile channel launch.

From an empirical perspective, these issues would result in bias in the estimation. To address these estimation issues, we use a DID approach, using the matched sample from identical hotels. Matched hotels are used to improve comparability between the treatment and control groups (Flammer, 2015). The DID approach is known to be a quasi-experimental approach which has advantages when controlling for the impacts of constant factors over time, such as unobservable hotel-level differences, and for those of time-varying factors like positive momentum in reviewers' posting tendency (Flammer, 2015; Fredriksson and Oliveira, 2019). The reason for using DID is that if there are significant causal influences from launching a mobile channel, they would be identified during the DID estimation process by controlling for the impact of constant factors and capturing that of time-varying factors.

3.3 Empirical Approach

To further control time and hotel-specific influences on review posting behavior, we use fixed-effects DID model specifications. This approach allows us to control the time-variant and hotel-variant influences present in the online review data used in this study. Our baseline model specification is as follows:

$$y_{igt} = \beta_0 + \beta_1 * Treatment_{ig} + \beta_2 * Post_{it} + \beta_3 * \left(Treatment_{ig} * Post_{it}\right) + \delta_i + \tau_t + \varepsilon_{igt} \qquad (1)$$

where y_{igt} represents the observed outcome variables. In this study, we consider the number of customer reviews, the average review ratings, and the positive/negative review ratio as the outcome variables in group g for hotel i in month t. These operational variables are used because volume represents the number of customer reviews, valance refers to the average review ratings, and variance reflects the positive/negative review ratio. There are two groups: the treatment and control. Online customer reviews for hotel i from Booking.com are considered as the treatment group, while online customer reviews for hotel i from TripAdvisor.com are regarded as the control group[1]. $Treatment_{ig}$ is defined as a dummy variable, where 1 is assigned if the online customer reviews for hotel i are from the treatment group (Booking.com) and 0 if not. $Post_{it}$ is defined as a dummy variable where 1 is assigned if the online customer reviews for hotel i are from the period after launching the mobile channel on Booking.com. The dummy, $Post_{it}$, captures unobservable factors that would cause variations in the observed outcome variables in the absence of a mobile channel (representing time trend). β_3 is our primary interest as it captures the treatment effects from the estimation. We consider the time-fixed effects (τ_t: monthly dummy variables) as well as the hotel fixed effects (δ_i:hotel-level heterogeneity). Finally, we use cluster-robust standard errors at the hotel level. By using hotel-level clustered error terms, we can account for heteroscedasticity as well as autocorrelation, which may exist within the online customer review data (Bertrand et al., 2004). Table 1 shows the definitions for the four dependent variables.

[Insert Table 1 About here]

To examine positive and negative review ratios, we need to define positive and negative reviews. To do this, we adhere to the definitions of positive and negative reviews delineated in Mayzlin et al. (2014). Following this, we consider reviews from the control group (TripAdvisor.com) with a rating of 1 or 2 as negative reviews, while considering reviews with a rating of 5 as positive reviews. On the other hand, Booking.com uses a 10-point scale for review ratings. If we simply convert the Booking.com ratings to a 5-point scale by dividing

[1] Due to the availability of Booking.com data before 2014 being limited, it was difficult to construct our DID model specifications with reviews from TripAdvisor.com as the treatment group. However, setting the DID model specifications using reviews from Booking.com as the treatment group can be an appropriate approach to determine whether there were indeed some changes that occurred in the trend of the dependent variables between the two time periods, pre-intervention and post-intervention (mobile channel). This is because DID can be used to examine whether the differences in the trend of the dependent variables of the control and treatment groups are maintained or change after some form of intervention.

them by 2, reviews with a rating equal to 2 on TripAdvisor.com correspond with the reviews with a rating equal to 4 on Booking.com, while the reviews with a rating equal to 5 on TripAdvisor.com correspond with reviews with a rating equal to 10 on Booking.com. Based on this definition, the percentage of negative reviews from the Booking.com sample was lower than 5%, and that of positive reviews was approximately 10%. To balance out the proportion of positive and negative reviews, we defined reviews with ratings less than or equal to 5 as negative reviews (Booking.com)[2]. Reviews with a rating of 10 are considered as positive reviews (Booking.com). For the Booking.com reviews, we use similar definitions for positive and negative reviews in line with prior literature (Kim et al., 2020).

The upper and lower 10% of review ratings may not be sufficient to accurately reflect both the positive and negative reviews. In the robustness check section, we perform the analysis with different rating thresholds to distinguish positive and negative reviews. Reviews with ratings less than or equal to 6.0 are treated as negative. Meanwhile, reviews with ratings greater than or equal to 9.6 are regarded as positive for the treatment group (Booking.com). This is based on the upper and lower 20% of review ratings. However, we still consider reviews with a rating of 1 or 2 as negative, and regard reviews with a 5 as positive reviews in the control group (TripAdvisor.com). Table 2 shows the definitions of positive and negative reviews for each group.

[Insert Table 2 About here]

[2] Prior literature (Mellinas and Martin-Fuentes, 2021) explored the impacts of the change in the Booking.com scoring system. In the study, they regard dissatisfied customers as posting a review with a score equal to or less than 4. Differently from this, in this current study, we define positive and negative reviews according to review rating distribution. Specifically, we consider the upper 10% of review scores as positive and the lower 10% as negative reviews (for robustness, the upper or the lower 20%, respectively). This would make the portions of positive or negative reviews symmetrical for both sites. That is, we define positive or negative reviews based on the percentage of review ratings rather than rating score itself.

4. Data

4.1 Data Collection

To collect the online review data for hotels in London from Booking.com and TripAdvisor.com, we accessed the HTML and XML pages of the websites and parsed those pages using a custom-made automated tool, written by "vb.net". For each hotel in London, we collected some basic hotel information, including the online customer reviews posted by reviewers from both sites. Basic hotel information included the hotel name, address, and hotel star rating assigned by each site. Online customer reviews included the review rating, review content, the channel used (whether posted via mobile or non-mobile channel), and the reviewer information.

As a result, 677,013 customer reviews from May 2014 to October 2015 were collected from Booking.com. However, because customer reviews posted before July 2014 were limited in number, we used the data from July 2014 to October 2015. From TripAdvisor.com, we collected all of the customer reviews corresponding to the same period as the data collected from Booking.com. Specifically, we matched the hotels from Booking.com and TripAdvisor.com according to the hotel name and manually confirmed whether the hotel names were correctly matched. As a result, our final sample for this study includes the online customer reviews for 348 matched hotels, posted from July 2014 to October 2015 on both sites.

Following this, we converted the online review data to monthly data using the hotel and month combination (i, t). Based on the data representing monthly review data (t) for the hotel (i), we calculated the number of customer reviews and the average review ratings as well as the positive and negative review ratios. As previously mentioned, the two sites released their mobile channels at different times, with Booking.com launching its mobile channel in

December 2014 and TripAdvisor.com launching its in late 2010. Due to the difference in the launch dates, there is an overlapping period when customers can post reviews via a mobile channel on TripAdvisor.com, while customers cannot do it on Booking.com. Therefore, if the mobile channel launch by Booking.com has a causal influence on the review posting behavior, a variation in the differences in the valence and variance of reviews between Booking.com and TripAdvisor.com would be observed. In particular, such variation would be reflected in the customer reviews posted from January 2015 to October 2015 after Booking.com launched its mobile channel in December 2014. Due to the possibility of a transition period[3] after the launch, we do not use the reviews posted in December 2014 in this study. As a result, the final sample includes the customer reviews posted over 15 months on both sites. The reviews posted in the period from January 2015 to October 2015 are represented as the "Post-period" in equation (1). Figure 3 summarizes the timeline of our research development.

