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Do submission devices influence online review ratings differently across different types of platforms? A big data analysis

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ABSTRACT

Deploying big data analytical techniques to retrieve and analyze a large volume of more than 2.7 million online consumer reviews (OCRs), this work sheds light on how mobile devices used by consumers to post online reviews influence their satisfaction with services. More specifically, we conduct a multi-platform study of TripAdvisor.com and Booking.com OCRs pertaining to hotel services across eight leading tourism destination cities in the American and European continents over the period 2017–2018. By adopting multivariate regression analyses, we show that OCR ratings are positively influenced by the use of mobile devices on Booking.com. The opposite effect is observed on TripAdvisor. These asymmetric effects can be explained in light of different online review policies across the platforms analyzed. Theoretical and managerial contributions and implications for digital platforms, big data analytics, electronic word of mouth, and marketing research are examined.

1. Introduction

Driven by the development of digital technologies, the consolidation of the internet into everyday life has significantly affected internet users' behaviors, making consumers increasingly dependent on digital platforms and, more specifically, on online review platforms. The latter constitute virtual environments where consumers both produce and consume user generated content (UGC) in the guise of user generated online consumer reviews (OCRs). On the one hand, consumers motivated by the desire to help other consumers can articulate their opinions and evaluations of products and services by generating OCRs (Hennig-Thurau et al., 2004). On the other hand, consumers gather OCRs to align their wants with extant economic offerings (Dellarocas, 2003) and to minimize the risk inherent in the purchase decision-making process (Cheung and Lee, 2012). Eventually, the consumers' generation and consumption of OCRs influences the quantity and price of transactions (Boccali et al., 2022; Chevalier and Mayzlin, 2006; Mayzlin et al., 2014).

The spread of mobile technologies that has accompanied the consolidation of digital platforms is increasingly impacting how consumers generate, share, and consume information online. Indeed, consumers increasingly access the internet and OCRs via their mobile devices from anywhere and at any time (Dwivedi et al., 2020), thus further magnifying the impact that OCRs have on both consumer behavior and firm performance (Ransbotham et al., 2019). Therefore, companies are increasingly investing in mobile channels and platforms to expand their business (Li et al., 2021a, 2021b).

The confluence of the upward trends in the adoption of online review platforms and mobile technologies and the increasing business importance of mobile channels (Burtch and Hong, 2014; Chevalier et al., 2018) has recently encouraged consumer behavior researchers to investigate electronic word-of-mouth (eWOM), and to compare OCRs generated via nonmobile devices to those generated via mobile devices (Kim et al., 2020; Mariani et al., 2019; Ransbotham et al., 2019). This has led to the formation of a nascent research stream revolving around the so-called mobile eWOM (Grewal and Stephen, 2019; Kim et al., 2020; Mariani et al., 2019; Ransbotham et al., 2019; Zhu et al., 2020).

Most of the mobile eWOM work is descriptive in nature and takes into account a single platform with a specific online review policy. For instance, Mariani et al. (2019) describe differences between mobile and non-mobile reviews. They find that Booking.com online review ratings are higher for mobile than for nonmobile reviews, that nonmobile reviews are more helpful than mobile reviews and that mobile reviews are more extreme than nonmobile reviews. Kim et al. (2020) examine how the features of mobile devices affect consumer review-posting behavior on Booking.com; they specifically look at the underlying mechanism of reduced review posting costs. They find that the relative ratio of

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extremely positive and negative mobile reviews is significantly higher than that for nonmobile reviews. Ransbotham et al. (2019) examine mobile and nonmobile OCRs posted on the platform Urbanspoon and find that mobile reviews are less extreme, more concrete, and more affective. Grewal and Stephen (2019) find that mobile reviews are perceived as more helpful than nonmobile reviews because they are perceived as more effortful to write. So far, none of the studies conducted on mobile eWOM have taken into account the different types of OCR platforms. Extant research has focused on a specific type of platform – namely OCR platforms, whereby the online review policy allows customers to write reviews of any length after a verified purchase. However, in the real world, OCR platforms shape and enforce different online review policies. For instance, TripAdvisor mandates that OCRs should be at least two hundred characters long, therefore requiring more effort from online reviewers.

More generally, extant studies revolving around mobile eWOM (Grewal and Stephen, 2019; Kim et al., 2020; Mariani et al., 2019; Park et al., 2022; Ransbotham et al., 2019; Zhu et al., 2020) have failed to investigate if and to what extent the behaviors of online consumers using mobile devices are different across different types of OCR platforms. This is a relevant research gap as it allows us to dig deeply into the behavioral patterns of a growing segment of online consumers, who are increasingly targeted by OCR platform managers, developers, and digital marketing managers. As researchers have not yet addressed whether the online behaviors of consumers using mobile device differ across different types of OCR platforms (i.e., platforms embracing and enforcing different online review policies), our objective is to address the following research question: *Do submission devices influence online review ratings differently across different types of platforms?*

To address this critical question and understand the extent to which mobile eWOM differs from nonmobile eWOM across platforms adopting distinctively different online review policies, we compare the effect of the use of mobile devices on online ratings across two different platforms: an OCR platform enforcing an online review policy allowing OCRs of any length (e.g., Booking.com) vs. an OCR platform enforcing an online review policy that sets constraints in terms of length of the text. More specifically, we leverage advanced big data analysis techniques to retrieve and analyze the entire population of TripAdvisor and Booking.com OCRs that relate to hotel services in eight leading tourist destination cities on the American (Las Vegas, Miami, New York City and Orlando) and European (London, Paris, Rome and Barcelona) continents, over a long period of time. The two OCR platforms considered represent two major types of platforms: TripAdvisor enforces a policy whereby OCRs should be at least 200 characters in length; Booking.com welcomes OCRs of any length. Building on >2.7 million OCRs, this study uses multivariate regression analyses to examine the effect of the submission device on online review ratings across the two different types of platforms. Our findings reveal that online consumers' use of submission devices influences OCR ratings on Booking.com positively, while it negatively affects OCR ratings on TripAdvisor. More generally, consumers' use of mobile devices on online review platforms enforcing lenient (strict) review policies, in terms of written content length, influences OCR valence positively (negatively). These results lend support to our theory-informed hypotheses.

As such, the study contributes to a nascent research stream at the intersection of digital platforms, mobile eWOM, and big data analytics. The study unfolds as follows. In the second section, the research streams pertaining to big data analytics, eWOM, and mobile eWOM are reviewed and the two focal hypotheses formulated. The third section portrays the methods deployed. The subsequent section illustrates the key findings. In the fifth and last section, we elaborate the theoretical contributions and practical implications and present the conclusions, limitations, and future research directions.

2. Literature review and theoretical background

2.1. Digital platforms, data science, and big data analytics

Digital technologies have been recognized as major drivers of the ongoing digital revolution (Rüßmann et al., 2015) and digital platforms have been identified as the means through which novel business models are developed (UNCTAD, 2019) and value is created in the platform economy (Kenney and Zysman, 2016). Big data (BD) and analytics have been recognized as one of the technological drivers of the digital revolution and transformation of business. Beyond representing a technological paradigm per se, BD has been demarcated and conceptualized as a vast amount of data, be it structured or unstructured, which is produced at high speed as a result of technological advancements and the growth and diffusion of automation, the internet, and connected devices (George et al., 2014; Mariani et al., 2018; McAfee et al., 2012; Wamba et al., 2015).