[Insert Figure 3 About here]

4.2 Summary Statistics

Table 3 provides the summary statistics of the matched 348 hotels in the final sample. To simplify the comparison of the review ratings between the two websites, we provide the summary statistics of the review ratings on Booking.com by dividing the ratings by 2, in order to convert them into a 5-point rating scale. It provides direct comparisons of the reviews from the two sites. Regarding the number of customer reviews, we use log transformation to reduce

[3]The mobile channel was launched in the middle of December 2014. Before the launch, review posters were only able to post their online reviews via a non-mobile channel. After the launch, they were able to use both mobile and non-mobile channels. As all our data has a monthly frequency and the launch happened in December 2014 (the exact day is not clearly recorded), we regard December 2014 as a transitional period. Therefore, we use the online review data collected from July 2014 to October 2015, excluding December 2014, to examine the causal impacts of the launch of a mobile channel on online review posting.

the skewness of the variable. The variables, log(NCR_{i1t}) and log(NCR_{i0t}), represent the log-transformed number of customer reviews on Booking.com and TripAdvisor.com respectively. We observe that the review volume on Booking.com is, on average, greater than that on TripAdvisor.com (3.62>2.02). The variables, ARR_{i1t} and ARR_{i0t}, represent the average rating of customer reviews on Booking.com and TripAdvisor.com respectively. The average review rating on Booking.com is greater than that on TripAdvisor.com (3.71>3.44). NRR and PRR stand for negative and positive review ratio respectively. The negative review ratios of customer reviews on Booking.com are less than those on TripAdvisor.com (.05<.23); the positive review ratios of customer reviews on Booking.com are also less than those on TripAdvisor.com (.09<.25).

[Insert Table 3 About here]

5. Findings

5.1 Model-Free Comparison

In this section, using online reviews from the treatment group (Booking.com), we explore the influences of launching mobile channels by comparing the four dependent variables from before and after the launch. Table 4 shows the model-free comparison (the mean-comparison test) before and after the mobile channel launch. In the first column, we report the average values before the launch; in the next column, we list the average values from after the launch. In the third column, the difference between before and after the launch is provided. Columns (4) and (5) show the t-values and p-values for the differences in the third column.

The first dependent variable that we tested is the number of customer reviews. Before launching the mobile channel, the average of the log-transformed numbers of customer reviews was 3.61; after the launch, it rose to 3.63. This shows that the review volume increased but the increase was not statistically significant (Diff=.02, *p-value*>.05). On the other hand, the other three differences in the dependent variables were all statistically significant. The average review rating is greater after the launch of the mobile channel (Diff=.11, *p-value*<.05). The average of the negative review ratios is lower after the launch of the mobile channel (Diff=-.02, *p-value*<.05), while the average of the positive review ratios is higher after the launch of the mobile channel (Diff=.02, *p-value*<.05). Based on the results of the model-free comparisons, we can see that customer review volume is not affected, while the review valence and variance are significantly influenced by the launch of the mobile channel, consistent with the *accessibility argument*. However, because there could be a time trend in review posting before and after the launch, it is necessary to further investigate the causal influences of the mobile channel on the valence and variance of generated reviews.

[Insert Table 4 About here]

5.2 Influences of Launching a Mobile Channel on Online Review Generation

We perform our regression analysis using the DID specification defined in Equation (1) and provide the empirical results in Tables 5 to 8. In the first column (1) of Table 5, we consider monthly dummies, which control for the variation in review posting due to temporal dynamics. In the second column, we include hotel-level cluster-robust errors to control for autocorrelation and heteroscedasticity (Bertrand et al., 2004). In the last column (3), we also consider hotel-level fixed effects to control for the influences of hotel-level heterogeneity on review posting behavior. In all regressions, the dependent variable is the number of customer reviews. *Treatment* is a dummy variable, which is 1 if the number of customer reviews calculated was from hotels on Booking.com. *Post* is a dummy variable, in which 1 is assigned if the number of customer reviews is calculated after the mobile channel launch on Booking.com. The estimated coefficient for *Treatment*Post* is our primary interest, representing the causal influences of the mobile channel. If the accessibility and portability provided by mobile channels attract the reviewers with lower motivation to post their experiences, the estimated coefficient for *Treatment*Post* should be positive.

Across all regressions, the estimated coefficients for the *Treatment* are significantly positive, showing that the number of reviews for a given hotel on Booking.com is higher than on TripAdvisor.com ($\beta_{Treatment} = 1.61$, *p-value* < 0.05). The estimated coefficients for *Post* are also significantly positive ($\beta_{Post} = .08$ or .09, *p-value* < 0.05). The increase in the volume of customer reviews is not evident in the model-free comparison in Table 4, but there was an increasing trend in the review posting after the mobile channel launch. However, this does not necessarily mean that it is caused by the mobile channel launch. As shown across all models, the estimated coefficients for the interaction *(Treatment*Post)* are not statistically significant ($\beta_{Treatment*Post}$=-.01, *p-value*>0.05). Consistent with the expectations stated in the *usability argument* on the effect of mobile channel launch on the number of customer reviews, the mobile channel is found to play no significant role in expanding the size of review posting.

[Insert Table 5 About here]

Table 6 shows the causal influences of the mobile channel on the average review ratings. Each column includes the same variables as those of Table 5. If the mobile channel only prompts behavioral changes among potential reviewers to write reviews but not among those with limited or low intention, the influence of the mobile channel on the average review ratings would be limited. Therefore, the average review ratings might not exhibit any significant change following the mobile channel launch.

Across all models, the average review ratings for a given hotel on Booking.com are higher than that for the same hotel on TripAdvisor.com ($\beta_{Treatment} = .26$, *p-value* < 0.05). After the mobile channel launch, the average review ratings increase ($\beta_{Post} = .08$ or .07, *p-value* < 0.05), which is also confirmed in the model-free comparison in Table 4. However, the causal impact of the mobile channel is not significantly positive ($\beta_{Treatment*Post} = -.00$, *p-value* > 0.05). This means that the role of the mobile channel in generating online reviews is limited in terms of persuading potential reviewers with lower intention to share their experiences in the form of online reviews.

[Insert Table 6 About here]

If reviews generated by mobile devices are more extreme, the negative or positive review ratios would increase after the mobile channel launch. This effect can be examined by the estimated coefficient for the interaction between *Treatment* and *Post* from a regression. Each column in Table 7 is constructed in the same way as Tables 5 and 6. Across the three models, from the estimated coefficient for *Treatment*, we find that the negative review ratio for a given hotel on Booking.com is lower than that of the same hotel on TripAdvisor.com ($\beta_{Treatment} = -.10$, $p\text{-}value < 0.05$). After the mobile channel launch, the negative review ratio decreases ($\beta_{Post} = -.02$, $p\text{-}value < 0.05$). This is also observed in the model-free comparison in Table 4. However, the causal influence of the mobile channel is not significant ($\beta_{Treatment*Post}$=.00 or .01, $p\text{-}value > 0.05$). This also shows that the launch of a mobile channel does not cause statistically significant changes in the valence and variance of reviews.

[Insert Table 7 About here]

Table 8 shows the influence of a mobile channel on positive posting after the launch. Similar to negative review posting, the causal influences of a mobile channel launch on positive review posting were not significant in the DID estimate ($\beta_{Treatment*Post} = -.00$, $p\text{-}value > 0.05$). The positive review ratio for a given hotel on Booking.com is also lower than that of the same hotel on TripAdvisor.com ($\beta_{Treatment} = -.16$, $p\text{-}value < 0.05$). As found from the model-free comparison in Table 4, the positive review ratio increases after the launch of a mobile channel ($\beta_{Post} = .02$, $p\text{-}value < 0.05$). However, this shift is likely to have been caused by the time trend in review posting, not from the causal influence of the mobile channel launch.

[Insert Table 8 About here]

In sum, the empirical results indicate that the launch of mobile channels does not affect the volume of customer reviews nor change the valence and variance of the reviews. These results do not necessarily mean that the launch of mobile channels is not associated with review posting behavior because our examination has been focused on the significance of the longitudinal shift for the effect of mobile channel launch. By examining the cross-sectional differences after the launch of mobile channels, in section 5.3, we explore whether there are any significant post-launch differences in the review distribution depending on the channel type (i.e., mobile vs. non-mobile).

5.3 Differences in Review Posting from Mobile versus Non-mobile Devices

To further investigate the impact of mobile channels in online review generation, we examine the cross-sectional differences in reviews posted via mobile versus non-mobile devices after the mobile channel is launched. Specifically, we predict that the differences in extreme review posting (positive and negative reviews) would be significant depending on the type of channel used for posting reviews. To explore the cross-sectional differences in the extreme review posting, we use online review data for hotels in London from Booking.com from January 2015 through October 2015, which is after the transition period[4] for the mobile channel launch. As described in section 3.1, each online review contains information about each reviewer's trip along with the key independent variable, whether the review was posted

[4]Because the mobile channel was launched in the middle of December 2014, there is no guarantee that the reviews posted during the month will be appropriate for use in an examination of the cross-sectional differences in reviews posted via mobile and non-mobile devices. In addition, our data has a monthly frequency and the launch happened in December 2014 (the specific day of the launch is unclear). Considering these, we regard December 2014 as the transition period and we use online review data collected from January 2015 to examine the differences.

using a mobile device or not.

Data description. The total number of customer reviews is 440,103. As shown in Table 9, about 50.84% (223,779) of the reviews were posted via mobile devices. The reviews with ratings less than or equal to 5.0 are about 10% of all reviews (negative reviews), while the reviews with a rating of 10 are about 10% (positive reviews). When the data are categorized based on the type of device used to post reviews, we can observe that it is more likely for the mobile device to be used particularly at both extremes of review ratings. Thus, we examine the relationship between extreme reviews and the device choice in the next section.

[Insert Table 9 About here]

Extreme review posting. To investigate the relationship between the review distribution channel choice and extreme review posting, we conduct logistic and regression analyses. Table 10 provides the empirical results of the relationship between review distribution channels and negative review posting, as defined in Table 2.

In the first column (1), the dependent variable is "Mobile", which is a binary variable identifying whether the review was posted using a mobile device or a non-mobile device. Our focus is the independent variable "Negative Review". This is a binary variable, indicating whether the rating of a review is less than or equal to 5. We also incorporate dummy variables to control for confounding effects of the following factors: different hotel star levels, the purpose of the trip being business or leisure (trip-type), and with whom they stayed at the hotel (companion). These factors have been shown to directly impact review posting behavior (Ahn et al., 2017; Borghi and Mariani, 2021; Hong et al., 2016). In particular, we included national cultures (nationality) in the first column (1) to account for the potential impacts on review posting behavior (Hong et al., 2016; Mariani and Matarazzo, 2020; Mariani et al., 2021). Furthermore, we control for the hotel-level heterogeneity by considering hotel-level fixed effects. In the second column (2), we also incorporate different room types, because the level of satisfaction can be closely related to the room type. For example, the base satisfaction of staying in a standard room could be different from the base satisfaction of staying in a deluxe room at the same hotel. Based on these variables, we conduct a logistic analysis. The results show that, when reviewers post negative reviews, they are more likely to use mobile devices ($\beta_{\text{Negative Review}}$=.08, *p-value*<0.05).

In the third column (3) and the fourth column (4), we conduct another analysis, a regression model, to confirm the results in the first (1) and the second (2) columns of logistic analyses. In the third column (3), the independent and control variables are the same as those in the first column (1), while the independent and control variables in the fourth column (4) are the same as those in the second column (2). Across these two regression models, the positive relationship between mobile device choice and negative reviews is confirmed. In columns (3) and (4), the estimated coefficients for "Negative Review" are all significantly positive ($\beta_{\text{Negative Review}}$=.01, *p-value*<0.05). These findings from the logistic and regression analyses show that a mobile channel is closely related to negative review posting.

[Insert Table 10 About here]

We also examine whether the choice of review distribution channel is associated with positive review posting as well. In Table 11, the independent and control variables are defined in the same way as in Table 10. The only difference is that "Positive Review" is used as the dependent variable. Following the definition in Table 2, we define reviews as "Positive Review" if reviews have ratings of 10. The first (1) and the second (2) column show the results of logistic analyses. The estimated coefficient for the "Positive Review" is significantly positive, showing that the mobile channel is positively associated with positive reviews ($\beta_{\text{Negative Review}}$ = .09, *p-value* < 0.05). This positive relationship between the mobile channel and positive review posting is also confirmed through the regression results in columns (3) and (4). The estimated coefficients for “Positive Review” are all significantly positive ($\beta_{\text{Negative Review}} = .02$, *p-value* < 0.05).

[Insert Table 11 About here]

Considering the empirical results from Tables 10 and 11, we can maintain that the choice of review distribution channel is closely associated with extreme reviews, and reviewers with extreme experiences are more likely to choose the mobile review distribution channel. In summary, based on the empirical results from Tables 5 to 11, the launch of a mobile channel tends to have a significant influence on the choice of review distribution channel but is less likely to have causal impacts on the valence and variance of online reviews, supporting the *usability argument*.

5.4 Robustness Check

For the robustness check, we expand the upper and lower percentages considered for positive and negative review ratios; now, the upper 20% of the customer review ratings are considered positive, while the lower 20% are considered negative. Therefore, reviews equal to or below 6 are regarded as negative reviews, and those with a rating of 9.6 and above are regarded as positive reviews. In Table 12, we test whether the presence of a mobile channel increases negative review posting. Similar to the empirical findings in Table 7, the estimated coefficients across all models are all insignificant, showing that the mobile channel launch did not affect the differences in the valence and variance of reviews following the mobile channel launch ($\beta_{\text{Treatment*Post}}$=-.00, *p-value*>0.05).

[Insert Table 12 About here]

Similar results are also found for positive review posting. Table 13 shows whether the presence of a mobile channel increases the positive review posting. Similar to the empirical findings in Table 8, the launch of a mobile channel did not affect positive review posting behavior ($\beta_{Treatment*Post}$=.01, *p-value*>0.05). However, we can conclude that there was a change in the review posting trend around the period of the mobile channel launch. This is because the estimated coefficients for *"Post"* are statistically significant (β_{Post}=-.02, *p-value*<0.05 in Table 12, β_{Post}=.02, *p-value*<0.05 in Table 13). However, the launch of a mobile channel did not affect review posting beyond the review posting trend.

[Insert Table 13 About here]

In Table 14, we investigate the difference in extreme review posting behavior between mobile and non-mobile devices after the launch of mobile channels. In this robustness check, we define the key independent variables, positive and negative reviews, as the upper and lower 20% of the customer review ratings. The empirical results also confirm that the review distribution channel choice is associated with extreme reviews. The reviewers who post negative reviews ($\beta_{Negative\ Review}$=.16, *p-value*<0.01) or positive reviews for hotel services are also more likely to use mobile devices ($\beta_{Positive\ Review}$=.22, *p-value*<0.01).

[Insert Table 14 About here]

Based on the empirical results from Table 5 to Table 14, we reach the conclusion that, unlike the generally admitted assumption of prior literature (Burtch and Hong, 2014; Ransbotham et al., 2019), the launch of mobile channels did not affect the distribution pattern of reviews in terms of review volume, valence, and variance. However, the launch of the new distribution channel is associated with device choice. Both satisfied and dissatisfied reviewers are more likely to choose to use mobile devices to post reviews.

6. Discussion

One common expectation in integrating mobile channels to generate and distribute eWOM is that the utilization of mobile channels would bring positive outcomes including increased review volume because of the consumers' enhanced accessibility to information channels (Burtch et al., 2018; Mayzlin et al., 2014). Consequently, a growing number of studies is exploring the characteristics and impacts of mobile eWOM (Grewal and Stephen, 2019; Kim et al., 2020; Mariani et al., 2019; Ransbotham et al., 2019; Zhu et al., 2020).

The findings of this study are contrary to such expectations. Our empirical results reveal instead that the introduction of mobile devices as a new form of online review channel does not necessarily expand the market size of the mobile platform in terms of review volume or change the dispersion and/or distribution patterns of online reviews, in terms of the average review ratings and extreme review posting. One possible reason behind such a phenomenon could be that the past predictions of the impact of the mobile channel integration are mainly focused on the assumption of enhanced accessibility (Burtch et al., 2018; Mayzlin et al., 2014). If consumers are solely influenced by the benefit of mobile devices which allow them to post online reviews regardless of time and space, then the generated online reviews should exhibit positive shifts in both volume and dispersion because more consumers can post reviews without having to find a desktop device or PC. However, our analysis results indicate that the enhanced accessibility may not be the only source of influence driving the shift brought by the mobile channel launch. Indeed, the limited usability of the mobile devices due to small display sizes may deter consumers from actively posting reviews using their mobile devices, countering the effect of mobile devices' enhanced accessibility. A recent study also showed that providing review posters with the ease of logging on through social network interface systems (SNISs) turns out to be ineffective in increasing the number of reviews (Kim and Hyun, 2021), thus reinforcing the findings of our study.