Originally used to visualize patterns in large volumes of data (Cox and Ellsworth, 1997), BD possesses three key characteristics known by the acronym of the 3Vs: “Volume” refers to the large size of data (arguably now in the order of exabytes if not zettabytes); “Velocity” refers to the rapidity of data generation, alteration, and transmission; and “Variety” indicates that data can come in the guise of a multiplicity of forms, such as text, photos, audio, and video. Interestingly, digital BD also encompasses metadata, which describes how digital data is grouped and classified. Examples of metadata include the time stamp (i.e., the date when the digital data was created) and the geo-location (i.e., the latitude and longitude of where the data was created). Further definitional efforts have been made, resulting in the Vs of “Value”, pertaining to the series of activities conducive to insights in the form of BD analytics (BDA), and that of “Veracity”, which refers to the extent to which data are reliable and complete (Mariani and Fosso Wamba, 2020).

Over the last decade an increasing number of scientists, scholars, and practitioners have relied on BD and analytics to uncover patterns in data which can be translated into competitive business intelligence (Davenport, 2014), as well as into knowledge relevant to multiple business functions, such as marketing (Erevelles et al., 2016). More specifically, the role of data (be it structured or unstructured) and data analytics has been increasingly explored and examined in the wider marketing field (Balducci and Marinova, 2018), to shed light on online users and online consumer behaviors (Saura et al., 2019; Vanhala et al., 2020).

A large amount of digital data is produced every day by millions of consumers, both intentionally and unintentionally. While using their smartphones, social media, and apps, consumers decide *intentionally* to create and share digital content, also known as user generated content (UGC), which reflects their opinions about (and evaluation of) products, services, and experiences (Chevalier and Mayzlin, 2006; Mayzlin et al., 2014). In addition to the content posted, however, consumers also leave a digital footprint as the data of the UGC is accompanied by other metadata (e.g., timestamp, geolocation, etc.), as well as by cookies that can be used by marketers to go beyond online consumers' opinions and also capture online consumer behavior, also known as user generated behavior (UGB) (Netzer et al., 2014; Vanhala et al., 2020).

Interestingly, a number of firms, practitioners, and researchers are deploying data science techniques (Akter et al., 2019; Provost and Fawcett, 2013; Waller and Fawcett, 2013; Witten et al., 2016), such as data mining (e.g., Villarroel Ordenes et al., 2019), machine learning (e.g., Vermeer et al., 2019), text analytics (e.g., Berger et al., 2020; Humphreys and Wang, 2018), and neuro-marketing (e.g., Cascio et al., 2015), to identify consumer behavioral patterns in large volumes of data. More specifically, these techniques allow them to generate *descriptive* and *explanatory* analytics, aiding the interpretation and description of online consumers' past and present opinions and behaviors (Verhoef et al., 2016). These techniques also allow firms to generate *predictive analytics*, which can help them to seize market potential and predict the success of new products before launch (Mariani and Fosso

Wamba, 2020). Data science and analytics has therefore become a highly critical area for businesses, helping them to gain and maintain a competitive edge in terms of market intelligence; this is mirrored by the evolution of marketing research over the last decade (Chintagunta et al., 2016). The increasing incorporation of (big) data analytics into marketing practice and research is witnessed by the consolidation of marketing analytics (Wedel and Kannan, 2016) and data scientists dealing specifically with market and consumer data (Balducci and Marinova, 2018).

User generated content, in the guise of social media content, posts, and online consumer reviews, is increasingly relevant in the service industries as services, unlike goods, are intangible and unknown before consumption and require ad hoc strategic and operational marketing (Kunz and Hogreve, 2011; Lovelock and Wright, 2001). Accordingly, an increasing number of service marketing scholars are deploying analytics from UGC, not only to understand more about consumers' opinions and preferences about services, but also to generate business intelligence to improve those services (Rust and Huang, 2014). The most popular form of BD from UGC is OCRs, whose importance and function are examined in the next section.

2.2. Electronic word-of-mouth and online reviews

The development and growth of the internet, as well as of digital platforms and social media, has led to a widespread proliferation of UGC, defined as "media content created or produced by the general public, rather than paid professionals and primarily distributed on the Internet" (Daughtery et al., 2008, p. 16). One of the most prevalent forms of UGC are OCRs; OCRs enable consumers to develop, articulate, and share their opinions about goods, services, firms, and brands in online contexts (Hennig-Thurau et al., 2004). In the wider marketing domain, OCRs constitute an important constituent of the so-called electronic word-of-mouth (eWOM), which has been subsequently termed online word-of-mouth (King et al., 2014; Verma and Yadav, 2021).

Researchers in disciplines such as marketing, computer science, and information management have analyzed both drivers and outcomes of eWOM (Hennig-Thurau et al., 2004; Rosario et al., 2016), on the ground that eWOM is much more dominant than simple WOM due to its rapidity of diffusion, potential anonymity, one-to-many and many-to-many reach, convenience, lack of face-to-face interaction, and communication effectiveness (Sun et al., 2006).

As far as the drivers of eWOM are concerned, several scholars have suggested that altruism plays a key role in the generation of OCRs, as consumers are willing to share their opinions about products and services with other like-minded consumers to help them in their purchase decisions (Hennig-Thurau et al., 2004), which are otherwise often characterized by uncertainty. In this context, social influence also plays a role (Sridhar and Srinivasan, 2012). Despite the majority of relationships between online consumers can be ascribed to weak ties (Granovetter, 1973), eWOM is driven by the strength of weak ties. Moreover, as consumers engender information based on their own experiences with products and services, this information is considered more credible and trustworthy than information generated by companies' marketing departments and professional advertizers (Walsh et al., 2009).

As far as the outcomes of eWOM are concerned, researchers have focused on several characteristics of eWOM, such as valence (i.e., the ratings or scores associated with OCRs), volume (i.e., the number of OCRs), and variance (i.e., the dispersion of the ratings or scores associated with OCRs), and have tried to understand how these characteristics influence consumer behaviors and firm performance (Rosario et al., 2020). eWOM has been found to influence different stages of the consumer decision-making process (Verma and Yadav, 2021). eWOM enhances purchase intentions (e.g., Park et al., 2007) when the valence and volume – indicators of product quality and product popularity (Zhu and Zhang, 2010), respectively – are high. By affecting purchase intentions, eWOM valence and volume also influence firm performance (e.g., Rosario et al., 2016; You et al., 2015). Higher levels of OCR valence have been found to influence sales positively (Dellarocas et al., 2007). In their meta-analyses, both Floyd et al. (2014) and You et al. (2015) discovered that the higher the OCR valence, the higher the sales and firms' performance. Also, OCR volume has been generally found to affect sales positively (Dhar and Chang, 2009) so that the higher the OCR volume, the higher the sales. In one of the meta-analyses (Rosario et al., 2016), OCR volume had a stronger impact on sales than valence. Studies examining the impact of OCR variance on sales display mixed findings, with some detecting a positive (Martin et al., 2007) and some a negative (Ye et al., 2009) effect.