For this investigation, we have examined the sole impact of mobile channel introduction while controlling the time trend in review posting as well as the potential changes in the firm's service quality. The utilization of an identification strategy based on DID models that use the differences across the times when the mobile channel was introduced allowed us to isolate and examine the causal impacts of the mobile channel launch. The review data for the firms (i.e., hotels) registered on two different review platforms were innovatively selected and analyzed as the "matched" data set. This approach is particularly useful for controlling the time trend in review posting, as well as the change in hotel service quality, while isolating the causal impacts of the mobile channel launch.

Our findings also indicate that while the volume and the dispersion of the generated online reviews do not exhibit significant shifts following the mobile channel launch, the frequency of mobile channel usage increases, especially among the reviewers who are either very satisfied or very dissatisfied with the services reviewed. Such a pattern indicates that those with a stronger attitude are more motivated to seek ways through which they can quickly express their thoughts. This is consistent with past studies on WOM (e.g., Anderson, 1998; Hennig-Thurau et al., 2004) that have shown that customers with stronger satisfaction are more likely to express their opinions and generate WOM.

To summarize, our findings suggest that the launch of mobile channels in the online eWOM context does not necessarily bring about significant shifts in the generation of online reviews – in the guise of online review volume and distributions of average online review ratings and extreme review posting – despite the benefits associated with the use of mobile devices.

6.1 Theoretical Contributions and Implications

Prior literature primarily focused on the usefulness of mobile devices as a tool for satisfying customer needs (Hsieh, 2020; Picoto et al., 2019). Hsieh (2020) showed that location-based mobile services could help industry practitioners to improve the effectiveness of marketing promotions. Picoto et al. (2019) explored what kinds of factors would affect the ranking of mobile apps. Differently from prior literature, we focus on how the characteristics of mobile devices, such as accessibility and usability, would affect device-dependent information generation behavior. Accordingly, this research makes several distinctive theoretical contributions to extant eWOM literature. First, we offer insights regarding the effectiveness of mobile channels on online review posting. While previous literature revolving around eWOM has examined the differences in customer reviews posted via mobile vs. non-mobile devices (e.g., Mariani et al., 2019), there is limited literature investigating whether mobile channels indeed have a causal influence on the volume, valence, or the variance of customer reviews. Our research adds to the extant body of eWOM literature by providing a comprehensive analysis of the influences that mobile channels have on online review posting, thus extending previous studies that have only descriptively compared mobile and non-mobile eWOM (e.g., Mariani et al., 2019).

Second, by discovering that mobile devices as review distribution channels do not expand the market size of the mobile platform in terms of review volume, do not change the distribution patterns of online reviews, and are more likely associated with extreme online ratings, we inform and extend the emerging research stream on mobile eWOM (Grewal and Stephen, 2019; Kim et al., 2020; Mariani et al., 2019; Ransbotham et al., 2019; Zhu et al., 2020).

Third, by employing an identification strategy based on DID models that use the differences across the times when the mobile channel was introduced, this study is able to examine the sole impact of mobile channel launch while controlling the time trend in review posting as well as the possible changes in firms' service quality. This approach is particularly useful for controlling the time trend in review posting, as well as the change in hospitality firms' service quality, while isolating the causal impacts of the mobile channel launch. Consequently, this approach can be applied further to other industries that are adopting mobile channels as a part of their review distribution channels to test the direct causal impact of a mobile channel launch. As such, this work is to the best of our knowledge the first contributing causal explanations in the emerging research stream on mobile eWOM (Grewal and Stephen, 2019; Kim et al., 2020; Ransbotham et al., 2019; Zhu et al., 2020).

Fourth, we extend the extant mobile eWOM literature by showing that the mobile channels do not influence online reviews in either volume, valence, or variance, findings that are contrary to what previous mobile eWOM literature had assumed (Mariani et al., 2019; Ransbotham et al., 2019). Previous studies have found that mobile channels spark changes to individuals' behavioral intention and actual behaviors because of increased accessibility and ease of communication (Dwivedi et al., 2016; Ghose and Han, 2011; Lurie et al., 2018; Mishra et al., 2021; Shareef et al., 2018). Mobile channels reduce the psychological barriers that individuals may have about generating online reviews, causing the assumption that more individuals would be motivated to provide reviews, and thus resulting in a greater number of reviews, which is not supported by our results. However, this does not imply that mobile channels do not provide individuals with enhanced accessibility or ease of communication. If the enhanced accessibility or ease of communication brought about by a mobile channel is not sufficient to motivate prospective reviewers to compose reviews, the launch of mobile channels might not drive any changes in the distributions.

Last, our findings illustrate that the mobile channels' increased accessibility acts as a motivational driver that influences the decision of "how" to generate reviews rather than "whether" to do so at all. In fact, much of the prior literature that had attempted to define the antecedents of eWOM has been consistent in that scholars define individuals' motivation or needs (such as the need for self-enhancement or need for social interaction) as the key drivers that increase the behavioral intention to post reviews (Bond et al., 2019; Cheung and Lee, 2012; King et al., 2014). These studies suggest that the intention to post reviews and share and express one's thoughts online are driven by motivational factors that underlie individuals' psychological processes. However, accessibility or the ease of communication from using mobile channels is more relevant to how easy or difficult it is to take action. In other words, we can infer that the mobile channel induces behavioral changes among individuals who already have the intention to post reviews, but not among those with limited or low intention.

6.2 Implications for Practice

The findings of our research collectively contribute to advance the practice of digital marketing (Dwivedi et al., 2020, 2021) and offer important managerial insights and implications to business practitioners, especially those in charge of running and managing online review platforms. First, online review platform managers need to understand that increasing the ease of communication by introducing mobile channels for eWOM might not be sufficient to increase customer review volume and create the added business value they hope for. Consequently, when they develop a new customer review program to generate a greater number of customer reviews, it might be more effective if they provide those who post via mobile channels with direct benefits, like financial incentives in the guise of price discounts or coupons, to improve intention to post.

Second, our findings suggest that the mobile channel may not be an effective way to attract prospective reviewers to share their experiences online. Considering the finding that online reviews posted via mobile devices tend to be shorter in length compared to those from non-mobile devices (Burtch and Hong, 2014), we can further infer that mobile channels have a limited business value from the perspective of encouraging reviewers to generate longer reviews in larger volumes. Accordingly, platform managers should engage in cost/benefit evaluations before launching a mobile channel.

Third, based on our findings that customers with extreme experiences are more likely to use mobile channels than non-mobile channels, we suggest that review platform managers be aware that reviews generated from mobile devices might suffer from more severe under-reporting biases (Hong et al., 2016). Accordingly, managers could shape mechanisms that make extreme reviews written using mobile channels even more visible for consumers.

Fourth, while some business practitioners for a few years have claimed that the "mobile mind shift" (Schadler et al., 2014) is a key consumer trend to ride, they have not sufficiently stressed that businesses need to undertake a careful assessment of the actual benefits attached to adapting to a mobile mind shift. Therefore, we encourage not only platform managers but also product and brand marketers to prioritize their objectives in the choice of the channels when it comes to online review generation.

Fifth and last, because incorporating mobile platforms into an existing business model requires a significant commitment of both human and financial resources (Mariani and Wamba, 2020), it is imperative that platform managers understand that mobile channels might not be the panacea for all business problems and that they might not always benefit the firm.

6.3 Limitations and Future Research Direction

Our research has limitations that need to be addressed in future research. First, we used online review data collected from two online travel agencies, both of which are in the form of observational data. However, there still remain unobservable factors which might have meaningful influences on the findings of our study in line with other studies that have used online reviews (Meek et al., 2021; Tang, 2017; Xu, 2020). Furthermore, due to the limitations of using observational data, we are unable to explain why the mobile channel is unable to attract new reviewers to share their experiences online even with its improved ease of communication. We need to further investigate how mobile channels influence consumers' review generation behaviors and the underlying psychological process that drives this relationship. Thus, to further explain our findings and explicate the underlying mechanism, future research could incorporate a survey-based approach conjointly with an experimental approach – comparing reviewers using mobile vs. non-mobile devices – to explore how reviewers perceive mobile channels. In addition, qualitative research in the form of in-depth interviews or focus group interviews could help future researchers to capture online reviewers' perceptions of review generation based on the submission devices that they use. Future research might also consider analyzing multiple services, not only confined to hotel services, but also covering restaurant services which are significantly reviewed, especially through TripAdvisor.

Second, according to our findings, there is a relationship between a review distribution channel choice and extreme review posting. However, reviewers could encounter a selection bias when choosing a device due to factors like Internet speed. This selection issue with channel choice might potentially bias our results. One of the possible ways to overcome the selection issue is to use randomized experiments to control for selection bias in device choice. This is connected to the third limitation.

Third, even though mobile channels have been proven to have no causal influences on the valence and variance of reviews, the launch of a mobile channel could have differential influences depending on the characteristics of reviewer segments. For instance, reviewers who primarily use mobile devices daily could be differently affected by the launch of mobile channels from those who use both mobile and non-mobile devices equally throughout the day. In this case, the launch of mobile channels could have differential influences on their review posting behaviors.

Last, in this study, we use the online review data from the hotel industries. The use of the DID approach would allow us to control for the potential impacts of extraneous variables while solely testing the causal impact of the mobile channel launch. However, to increase the generalizability of our findings, it would be important to validate them in the future using more data from other hotels in other regions, as well as data from other industries.

7. Conclusion

In conclusion, this work illustrates that mobile channels' increased accessibility acts as a motivational driver supporting the decision of "how" to generate reviews rather than "whether" to do so at all. This extends theoretically prior eWOM literature that had mainly identified individuals' motivation or needs as key drivers of behavioral intention to post reviews. Our findings suggest that in addition to motivational factors, accessibility or the ease of communication inherent in mobile channels can induce behavioral changes among individuals who already have the intention to post reviews, but not among those with limited or low intention. Managers and practitioners, especially those in charge of running and managing online review platforms, can use the insights stemming from this study to support their decisions in relation to enhancing online review generation through mobile channels and devices. It is our hope that our study might inspire further research on the interplay between (the introduction of) mobile channels and online review generation.

REFERENCES

Adipat, B., Zhang, D., and Zhou, L. (2011). The Effects of Tree-View Based Presentation Adaptation on Mobile Web Browsing. *MIS Quarterly, 35*(1), 99-121.

Ahn, D., Park, H., and Yoo, B. (2017). Which Group Do You Want to Travel With? A Study of Rating Differences Among Groups in Online Travel Reviews. *Electronic Commerce Research and Applications, 25*(September-October), 105-114.

Akter, S., Hossain, M.I., Lu, S., Aditya, S., Hossain, T.M.T., and Kattiyapornpong, U. (2019). Does Service Quality Perception in Omnichannel Retailing Matter? A Systematic Review and Agenda for Future Research. In: Piotrowicz, W. and Cuthbertson, R. (eds). *Exploring Omnichannel Retailing*. Springer, Cham. https://doi.org/10.1007/978-3-319-98273-1_4

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

Baabdullah, A.M., Rana, N.P., Alalwan, A.A., Islam, R., Patil, P., and Dwivedi, Y.K. (2019). Consumer Adoption of Self-Service Technologies in the Context of the Jordanian Banking Industry: Examining the Moderating Role of Channel Types. *Information Systems Management, 36*(4), 286-305.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How Much Should We Trust Differences-in-Differences Estimates? *The Quarterly Journal of Economics, 119*(1), 249–275.

Bond, S., He, S., and Wen, W. (2019). Speaking for "Free": Word of Mouth in Free- and Paid-Product Settings. *Journal of Marketing Research, 56*(2), 276-290.

Borghi, M., & Mariani, M. M. (2021). Service robots in online reviews: Online robotic discourse. *Annals of Tourism Research*, 87(C).

Burtch, G. and Hong, Y. (2014). What Happens When Word of Mouth Goes Mobile? *Proceedings of the International Conference on Information Systems*, Auckland, New Zealand. Available at SSRN: https://ssrn.com/abstract=2519931

Cabral, L. and Li, L. (2015). A Dollar for Your Thoughts: Feedback Conditional Rebates on eBay. *Management Science, 61*(9), 2052-2063.

Cai, H., Chen, Y., and Fang, H. (2009). Observational Learning: Evidence from a Randomized Natural Field Experiment. *American Economic Review, 99*(3), 864-882.

Chae, M. and Kim, J. (2004). Do Size and Structure Matter to Mobile Users? An Empirical Study of the Effects of Screen Size, Information Structure, and Task Complexity on User Activities with Standard Web Phones. *Behaviour & Information Technology, 23(*3), 165-181.

Cheung, C. and Lee, M. (2012). What Drives Consumers to Spread Electronic Word of Mouth in Online Consumer-Opinion Platforms. *Decision Support Systems, 53*(1), 218-225.

Chevalier, J., Dover, Y., and Mayzlin, D. (2018). Channels of Impact: User Reviews When Quality is Dynamic and Managers Respond. *Marketing Science, 37*(5), 688-709.

Chevalier, J. and Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research, 43*(3), 345-354.

Chin, E., Felt, A., Sekar, V., and Wagner, D. (2012). Measuring User Confidence in Smartphone Security and Privacy. *SOUPS'12: Proceedings of the Eighth Symposium on Usable Privacy and Security*. Washington, DC, USA.

Chu, J., Arce-Urriza, M., Cebollada-Calvo, J.J., and Chintagunta, P.K. (2010). An Empirical Analysis of Shopping Behavior Across Online and Offline Channels for Grocery Products: The Moderating Effects of Household and Product Characteristics. *Journal of Interactive Marketing, 24*(4), 251-268.

De Haan, E., Kannan, P.K., Verhoef, P., and Wiesel, T. (2018). Device Switching in Online Purchasing: Examining the Strategic Contingencies. *Journal of Marketing, 82*(5), 1-19.

De Matos, C.A. and Rossi, C.A.V. (2008). Word-of-Mouth Communications in Marketing: A Meta-Analytic Review of the Antecedents and Moderators. *Journal of the Academy of Marketing Science, 36*(4), 578-596.

Dellarocas, C. (2003). The Digitization of Word-of-Mouth: Promise and Challenges of Online Feedback. *Management Science, 49*(10), 1407-1424.

Dellarocas, C., Zhang, X., and Awad, N. (2007). Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures. *Journal of Interactive Marketing, 21*(4), 23-45.

Dhar, V. and Chang, E. (2009). Does Chatter Matter? The Impact of User-Generated Content on Music Sales. *Journal of Interactive Marketing, 23*(4), 300-307.

Duflo, E. and Saez, E. (2002). Participation and Investment Decisions in a Retirement Plan: The Influence of Colleagues' Choices. *Journal of Public Economics, 85*(1), 121-148.

Dwivedi, Y.K., Ismagilova, E. et al. (2021). Setting the Future of Digital and Social Media Marketing Research: Perspectives and Research Propositions. *International Journal of Information Management,* 102168. https://doi.org/10.1016/j.ijinfomgt.2020.102168.

Dwivedi, Y.K., Rana, N.P., Slade, E.L., Singh, N., and Kizgin, H. (2020). Editorial Introduction: Advances in Theory and Practice of Digital Marketing. *Journal of Retailing and Consumer Services, 53*(March), 101909.

Dwivedi, Y.K., Shareef, M.A., Simintiras, A.C., Lal, B., and Weerakkody, V. (2016). A Generalised Adoption Model for Services: A Cross-Country Comparison of Mobile Health (M-Health), *Government Information Quarterly*, *33*(1), 174-187.

Ek Styvén, M., & Mariani, M. M. (2020). Understanding the intention to buy secondhand clothing on sharing economy platforms: The influence of sustainability, distance from the consumption system, and economic motivations. *Psychology & Marketing*, 37(5), 724-739.

Fan, Y.W. and Miao, Y.F. (2012). Effect of Electronic Word-of-Mouth on Consumer Purchase

Intention: The Perspective of Gender Differences. *International Journal of Electronic Business Management, 10*(3), 175-181.

Flammer, C. (2015). Does Product Market Competition Foster Corporate Social Responsibility? Evidence from Trade Liberalization. *Strategic Management Journal, 36*(10), 1469-1485.