In sum, eWOM and its characteristics (valence, volume, and variance) have been found to affect both consumers' buying intentions and firms' performance. Therefore, it becomes increasingly important to make sense of large volumes of OCRs through big data analytical techniques. In addition to OCR valence, in this study we also focus on communication channels, such as desktop or mobile devices, which can influence OCR generation and consumption, as illustrated in the following paragraph.

2.3. Electronic word-of-mouth on mobile channels and across different types of OCR platforms

A growing number of online review platforms allow consumers to post OCRs via mobile devices and mobile channels. This is the case for independent online travel review websites, such as TripAdvisor.com, and online travel agencies (OTAs), like Booking and Expedia. This trend, which testifies to the increasing business importance of mobile channels (Burtch and Hong, 2014; Chevalier et al., 2018; Kim et al., 2021) März et al., 2017), has recently encouraged scholars and researchers interested in consumer behavior to investigate how mobile devices and channels impact consumer behaviors. Indeed, mobile devices are portable and easier to use than nonmobile devices, and therefore they are generally preferred over nonmobile devices (Ghose and Han, 2011; Okazaki, 2009) as they can be carried anywhere and anytime for communication purposes (Lurie et al., 2018; Ransbotham et al., 2019). Portability and accessibility allow users to post reviews about their experiences right away, immediately after consumption. These distinctive features of mobile devices have encouraged researchers to examine consumers' eWOM and to compare OCRs generated via nonmobile devices with OCRs generated via mobile devices (Mariani et al., 2019; Ransbotham et al., 2019). Consequently, a nascent research stream revolving around so-called mobile eWOM is emerging and consolidating (Kim et al., 2020; Kim and Hyun, 2021; Mariani et al., 2019; Orimoloye et al., 2022; Ransbotham et al., 2019). For instance, by examining >1.2 million OCRs related to London-based hotels, Mariani et al. (2019) describe differences between mobile and desktop OCRs, and find that Booking.com OCR ratings are higher for mobile than for nonmobile reviews. They also empirically observe that nonmobile OCRs are more helpful than mobile OCRs, and that mobile OCRs are more extreme than nonmobile OCRs. Accordingly, they suggest that scholars should develop an awareness of the distinctiveness of mobile eWOM vis-à-vis desktop eWOM. Ransbotham et al. (2019) examine mobile and nonmobile OCRs posted on the platform Urbanspoon and find that mobile reviews are less extreme, more concrete, and more affective. They also observe that OCRs written via mobile are related to lower consumption value and this negative relationship becomes stronger as time goes by; consequently, consumers find mobile OCRs less valuable than nonmobile OCRs. Kim et al. (2020) examine how the features of mobile devices affect consumer review-posting behavior, using both a field study on Booking.com and two experiments. They observe that greater accessibility of mobile devices immediately after consumption can affect the extremity of review ratings and that lower usability of mobile devices, in relation to the difficulty faced when writing long reviews, discourages online reviewers to write negative reviews.

Moreover, and consistently with Mariani et al. (2019), they find that the relative ratio of extremely positive and negative OCRs posted through mobile devices is considerably higher than that of OCRs posted through nonmobile devices. Orimoloye et al. (2022) find that device modality drives purchase frequency, likely due to the differential ease of use of PCs, tablets, and smartphones. More specifically, they find that reading reviews has the most positive effect on purchase frequency when it happens on PCs, followed by tablets. Through a web-based experiment, Lim and Maslowska (2022) find that the presence of a mobile cue negatively affects the assessment and adoption of information in OCRs; this is also the case when typographical errors are absent.

Leveraging data from the Chinese restaurant platform Xiaomishu, Li et al., 2021b find that reviews posted via mobile devices weaken the positive effect of temporal distance on review conformity and that mobile reviewers are less likely to be influenced by prior reviews than PC reviewers. By leveraging 677,013 Booking OCRs, Kim et al. (2021) find that launching a mobile channel does not influence volume and average valence of OCRs and that reviewers with extreme service experiences tend to use mobile devices to post their online reviews. By examining Booking.com hotel reviews, Park et al. (2022) find that mobile users are less likely than nonmobile users to post text in their OCRs and, when they do, the text is short and lacks analytical thinking.

Overall, most of the scholarly work produced in the nascent stream of mobile eWOM have the following characteristics:

1) They are descriptive in nature, focusing prevalently on differences in means of OCR valence, extremity, helpful votes (e.g., Mariani et al., 2019; Kim et al., 2020)
2) They take into account only one type of platform (e.g., Kim et al., 2021; Li et al., 2021a, 2021b; Lim and Maslowska, 2022; Orimoloye et al., 2022), with a specific online review policy: either platforms enforcing lenient online review policies in terms of written content length, such as Booking (examined in the studies Mariani et al., 2019; Kim et al., 2020, 2021; Park et al., 2022), or platforms enforcing strict online review policies in terms of written content length, such as TripAdvisor (examined in the study of Grewal and Stephen, 2019).

In this study we take into account platforms with both lenient and strict online review policies. As far as platforms lenient on written review length are concerned, based on the findings of researchers that have examined such platforms (e.g., Booking.com), the distributions of OCR ratings are expected to be more left-skewed for mobile vs. nonmobile OCRs (Mariani et al., 2019; Kim et al., 2020). Therefore, we hypothesize that:

H1. Consumers' use of mobile devices on online review platforms enforcing lenient review policies in terms of written content length, influences OCR valence positively.

For platforms enforcing strict online review policies regarding written content length, such as TripAdvisor, it seems that the use of mobile devices will generate a distinctively different effect. Based on Grewal and Stephen's (2019) work on such platforms, OCRs endowed with the "*submitted via mobile*" label are perceived as more credible by online readers because posting long OCRs via mobile is thought to require greater physical effort than when done via desktop devices. For instance, as of writing this study, TripAdvisor does not allow reviewers to submit an OCR fewer than 200 characters long. While the study of Grewal and Stephen (2019) focuses mostly on review helpfulness, other eWOM research has suggested that longer reviews are a signal of an online review's credibility, which encourages reviewers to assess the review as more objective and ultimately lower valenced (Gao et al., 2018; Mariani and Predvoditeleva, 2019; Poncheri et al., 2008). The negative effect of credibility cues on OCR valence has been found to be apparent in relation to reviewer experience (Gao et al., 2018), reviewer expertise (Mariani and Predvoditeleva, 2019), and review length (Poncheri et al., 2008). Thus, consistent with Grewal and Stephen (2019), who consider the "submitted by mobile" label a credibility cue, we hypothesize that mobile OCRs might be perceived as more credible and, ultimately, more objective and lower valenced. Therefore, we hypothesize that:

H2. Consumers' use of mobile devices on online review platforms enforcing strict review policies in terms of written content length, negatively influences OCR valence.

The conceptual model object of this study is represented in Fig. 1.

3. Methodology

3.1. Data and sample

We collected data from Booking.com and TripAdvisor to try to understand if and to what extent submission devices influence online review ratings differently across online review platforms – specifically, between those enforcing lenient policies and those enforcing strict ones, with regards to review character length. Booking.com is a good example of the former; it is an online review platform with lenient review length policies, where consumers are not forced to comply with a minimum number of characters for their OCRs. TripAdvisor, meanwhile, is a good example of an online review platform enforcing strict review length policies; consumers are forced to write at least 200 characters to be able to submit an online review. Both selected platforms play a significant role in the travel business: they constitute the two leading OCR platforms in the travel, tourism, and hospitality domain (Revinate, 2017).

Data was collected through two scrapers developed in the Python programming language (by leveraging the Selenium and Beautiful Soup libraries) at the beginning of 2019. First, we sampled the top 10 city tourism destinations in terms of international tourist arrivals in both the American and European continents (Geerts, 2018). Then we focused on four city destinations in each continent: Barcelona, London, Paris, and Rome, in Europe; Las Vegas, Miami, New York City, and Orlando, in America. We used the crawlers to retrieve the full list of reviewed hotels across our reference platforms.

Second, we collected the entire population of OCRs covering the hotels located in the aforementioned destinations across both platforms (i.e., Booking and TripAdvisor) over two years: 2017–2018.

Third, in line with other studies adopting text analytics (e.g., Xiang et al., 2017; Zhao et al., 2019), we kept in our final database only the online reviews that were written in English. We performed this task adopting the Language Detection Package (langdetect) available in Python (see https://www.python.org) which allows the detection of the language of a review through a lexicon-based analysis (Xiang et al., 2017). Overall, 2,702,227 OCRs were retrieved: 1,144,461 OCRs from TripAdvisor and 1,557,766 OCRs from Booking.com. The data therefore builds on a very large number of reviews extracted from different types of OCR platforms (depending on the online review policies regarding written content length) and pertaining to hotel services across multiple countries and continents.

3.2. Techniques adopted

To address our research question, we deployed model specifications with variables that are illustrated in the following section. More specifically, we used Tobit regression analysis (Tobin, 1958) for the Booking.com OCRs (as the dependent variable of rating is close to a continuous variable but is left and right censored). We used Ordinal Logistic Regression analysis (Greene, 1999; McFadden, 1974) for the TripAdvisor OCRs (as the dependent variable is ordinal and can assume only five categorical values).

3.3. Variables

The key variables used in this study are illustrated and described in

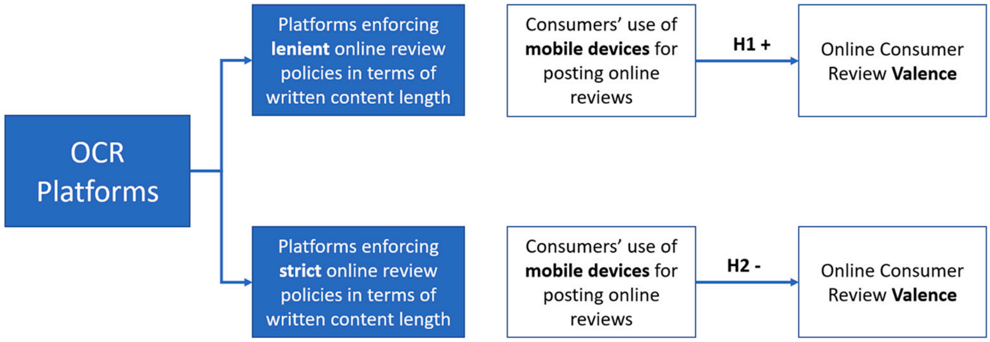

Fig. 1. Conceptual framework.

Table 1
Variables description.

Variable	Description
Review Rating	Online review rating posted by an online reviewer to summarize with a number her/his satisfaction with the hospitality service
Submission Device	It is a dummy variable that is equal to 1 if the review has been written using a mobile device, and zero otherwise
Observed Average Rating (Observed Avg Rating)	Hotels' review average rating as observed by the reviewing guest at the time when s/he posted his/her review (see Sridhar and Srinivasan, 2012)
Reviewer Experience	It is the overall number of online reviews written by the reviewer in the platform.
Reviewer Image	It is a dummy variable that is equal to 1 if the reviewer used a personalized image for its social profile in the platform, and zero otherwise (Forman et al., 2008).
Country of origin disclousure (Country Disclosure)	It is a dummy variable that is equal to 1 if the reviewer did not disclose her/his country of origin, and zero otherwise (see Filieri et al., 2019)
Review Length	It represents the number of words included in each online review (Chevalier and Mayzlin, 2006; Zhang et al., 2016).
Review Polarity	The *polarity*, also known as sentiment score, was operationalized using a continuous variable ranging from −1 to +1 respectively equating to extremely negative and extremely positive content and emotions. To create this measure we used the Valence aware dictionary for sentiment reasoning (VADER), which exploits a set of heuristics along with a specific lexicon dictionary for this particular task (Hutto and Gilbert, 2014).
Type of Trip	It is a categorical variables which embeds two options: Leisure and Business
Type of Group	It is a categorical variables which embeds 4 different options: Couple, Solo, Family and Group.
Destination City	It is a categorical variable that indicates the city where the reviewed hotel is located.
Year	It represents the year in which the review has been written
Chain	A dummy variable that is equal to 1 if the hotel is part of a chain company and zero otherwise.
Star Rating	It is a categorical variable that describes the hotel class category adopted to classify hotels according to their quality (from 1- to 5-stars). It has been retrieved directly from the page of each hotel as displayed in the online review platform (Booking.com or TripAdvisor).[a]

[a] Since TripAdvisor uses a customized rating system including half-star rating in order to obtain the final value we rounded the retrieved value to the closest half-star rating (Gao et al., 2018).

Table 1.

The focal variable – *Submission Device* – is operationalized as a dummy variable that is equal to 1 if the review has been written using a mobile device, and zero otherwise. Following the lead of Sridhar and Srinivasan (2012), the *Observed Average Rating* is defined as the average hotel's OCR rating as observed by the reviewer at the time of posting their review. *Country of Origin Disclosure* is a dummy variable that is equal to 1 if the reviewer did not disclose their country of origin (see Forman et al., 2008). *Reviewer Experience* is a proxy of the experience in online reviewing in the focal OCR platform, and it is measured as the overall number of OCRs written by the reviewer in the focal platform (i.e., either TripAdvisor or Booking.com). *Reviewer Image* is a dummy variable that equals 1 if the reviewer used a personalized image for their profile on the platform (Forman et al., 2008).

In terms of text analytics, we focused on *Review Length* and *Review Polarity*. The former consists of the number of words in the OCR (e.g., Chevalier and Mayzlin, 2006; Zhang et al., 2016). The latter, sometimes termed as sentiment score, is a continuous variable ranging from −1 to +1 and was computed using the Valence Aware Dictionary for sEntiment Reasoning (VADER), which is based on a dictionary and heuristics (Hutto and Gilbert, 2014). The measure was preferred over alternative measures as recent research has found that it performs other functions in the tourism domain (Alaei et al., 2019).

A number of control variables were used including *Type of Trip, Type of Group, Destination City, Year, Chain,* and *Star rating*. *Type of Trip* is a categorical variable that describes the trip purpose: leisure or business. *Type of Group* is a categorical variable that indicates if the travelers were a couple, solo, family, or group. *Destination City* is a categorical variable that indicates the city where the reviewed hotel is located. *Year* represents the year in which the review was written. *Chain* is a dummy variable that indicates whether the hotel belongs to a hotel chain or not. *Star rating* is a categorical variable that describes the hotel class category adopted to classify hotels according to their quality (from 1 to 5 stars). Overall, the aforementioned controls have been used in extant tourism and hospitality literature trying to identify and explain the determinants of online review ratings (e.g., Gao et al., 2018; Mariani et al., 2019). In line with extant literature (Mariani et al., 2018; Mariani and Borghi, 2022), *Online Review Rating* has been used as a dependent variable to address our research question and it represents the OCR rating posted by an online reviewer to express their satisfaction with the hospitality service.