Fredriksson, A. and Oliveira, G.M.d. (2019). Impact Evaluation Using Difference-in-Differences. *RAUSP Management Journal, 54*(4), 519-532.

Ghose, A. and Han, S.P. (2011). An Empirical Analysis of User Content Generation and Usage Behavior on the Mobile Internet. *Management Science, 57*(9), 1671-1691.

Gligorijevic, B. (2016). Review Platforms in Destinations and Hospitality. In: R. Egger, R., Gula, I., and Walcher, D. (eds). *Open Tourism*. Springer Berlin Heidelberg, 215-228.

Grewal, L. and Stephen, A.T. (2019). In mobile we trust: The Effects of Mobile Versus Nonmobile Reviews on Consumer Purchase Intentions. *Journal of Marketing Research, 56*(5), 791-808.

Gruen, T., Osmonbekov, T., and Czaplewski, A. (2006). EWOM: The Impact of Customer-to-Customer Online Know-how Exchange on Customer Value and Loyalty. *Journal of Business Research, 59*(4), 449-456.

Hennig-Thurau, T., Gwinner, K., Walsh, G., and Gremler, D. (2004). Electronic Word-of-Mouth Via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on the Internet? *Journal of Interactive Marketing, 18*(1), 38-52.

Hong, Y., Huang, N., Burtch, G., and Li, C. (2016). Culture, Conformity and Emotional Suppression in Online Reviews. *Journal of the Association for Information Systems, 17*(11), 737-758.

Hsieh, J.K. (2020). The Effects of Transforming Mobile Services into Mobile Promotions. *Journal of Business Research, 121*, 195-208.

Kim, J., Han, J., and Jun, M. (2020). Differences in Mobile and Nonmobile Reviews: The Role of Perceived Costs in Review-Posting. *International Journal of Electronic Commerce, 24*(4), 450-473.

Kim, J.M. and Hyun, S. (2021). Differences in Online Reviews Caused by Distribution Channels. *Tourism Management, 83*(April), 104230.

King, R., Racherla, P., and Bush, V. (2014). What We Know and Don't Know About Online Word-of-Mouth: A Review and Synthesis of the Literature. *Journal of Interactive Marketing, 28*(3), 167-183.

Lee, S., Lee, S., and Baek, H. (2021). Does the Dispersion of Online Review Ratings Affect Review Helpfulness? *Computers in Human Behavior, 117*(April), 106670.

Lurie, N.H., Berger, J., Chen, Z., Li, B., Liu, H., Mason, C.H., Muir, D.M., Packard, G., Pancras, J., Schlosser, A.E., Sun, B., and Venkatesan, R. (2018). Everywhere and at All Times: Mobility, Consumer Decision-Making, and Choice. *Customer Needs and Solutions, 5*, 15-27.

Mariani, M. and Borghi, M. (2018). Effects of the Booking.com Rating System: Bringing Hotel Class into the Picture. *Tourism Management, 66*(June), 47-52.

Mariani, M. and Borghi, M. (2021a). Are Environmental-Related Online Reviews More Helpful? A Big Data Analytics Approach. *International Journal of Contemporary Hospitality Management,* Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/IJCHM-06-2020-0548

Mariani, M. and Borghi, M. (2021b). Environmental Discourse in Hotel Online Reviews: A Big Data Analysis. *Journal of Sustainable Tourism, 29*(5), 829-848.

Mariani, M., Borghi, M., and Gretzel, U. (2019). Online Reviews: Differences by Submission Device. *Tourism Management, 70*(February), 295-298.

Mariani, M. M., Borghi, M., & Okumus, F. (2020). Unravelling the effects of cultural differences in the online appraisal of hospitality and tourism services. *International Journal of Hospitality Management*, 90, 102606.

Mariani, M. M., & Matarazzo, M. (2020). Does cultural distance affect online review ratings? Measuring international customers' satisfaction with services leveraging digital platforms and big data. *Journal of Management and Governance*, 1-22.

Mariani, M. M., & Visani, F. (2019). Embedding eWOM into efficiency DEA modelling: An application to the hospitality sector. *International Journal of Hospitality Management*, 80, 1-12.

Mariani, M. M., & Wamba, S. F. (2020). Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies. *Journal of Business Research*, 121, 338-352.

Martin, J., Barron, G., and Norton, M.I. (2007). Choosing to be Uncertain: Preferences for High-Variance Experiences. *Working Paper*, *Harvard Business School*, Boston.

Mayzlin, D., Dover, Y., and Chevalier, J. (2014). Promotional reviews: An Empirical Investigation of Online Review Manipulation. *The American Economic Review, 104(*8), 2421-2455.

Mazursky, D. and Geva, A. (1989). Temporal Decay in Satisfaction – Purchase Intention Relationship. *Psychology & Marketing, 6(*3), 211-227.

Meek, S., Wilk, V., and Lambert, C. (2021). A Big Data Exploration of the Informational and Normative Influences on the Helpfulness of Online Restaurant Reviews. *Journal of Business Research, 125*(March), 354-367.

Mellinas, J.P. and Martin-Fuentes, E. (2021). Effects of Booking.com's New Scoring System. *Tourism Management, 85*, 104280.

Mishra, A., Shukla, A., Rana, N.P., and Dwivedi, Y.K. (2021). From "Touch" to a "Multisensory" Experience: The Impact of Technology Interface and Product Type on Consumer Responses. *Psychology and Marketing, 38*(3), 385-396.

Okazaki, S. (2009). The Tactical Use of Mobile Marketing: How Adolescents' Social Networking Can Best Shape Brand Extensions. *Journal of Advertising Research, 49*(1), 12-26.

Picoto, W.N., Duarte, R., and Pinto, I. (2019). Uncovering Top-Ranking Factors for Mobile Apps Through a Multimethod Approach. *Journal of Business Research, 101*, 668-674.

Ransbotham, S., Lurie, N., and Liu, H. (2019). Creation and Consumption of Mobile Word-of-Mouth: How Are Mobile Reviews Different? *Marketing Science, 38*(5), 773-792.

Rosario, A.B., De Valck, K., and Sotgiu, F. (2020). Conceptualizing the Electronic Word-of-Mouth Process: What We Know and Need to Know About eWOM Creation, Exposure, and Evaluation. *Journal of the Academy of Marketing Science, 48*, 422-448.

Rosario, A., Sotgiu, F., De Valck, K., and Bijmolt, T. (2016). The Effect of Electronic Word of Mouth on Sales: A Meta-Analytic Review of Platform, Product, and Metric Factors. *Journal of Marketing Research, 53*(3), 297-318.

Salganik, M., Dodds, P., and Watts, D. (2006). Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market. *Science, 311*(5762), 854-856.

See-To, E. and Ho, K. (2014). Value Co-Creation and Purchase Intention in Social Network Sites: The Role of Electronic Word-of-Mouth and Trust – A Theoretical Analysis. *Computers in Human Behavior, 31*(February), 182-189.

Schadler, T., Bernoff, J., and Ask, J. (2014). *The Mobile Mind Shift: Engineer Your Business to Win in the Mobile Moment*. Greenleaf Book Group.

Schonfeld, E. (2011). Yelp Brings Local Deals to Mobile and Gives Groupon Now a Run for its Money. TechCrunch, retrieved 11.05.2021. https://techcrunch.com/2011/06/29/yelp-deals-mobile-groupon/

Shankar, V., Venkatesh, A., Hofacker, C., and Naik, P. (2010). Mobile Marketing in the Retailing Environment: Current Insights and Future Research Avenues. *Journal of Interactive Marketing, 24*(2), 111-120.

Shareef, M.A., Baabdullah, A., Dutta, S., Kumar, V., and Dwivedi, Y.K. (2018). Consumer Adoption of Mobile Banking Services: An Empirical Examination of Factors According to Adoption Stages. *Journal of Retailing and Consumer Services, 43*(July), 54-67.

Sridhar, S. and Srinivasan, R. (2012). Social Influence Effects in Online Product Ratings. *Journal of Marketing, 76*(5), 70-88.

Tang, L. (2017). Mine Your Customers or Mine Your Business: The Moderating Role of Culture in Online Word-of-Mouth Reviews. *Journal of International Marketing, 25*(2), 88-110.