Finally, reviewer experience and review length were log transformed given the skewness of the variables' distribution. Tables 2.a and 2.b illustrate the descriptive statistics of the variables under consideration for the period 2017–2018.

In relation to the descriptive statistics, it is interesting to notice how mobile consumption is significantly different between the two OCR platforms analyzed. Indeed, mobile OCRs account for 66.5 % on Booking.com, while only 31.8 % of OCRs are submitted by mobile on TripAdvisor. If we inspect the monthly trends (Fig. 2.a and b), it is clear how reviewers are gradually moving to the adoption of mobile devices for writing their reviews on both platforms. However, there is a relevant difference: on Booking.com, mobile devices (orange line in Fig. 2.a) have clearly overtaken desktop devices in consumers' online review

Table 2.a
Descriptive statistics for the TripAdvisor sample, 2017–2018.

	Mean	SD	Min	Max
Rating	4.120	1.164	1	5
Submission Device	0.318	0.466	0.000	1.000
Observed Average Rating	4.123	0.526	1	5
Reviewer Expertise	39.707	116.219	1	10,756.000
Log (Reviewer Expertise)	2.204	1.747	0	9.283
Reviewer Image	0.278	0.448	0	1
Country Disclosure	0.766	0.423	0	1
Review Length	108.103	103.693	1	3603.000
Log (Review Length)	4.411	0.684	0	8.190
Review Polarity	0.742	0.484	−0.999	1
Chain	0.514	0.500	0.000	1.000
Observations	1,144,461			

Table 2.b
Descriptive statistics for the Booking sample, 2017–2018.

	Mean	SD	Min	Max
Rating	7.950	1.919	2.5	10
Submission Device	0.665	0.472	0.000	1.000
Observed Average Rating	7.954	0.942	2.5	10
Reviewer Expertise	7.617	12.433	1	1047.000
Log (Reviewer Expertise)	1.330	1.136	0	6.954
Reviewer Image	0.411	0.492	0	1
Country Disclosure	0.999	0.035	0	1
Review Length	34.454	41.340	1	772.000
Log (Review Length)	2.956	1.157	0	6.649
Review Polarity	0.392	0.516	−0.998	0.999
Chain	0.486	0.500	0.000	1.000
Observations	1,557,766			

activity. On the other hand, mobile adoption while increasing, has not overcome the use of desktop devices on TripAdvisor (orange line in Fig. 2.b).

To provide empirical evidence of the differences across platforms in terms of the outcomes of the enforcement of lenient vs. strict review policies about written content length, we detected that, unlike Booking.com, TripAdvisor does not allow users to submit a review with fewer than 200 characters. This represents an important constraint for mobile users. Nonetheless, given that the length of online reviews was recently used as a proxy of review effort (i.e., Xu et al., 2020), we delved deeper in the exploration of this specific dimension for the different submission devices. Fig. 3.a–d report the average text length – in words and characters – by device. Analyzing the graphs, it is apparent that Booking.com reviews submitted by mobile are significantly shorter than their desktop counterparts (of an order of magnitude of approximately 15 words). On the contrary, on TripAdvisor, where reviews are on average almost three times longer than Booking.com OCRs, reviews submitted by mobile are as wordy as their desktop counterparts. Moreover, in 2018, mobile OCRs on TripAdvisor seem to include a higher number of words than desktop OCRs. This seems to indicate that mobile reviewers are highly committed on TripAdvisor.

3.4. Model specification

Based on the samples indicated in the research design, we developed two model specifications that are presented in the following equations:

$$\begin{aligned} Rating_i = & \beta_0 + \beta_1(Submission\ Device)_{h,t} + \beta_2(Observed\ Avg\ rating)_{h,t} \\ & + \beta_3(Reviewer\ Experience)_{h,t} + \beta_4(Reviewer\ Image)_{h,t} \\ & + \beta_5(Country\ Disclosure)_{h,t} + \beta_6(Review\ Length)_{h,t} \\ & + \beta_7(Review\ Polarity)_{h,t} + Type\ of\ Trip + Type\ of\ Group \\ & + Destination\ City + Year\ Dummy + Chain + Star\ Rating + \varepsilon_{h,t} \end{aligned} \tag{1}$$

As clear from the equation, the model explores the extent to which the submission device influences online review valence. As clear from the models, the reference dependent variable is online review valence (namely the OCR ratings) and it was regressed against the focal independent variable (submission device), as well as a series of other explanatory and control variables. Explanatory variables included observed average rating, reviewer experience, reviewer image, country disclosure, and text analytics (namely review length and review polarity). Control variables included type of trip, type of group, destination city, year, chain, and star rating.

When analyzing Booking.com OCRs, we adopted a Tobit multivariate regression because the dependent variable (i.e., the overall online rating) is continuous but both left and right censored, with the minimum and maximum variables being respectively 2.5 and 10.0 (Kim et al., 2020; Mariani and Borghi, 2018). When analyzing TripAdvisor OCRs, we used an ordered logit regression models because the dependent variable (i.e., the overall online rating) is a categorical variable assuming only five values (see Sridhar and Srinivasan, 2012; Zhang et al., 2016).

4. Findings

The results of the regression analyses capturing the influence of submission device on OCR ratings are illustrated in Table 3.

Online consumers' use of submission devices appears to influence positively OCR ratings on Booking.com ($p < 0.001$), while it affects negatively OCR on TripAdvisor ($p < 0.001$) (see, respectively, models 1 and 2 in Table 3). On the one hand, the first result related to Booking.com supports our first hypothesis, whereby consumers' use of mobile devices on online review platforms enforcing lenient review policies in terms of written content length influences OCR valence positively. This result enriches the descriptive findings obtained by Mariani et al. (2019) and Kim et al. (2020), who observed a more left-skewed distribution for mobile vs. nonmobile OCRs. On the other hand, the second result obtained on TripAdvisor supports our second hypothesis, whereby OCR valence is negatively influenced by consumers' use of mobile devices on online review platforms enforcing strict review policies around written content length (e.g., TripAdvisor). Thus, the "submitted by mobile" label can be considered a credibility cue, as suggested by Grewal and Stephen (2019). However, this does not only affect review helpfulness, as suggested by the authors, it also affects OCR valence. This is because, ultimately, reviews submitted via mobile on online review platforms that enforce strict review policies are considered more objective. All in all, these findings support

our hypotheses and extend the emerging empirical literature on mobile eWOM (Kim et al., 2020, 2021; Li et al., 2021b; Mariani et al., 2019; Orimoloye et al., 2022; Park et al., 2022). The analysis of the focal independent variable (*Submission Device*) suggests that the device used to leave a review can make a difference for OCR ratings and, ultimately, for customers' online satisfaction. The effects measured are asymmetric and dependent on the type of platform – or, more precisely, on the online review policy enforced by the platform. This significantly extends recent empirical research seeking to evaluate the impacts of mobile devices on eWOM (Kim et al., 2021; Li et al., 2021a; Orimoloye et al., 2022; Park et al., 2022); compared to other studies, it distinctively analyses the effect of online review policies on OCR valence.