Wang, D., Xiang, Z., Law, R., and Ki, T.P. (2016). Assessing Hotel-Related Smartphone Apps Using Online Reviews. *Journal of Hospitality Marketing & Management, 25*(3), 291-313.

Wu, C., Che, H., Chan, T.Y., and Lu, X. (2015). The Economic Value of Online Reviews. *Marketing Science, 34*(5), 739-754.

Xu, X. (2020). Examining an Asymmetric Effect Between Online Customer Reviews

Emphasis and Overall Satisfaction Determinants. *Journal of Business Research, 106*(January), 196-210.

Ye, Q., Law, R., and Gu, B. (2009). The Impact of Online User Reviews on Hotel Room Sales. *International Journal of Hospitality Management, 28*(1), 180-182.

Zhu, D.H., Deng, Z.Z., and Chang, Y.P. (2020). Understanding the Influence of Submission Devices on Online Consumer Reviews: A Comparison Between Smartphones and PCs. *Journal of Retailing and Consumer Services, 54*, 102028.

Zhu, F. and Zhang, X. (2010). Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics. *Journal of Marketing, 74(*2), 133-148.

Zhu, D., Zhang, Z., Chang, Y.P., and Liang, S. (2019). Good Discounts Earn Good Reviews in Return? Effects of Price Promotion on Online Restaurant Reviews. *International Journal of Hospitality Management, 77*(January), 178-186.

Zwick, D., Bonsu, S.K., and Darmody, A. (2008). Putting Consumers to Work: ‘Co-Creation’ and New Marketing Govern-Mentality. *Journal of Consumer Culture, 8*(2), 163-196.

Figure 1. Online review screenshot from TripAdvisor.com

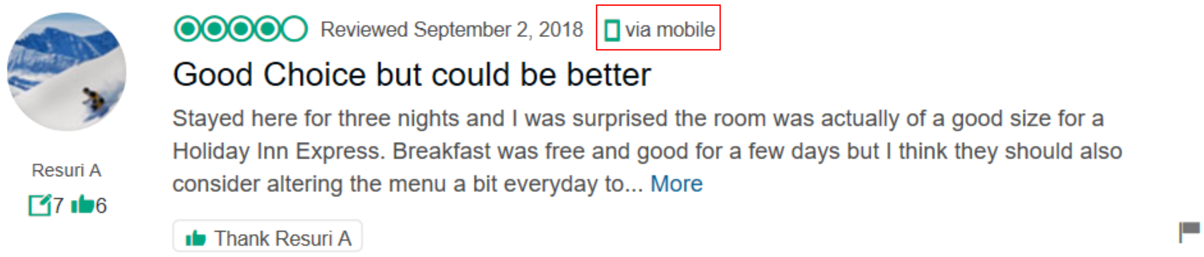

Figure 2. Online review screenshot from Booking.com

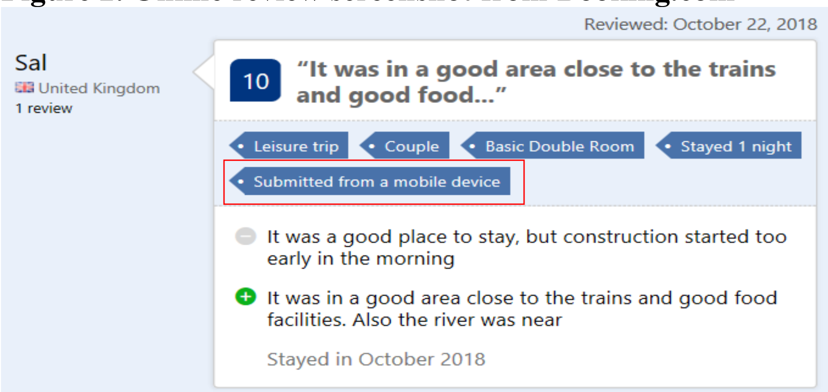

Figure 3. Timeline of the research development and evolution of mobile channels for the focal online review platforms

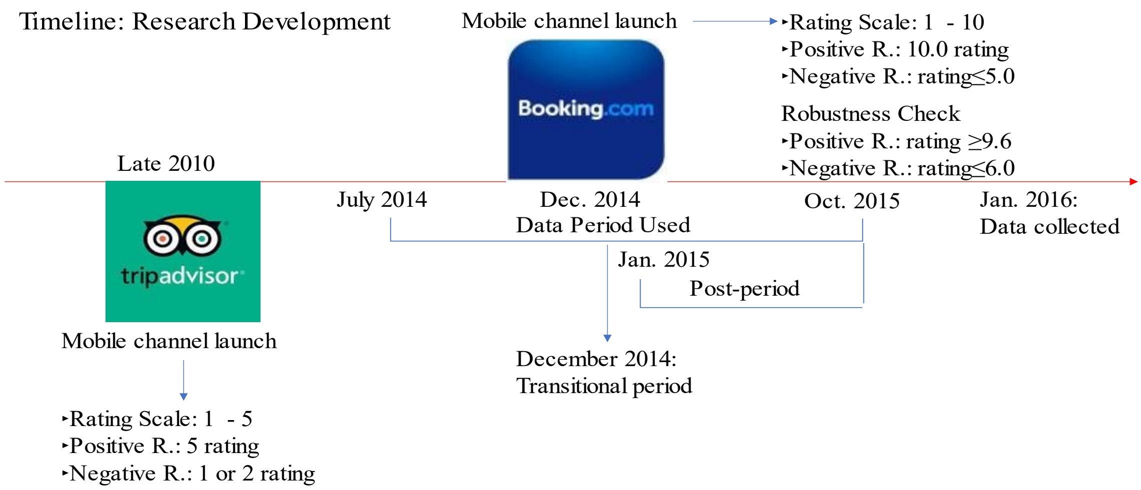

Table 1. Definitions of dependent variables

Variables	Description (i = the subscript for the hotel, g = group, t = the month)
Number of customer reviews $(NCR)_{igt}$	The cumulative number of customer reviews measured on the last day of the month (t) for the hotel (i) in the group (g).
average review ratings $(ARR)_{igt}$	The cumulative average review ratings measured on the last day of the month (t) for the hotel (i) in the group (g).
negative review ratio $(NRR)_{igt}$	The cumulative number of negative reviews divided by the total number of reviews in the month (t) for the hotel (i) in the group (g).
positive review ratio $(PRR)_{igt}$	The cumulative number of positive reviews divided by the total number of reviews in the month (t) for the hotel (i) in the group (g).

Table 2. Definitions of positive and negative reviews

Variables	Empirical Results		Robustness Check
	TripAdvisor.com	Booking.com	Booking.com
Treatment group	No	Yes	Yes
Control group	Yes	No	No
Review rating range	1.0–5.0	1.0–10.0	1.0–10.0
Positive Review	Rating=5	Rating=10.0	Rating≥9.6
Negative Review	Rating≤2	Rating≤5.0	Rating≤6.0

Table 3. Summary statistics of the matched hotels

Variable	Description (i = the subscript for the hotel, t = the month)	Mean	S.D.	Min	Max
$\log(NCR_{i1t})$	Log-transformed number of customer reviews on Booking.com	3.62	.85	.69	5.94
$\log(NCR_{i0t})$	Log-transformed number of customer reviews on TripAdvisor.com	2.02	.94	.69	5.17
ARR_{i1t}	Average rating of customer reviews on Booking.com	3.71	.50	1.25	5
ARR_{i0t}	Average rating of customer reviews on TripAdvisor.com	3.44	.99	1	5
NRR_{i1t}	Negative review ratio of customer reviews on Booking.com	.05	.08	0	1
NRR_{i0t}	Negative review ratio of customer reviews on TripAdvisor.com	.23	.31	0	1
PRR_{i1t}	Positive review ratio of customer reviews on Booking.com	.09	.09	0	1
PRR_{i0t}	Positive review ratio of customer reviews on TripAdvisor.com	.25	.26	0	1

Table 4. Model-free comparison

Variable	(1) Before Mobile App. launch	(2) After Mobile App. launch	(3) Difference (2)–(1)	(4) *t-value*	(5) *p-value*
$\log(NCR_{i1})$	3.61	3.63	.02	.54	.58
ARR_{i1}	3.64	3.75	.11	7.08	.00
NRR_{i1}	.15	.13	-.02	-4.53	.00
PRR_{i1}	.07	.09	.02	7.89	.00

Table 5. Does the presence of a mobile channel raise the volume of customer reviews?