In relation to the reviewer-level control variables, the reviewer's experience in online reviewing is negative and significant ($p < 0.001$) in both models, which is consistent with previous research (e.g., Ma et al., 2013). Given that experience in online reviewing is, to a certain extent, connected to travel experience (Gao et al., 2018), this result is consistent with extant research showing that experience has a negative impact on reviewers' online ratings.

A reviewer's disclosure of their image influences online ratings positively ($p < 0.001$) in both models, which is in line with extant research showing that reviewers' personal information might influence OCR ratings (Forman et al., 2008).

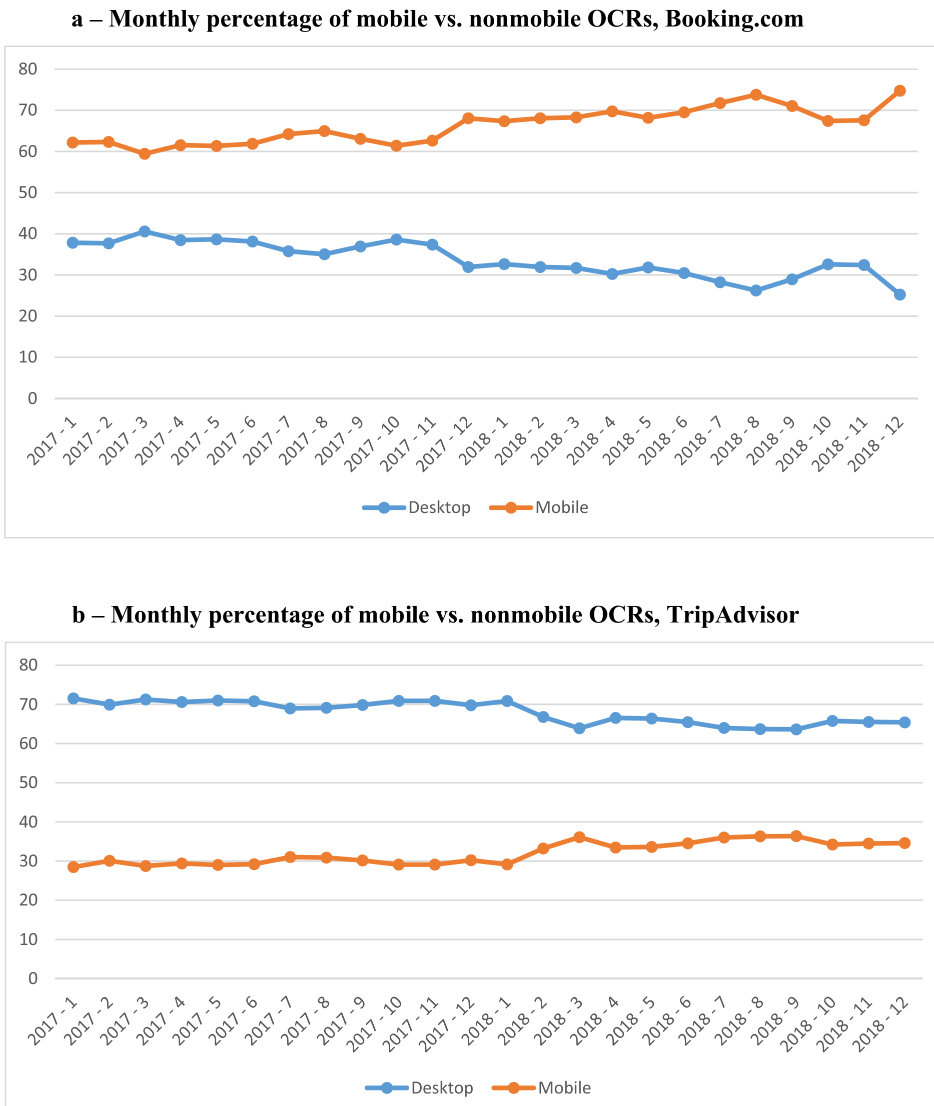

Fig. 2. .a Monthly percentage of mobile vs. nonmobile OCRs, Booking.com.
b. Monthly percentage of mobile vs. nonmobile OCRs, TripAdvisor.

As far as the text analytics are concerned, *review length* influences ($p < 0.001$) OCRs ratings negatively in both models considered, which is in line with extant literature (Berezina et al., 2016; Chevalier and Mayzlin, 2006); customers tend to put more effort into writing and end up writing longer reviews when they are dissatisfied with a product or service. *Review Polarity* affects OCR ratings positively ($p < 0.001$) in all the four models considered, which is in line with extant literature (Geetha et al., 2017); customers evaluate their consumption experience more positively when they are in a positive emotional state (Isen, 1987).

5. Discussion and conclusions

5.1. Summary of key findings

In this research, we leveraged >2.7 million online consumer reviews (OCRs) collected from two OCR platforms with distinctly different online review policies – namely, Booking.com and TripAdvisor.com – and processed and examined them by means of sophisticated, big data analytical techniques. This work has generated several key findings. By adopting multivariate regression analyses (Tobit regression for the Booking.com OCRs and ordinal logistic regression for the TripAdvisor OCRs), we have shown that OCR ratings are influenced by the adoption of mobile devices in different ways across different platforms. More specifically, we detected that consumers' use of mobile devices on OCR platforms that enforce lenient review policies (in terms of written content length), influences OCR valence positively. On the other hand, consumers' use of mobile devices on OCR platforms that enforce strict review policies, influences OCR valence negatively. Overall, our findings contribute by offering insights on the asymmetric effect of consumers' use of mobile devices and channels to post OCRs across different types of platforms that enforce different online review policies. We thereby contribute to the emerging research stream of mobile eWOM (e.g., Grewal and Stephen, 2019; Kim et al., 2020; Mariani et al., 2019; Ransbotham et al., 2019; Zhu et al., 2020). Theoretical and managerial contributions and implications are discussed in the following subsections.

5.2. Theoretical contributions

This study contributes to the nascent research stream at the intersection of digital platforms, mobile eWOM, and big data analytics in multiple ways. First, to the best of our knowledge, this is among the first studies in business research to address how online consumers' use of mobile devices and channels to post OCRs influences OCR ratings

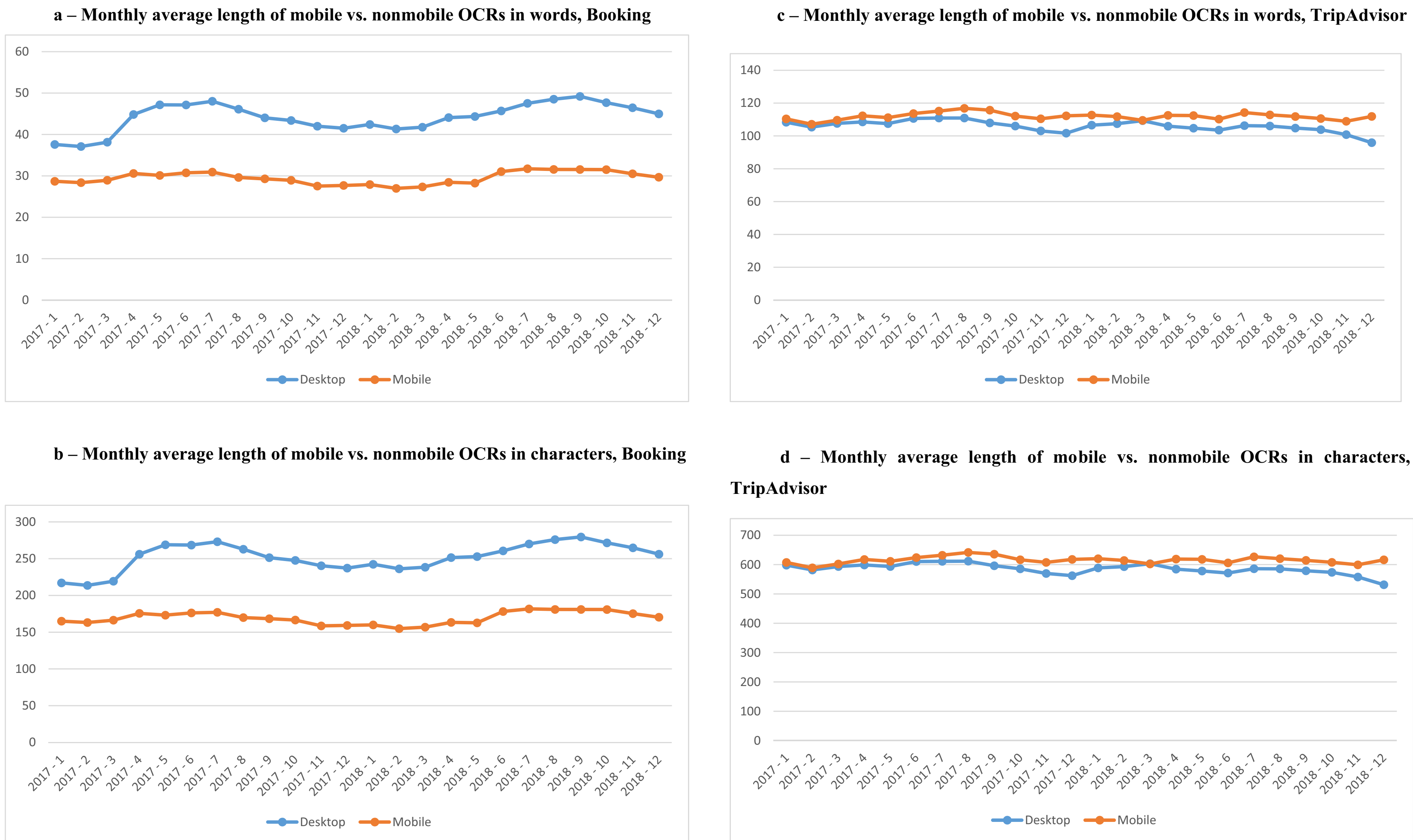

Fig. 3. a – Monthly average length of mobile vs. nonmobile OCRs in words, Booking.
b – Monthly average length of mobile vs. nonmobile OCRs in characters, Booking.
c – Monthly average length of mobile vs. nonmobile OCRs in words, TripAdvisor.
d – Monthly average length of mobile vs. nonmobile OCRs in characters, TripAdvisor.

Table 3
Econometric Models Mobile impact on review rating.

	Booking (1)	TripAdvisor (2)
	Rating	Rating
Submission Device	0.0261***	−0.0675***
	(0.00312)	(0.00427)
Observed Avg Rating	0.836***	1.419***
	(0.00184)	(0.00434)
Log Reviewer Experience	−0.00941***	−0.0751***
	(0.00129)	(0.00133)
Country Disclosure	0.0633***	0.0298***
	(0.00290)	(0.00493)
Reviewer Image	0.140***	0.0528***
	(0.0408)	(0.00464)
Log Review Length	−0.402***	−0.702***
	(0.00128)	(0.00300)
Review Polarity	1.955***	2.557***
	(0.00292)	(0.00490)
Control Variables		
Type of Trip & Group	YES	YES
Destination Country	YES	YES
Year	YES	YES
Chain	YES	YES
Star Rating	YES	YES
Constant	1.716***	
	(0.00114)	
Intercept-1		0.133***
		(0.0272)
Intercept-2		1.418***
		(0.0271)
Intercept-3		2.955***
		(0.0273)
Intercept-4		4.746***
		(0.0275)
Observations	1,557,766	1,144,461
Pseudo R^2	13.3 %	22.7 %
AIC	5,408,306.8	2,233,794.9
LR Chi2	829,276.3	654,259.3
Log Likelihood	−2,704,126.4	−1,116,867.5

Standard errors in parentheses.
*** $p < 0.001$.

differently across OCR platforms that use distinctively different online review policies. We thus extend and complement a nascent research stream (e.g., Mariani et al., 2019; Kim et al., 2020) that has described how mobile eWOM differs from nonmobile eWOM in a purely descriptive way. Indeed, previous literature revolving around eWOM has examined the differences in customer reviews posted via mobile and nonmobile devices (e.g., Mariani et al., 2019). However, little is known about whether the adoption of mobile channels has different effects on OCR valence across types of platforms applying distinctively different online review policies. Therefore, our research adds to the extant body of literature by providing a *multi-platform* and *cross-platform* analysis of the influences that mobile channels have on online review posting behaviors – and, ultimately, on OCR valence. Secondly, our findings seem to broadly suggest that consumers display different behaviors according to the online review policies enforced by OCR platforms. This finding adds to extant research that has mostly tackled one of the possible differences in terms of online review policies, namely the difference between platforms allowing consumers to leave only verified vs. nonverified OCRs (e.g., Mayzlin et al., 2014). Third, and related to the previous point, we suggest that consumer behavior in adopting and using mobile devices to post OCRs is influenced by a specific online review policy which consists of a minimum length for written content. This finding links back to other eWOM literature that has found that OCR length is often associated with other elements of an OCR, such as helpfulness and readability (Grewal and Stephen, 2019; Filieri and Mariani, 2021; Mudambi and Schuff, 2010; Yin et al., 2014). Fourth, by suggesting that online review policies related to the length of posted content generate differentiated effects in terms of the nature of mobile eWOM, we move beyond extant literature that has suggested that the length of mobile OCRs is shorter than the length of nonmobile OCRs (e.g., Mariani et al., 2019; März et al., 2017; Piccoli and Ott, 2014; Zhu et al., 2020). Indeed, we suggest that the specific online review policy adopted by the platform – in terms of OCR length – can influence consumers to behave differently. Accordingly, we contribute to consumer behavior literature (e.g. Darley et al., 2010) suggesting that not all mobile online reviewers are equal and behave similarly. Rather, their posting behavior will be influenced by the policy enforced by the platform. Fifth, as mobile posting behaviors are influenced by the online review policy enforced by the OCR platform, mobile vs. nonmobile devices do not represent per se a segmentation variable (Dolnicar and Leisch, 2014) to effectively segment online consumers. Sixth, we extend recent literature that has emphasized the role of data and data analytics to shed light on online users and online consumer behaviors (Saura et al., 2019; Vanhala et al., 2020) by leveraging a large amount of structured and unstructured data through a data science approach (Provost and Fawcett, 2013; Waller and Fawcett, 2013; Witten et al., 2016), thereby shedding light on the nuances of a particular segment of online consumers: mobile consumers and their online behaviors. Seventh, our study contributes to the burgeoning research area at the intersection of data science and marketing (Balducci and Marinova, 2018; Chintagunta et al., 2016), witnessing the increasing relevance of marketing analytics (Wedel and Kannan, 2016) to shed light on markets and consumer behaviors. Eight, we expand research in the service marketing field where services, unlike goods, are intangible and unknown before consumption and require ad hoc strategic and operational marketing (Kunz and Hogreve, 2011; Lovelock and Wright, 2001). Our study deploys analytics from UGC to gain a better understanding of mobile consumers' behaviors and their preferences about services. Lastly, we suggest that in today's digital world, online consumer behavior is not only influenced by the channel deployed (e.g., mobile vs. nonmobile), but also is significantly affected by the platforms' business model (Mayzlin et al., 2014) and especially the policies they enforce. Consequently, consumer behaviors can be captured effectively by relying on digital platforms (Nambisan, 2017), which offer a rich data source in the guise of consumer reviews.