Dependent Variable	$\log(NCR_{it})$ (1)	$\log(NCR_{it})$ (2)	$\log(NCR_{it})$ (3)
Treatment*Post	-.01 (.04)	-.01 (.02)	-.01 (.02)
Treatment	1.61*** (.03)	1.61*** (.05)	1.61*** (.05)
Post	.08*** (.03)	.08*** (.02)	.09*** (0.1)
Time Dummy	Yes	Yes	Yes
Hotel FE	No	No	Yes
Cluster-robust standard errors (hotel level)	No	Yes	Yes
R-Squared	44.43%	44.43%	65.36%
Observations	9,000	9,000	9,000

<0.05 and *<0.01

Table 6. Does the presence of a mobile channel raise average customer review ratings?

Dependent Variable	$\log(ARR_{it})$ (1)	$\log(ARR_{it})$ (2)	$\log(ARR_{it})$ (3)
Treatment*Post	-.00 (.03)	-.00 (0.02)	-.00 (.02)
Treatment	.26*** (.03)	.26*** (.02)	.26*** (.02)
Post	.08** (.03)	.08*** (.03)	.07*** (.02)
Time Dummy	Yes	Yes	Yes
Hotel FE	No	No	Yes
Cluster-robust standard errors (hotel level)	No	Yes	Yes
R-Squared	3.65%	3.65%	8.31%
Observations	9,000	9,000	9,000

<0.05 and *<0.01

Table 7. Does the presence of a mobile channel raise the negative review ratio?

Dependent Variable	log(NRR_{it}) (1)	log(NRR_{it}) (2)	log(NRR_{it}) (3)
Treatment*Post	.01 (.01)	.01 (.01)	.01 (.01)
Treatment	-.10*** (.01)	-.10** (.01)	-.10*** (.01)
Post	-.02** (0.01)	-.02*** (.01)	-.02*** (.01)
Time Dummy	Yes	Yes	Yes
Hotel FE	No	No	Yes
Cluster-robust standard errors (hotel level)	No	Yes	Yes
R-Squared	4.70%	4.70%	8.60%
Observations	9,000	9,000	9,000

<0.05 and *<0.01

Table 8. Does the presence of a mobile channel raise the positive review ratio?

Dependent Variable	log(PRR_{it}) Model 1_1	log(PRR_{it}) Model 1_2	log(PRR_{it}) Model 1_3
Treatment*Post	-.00 (.01)	-.00 (.01)	-.00 (.01)
Treatment	-.16*** (.01)	-.16*** (.01)	-.16*** (.01)
Post	.02*** (.00)	.02*** (.00)	.01** (.00)
Time Dummy	Yes	Yes	Yes
Hotel FE	No	No	Yes
Cluster-robust standard errors (hotel level)	No	Yes	Yes
R-Squared	14.85%	14.85%	21.58%
Observations	9,000	9,000	9,000

<0.05 and *<0.01

Table 9. Distribution of online customer reviews

Variables	Mobile Device	Non-Mobile Device
Review Score<4.0	10,224 (4.57%)	8,969 (4.15%)
4.0<=Review Score<5.0	9,620 (4.30%)	9,347 (4.32%)
5.0<=Review Score<6.0	21,014 (9.39%)	21,476 (9.92%)
6.0<=Review Score<7.0	22,371 (10.00%)	23,093 (10.68%)
7.0<=Review Score<8.0	56,171 (25.10%)	58,119 (26.87%)
8.0<=Review Score<9.0	36,493 (16.30%)	37,857 (17.50%)
9.0<=Review Score<10.0	38,583 (17.25%)	34,613 (16.00%)
Review Score=10	29,303 (13.09%)	22,850 (10.56%)
Total	223,779 (100%)	216,324 (100%)

Table 10. Review distribution channel choice with respect to negative reviews

Analysis	Logistic Analysis		Regression Analysis	
Dependent Variable	Mobile (1)	Mobile (2)	Mobile (3)	Mobile (4)
Negative Review	.08*** (.01)	.08*** (.01)	.01*** (.00)	.01*** (.00)
Hotel-Star Dummy	Yes	Yes	Yes	Yes
Trip-Type Dummy	Yes	Yes	Yes	Yes
Companion Dummy	Yes	Yes	Yes	Yes
Nationality	Yes	Yes	Yes	Yes
Room-Type Dummy	No	Yes	No	Yes
Hotel FE	Yes	Yes	Yes	Yes
Cluster-robust standard errors (hotel level)	Yes	Yes	Yes	Yes
Log-pseudo likelihood	-293923.99	-292461.17	N/A	N/A
R-Squared	N/A	N/A	4.18%	4.64%
Observations	439,978	439,572	440,034	440,034

where Mobile is a binary variable indicating whether the review is posted via a mobile device. **<0.05 and ***<0.01

Table 11. Review distribution channel choice with respect to positive reviews

Analysis	Logistic Analysis		Regression Analysis	
Dependent Variable	Mobile (1)	Mobile (2)	Mobile (3)	Mobile (4)
Positive Review	.09*** (.01)	.09*** (.01)	.02*** (.00)	.02*** (.00)
Hotel-Star Dummy	Yes	Yes	Yes	Yes
Trip-Type Dummy	Yes	Yes	Yes	Yes
Companion Dummy	Yes	Yes	Yes	Yes
Room-Type Dummy	No	Yes	No	Yes
Nationality	Yes	Yes	Yes	Yes
Hotel FE	Yes	Yes	Yes	Yes
Cluster-robust standard errors (hotel level)	Yes	Yes	Yes	Yes
Log-pseudo likelihood	-293911.71	-292459.01	N/A	N/A
R-Squared	N/A	N/A	4.19%	4.66%
Observations	439,978	439,572	440,034	440,034

where Mobile is a binary variable indicating whether the review is posted via a mobile device. **<0.05 and ***<0.01

Table 12. Does the presence of a mobile channel raise the negative review ratio?

	$\log(NRR_{it})$	$\log(NRR_{it})$	$\log(NRR_{it})$
Dependent Variable	(1)	(2)	(3)

Treatment*Post	-.00 (.01)	-.00 (.00)	-.00 (.00)
Treatment	-.01 (0.01)	-.01** (0.00)	-.01** (.00)
Post	-.02** (0.01)	-.02*** (0.01)	-.02*** (0.01)
Time Dummy	Yes	Yes	Tes
Hotel FE	No	No	Yes
Cluster-robust standard errors (hotel level)	No	Yes	Yes
R-Squared	1.00%	1.00%	1.77%
Observations	9,000	9,000	9,000

<0.05 and *<0.01

Table 13. Does the presence of a mobile channel raise the positive review ratio?

Dependent Variable	$\log(PRR_{it})$ (1)	$\log(PRR_{it})$ (2)	$\log(PRR_{it})$ (3)
Treatment*Post	.01 (.01)	.01 (.00)	.01 (.00)
Treatment	-.10*** (.00)	-.10*** (.00)	-.10*** (.00)
Post	.02** (.00)	.02*** (.00)	.01** (.00)
Time Dummy	Yes	Yes	Yes
Hotel FE	No	No	Yes
Cluster-robust standard errors (hotel level)	No	Yes	Yes
R-Squared	5.69%	5.69%	9.87%
Observations	9,000	9,000	9,000

<0.05 and *<0.01

Table 14. Review distribution channel choice with respect to positive and negative reviews

Analysis Dependent Variable	Logistic Analysis Mobile	Logistic Analysis Mobile
Negative Review	.16*** (.01)	N/A
Positive Review	N/A	.22*** (.01)
Hotel-Star Dummy	Yes	Yes
Trip-Type Dummy	Yes	Yes
Companion Dummy	Yes	Yes
Cluster-robust standard errors (hotel level)	Yes	Yes
Log-pseudo likelihood	-302555.46	-302352.66
Observations	440,103	440,103

where Mobile is a binary variable indicating whether the review is posted via a mobile device. **<0.05 and ***<0.01