5.3. Practical implications

Several practical implications stem from this work, including implications for marketing managers and practitioners, and digital platform managers and developers.

As far as marketing managers and practitioners are concerned, they should recognize that consumers using mobile devices give better evaluations to services when using online review platforms whose review policies are lenient in relation to the length of the written text posted. This is clear from the positive vs. negative effect of consumers' use of mobile on OCR valence on Booking vs. TripAdvisor. This finding should encourage marketing managers to: 1) avoid considering mobile OCRs as a homogenous segment of reviews/reviewers and therefore to de-emphasize the deployment of mobile devices as a segmentation variable; 2) analyze differently mobile OCRs generated on different websites, as the online review policies of OCR platforms affect OCR generation and OCR valence; 3) control accurately for whether the reason for the low valence of mobile OCRs posted on platforms such as TripAdvisor is actually due to the service quality or whether it has something to do with the stricter online review policy enforced by the platform; 4) give preference, in assessing mobile users' evaluations of products/services, to OCR platforms such as Booking, because they display online review policies that do not constrain consumers (in addition to hosting mostly verified OCRs); 5) clarify with platform managers the extent to which platforms' online review policies can impact online consumer behavior; 6) select only mobile OCRs posted on platforms such as Booking to appear in their company's website. More specifically, services' marketing managers might use mobile OCRs selectively – depending on the type of platform (and its online review policy) – to generate business intelligence conducive to improving their services (Rust and Huang, 2014).

Platform developers and managers that deal with OTAs (such as Booking) and online community review platforms (such as TripAdvisor), would benefit from the findings of this study; they are increasingly hosting OCRs on their platforms that have been posted using mobile devices, such as smartphones and tablets. Since strict online review policies with regards to content length can be detrimental to OCR valence – thus impacting negatively consumers' online evaluations of products and services and, ultimately, companies' online reputation – platform developers should consider whether limiting OCR content length is the right online review policy to adopt. Secondly, as OCR platforms that enforce a strict online review length policy might not be seen favorably by marketers, they need to foster a dialogue with marketers and consider whether the policy enforced should be kept, modified, or discontinued. Third, even consumers might consider strict online review policies to be not user friendly; this is clear from the TripAdvisor-related forum entitled "Minimum 200 characters restriction – stupid idea", which was started six years ago by British traveler Peter Budden (2015). Platform managers and developers should engage more with consumers (especially repeat consumers, like business tourists) to understand how and if the online review policy might be improved. Fourth, for the sake of transparency about their online review policies, platforms might disclose explicitly on their websites, for the benefit of all the OCR readers, that there is an online review policy that could affect OCR ratings in a specific way. Platform managers might offer consumers simple tools for interpreting OCR ratings in light of the online review policy enforced.

5.4. Conclusion, limitations, and future research directions

This work contributes insights on online consumers' perceptions and behaviors with a focus on mobile users adopting different types of platforms to post their OCRs. In particular, we measure empirically the effect of the adoption of mobile devices on OCR ratings across two types of platforms – those with lenient review length policies and those enforcing strict review length policies. The objective is pursued by leveraging large volumes (big data) of OCRs sourced from two distinctively different platforms (Booking vs. TripAdvisor) in terms of online review policies, and pertaining to services consumed across different firms, destinations, continents, and countries. Accordingly, this paper contributes to the area at the intersection of digital platforms, mobile eWOM, and big data analytics.

After the collection, processing, and analysis of almost 3 million OCRs sourced from Booking and TripAdvisor by means of big data analytical techniques, we notice that consumers' use of mobile devices on OCR platforms enforcing lenient/strict review policies, influences positively/negatively OCR valence. This supports our theory-informed hypotheses. Overall, our findings contribute by offering insights on the asymmetric effect of consumers' use of mobile devices and channels to post OCRs across different types of platforms enforcing different online review policies, thus contributing to the emerging research stream of mobile eWOM (e.g., Grewal and Stephen, 2019; Li et al., 2021a; Kim et al., 2020, 2021; Mariani et al., 2019; Orimoloye et al., 2022; Park et al., 2022; Ransbotham et al., 2019; Zhu et al., 2020). This relationship between the use of mobile devices, the types of platforms, and their online review policies, with OCR valence, has never been empirically examined. While the study offers a rich set of theoretical contributions and practical implications for multiple platform stakeholders (including marketing managers and platforms managers), as discussed in Section 5, the study is not without its limitations. Firstly, while we have used a number of controls, further variables such as the demographics could be included in the analysis. It is well known that OCR platforms often display many missing values in relation to demographics; accordingly, further research might be combined with experiments allowing for the collection of demographic data in a more precise and granular way. Secondly, while this work represents the first attempt to measure quantitatively the effect of online consumers' use of mobile devices to post OCRs on OCR ratings across OCR platforms that enforce distinctively different online review policies, other platforms covering a wider range of online review policies might be considered over different and more recent timeframes. This might allow for the modeling of the continuum of online review policies that, in practice, can be found. Thirdly, while this is a cross-platform study that has examined platforms enforcing different online review policies, future studies might embed sharing economy platforms (which display a hybrid nature) as sources of online review data. Fourth, given the increasing share of non-authentic online reviews produced by online review generators (Kim et al., 2023), it might be useful to deploy fake review detection systems to control for fake versus authentic online reviews. Lastly, experimental studies might be an interesting research avenue to manipulate the types of online review policies and thus examine how low, medium, and high levels of leniency might impact the way the use of mobile devices influences online consumer behavior and online reviews.

CRediT authorship contribution statement

Marcello Mariani: Conceptualization; Methodology; Data curation; Formal analysis; Writing- Original draft preparation; Writing- Reviewing and Editing.

Matteo Borghi: Data curation; Writing- Original draft preparation, Writing- Reviewing and Editing.

Ben Laker: Writing- Original draft preparation; Writing- Reviewing and Editing.

Data availability

Data will be made available on request.

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