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How power distance affects online hotel ratings: The positive moderating roles of hotel chain and reviewers' travel experience

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HIGHLIGHTS

- Reviewers from countries with high power distance (PD) make low hotel ratings.
- The negative effect of PD is weaker for hotel chains than for independent hotels.
- The negative effect of PD is weaker as reviewers' travel experience increases.
- 243,000 TripAdvisor reviews for 3081 hotels in 24 U.S. cities are used.
- Robustness check is conducted to validate the findings.

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ABSTRACT

This study investigates the collective influences of cultural, hotel, and reviewer characteristics on online ratings in the hotel sector. Based on over 243,000 TripAdvisor reviews for hotels in 24 US cities, we empirically find a negative relationship between the reviewers' power distance and their online hotel ratings, thereby indicating that cultural factor plays a significant role in the customers' online rating behavior. The negative effect of power distance on online hotel ratings is weaker for chained hotels than for independent hotels. This negative effect is also weaker for reviewers with more travel experience than for those with less travel experience. The robustness check demonstrates that these findings are applicable for ratings on product features that involve staff interactions, such as service, value, rooms, and cleanliness.

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1. Introduction

Online reviews have attracted increasing attention from researchers and managers over the past decade because favorable reviews generated by consumers can facilitate product sales (Chevalier & Mayzlin, 2006; Forman, Ghose, & Wiesenfeld, 2008; Goh, Heng, & Lin, 2013) and even improve firm value (Luo, Raithel, & Wiles, 2013; Tirunillai & Tellis, 2012). Nowadays, reviewing a product or service online is common for consumers. In doing so, reviewers leave a numeric rating to briefly indicate their evaluation of a product or service. In some cases, they supplement open-ended text comments to disclose details further about their consumption experience.

Given the great value of online reviews, understanding why consumers leave positive or negative reviews presents a fundamental question for firms to gain benefits from online reviews. Given that numeric ratings can reflect the reviewer's polarity, the determinants of online ratings have been intensively investigated. Many studies confirm that online ratings are affected by extrinsic factors, such as social influence (Deng & Liu, 2017; Ma, Khansa, Deng, & Kim, 2013; Sridhar & Srinivasan, 2012) and opinions of friends (Lee, Hosanagar, & Tan, 2015). However, others argue that online ratings are driven by the reviewers' personal characteristics (Gao, Hu, & Bose, 2017; Ma et al., 2013) or represent a strategic behavior that aims to draw attention (Shen, Hu, & Ulmer, 2015). Meanwhile, this work will focus on how the customers' cultural







value affects their online rating behavior, a topic that has been insufficiently investigated in the literature.

According to Hofstede's cultural theory (Hofstede, Hofstede, & Minkov, 2010), the culture of a nation differs from that of others in five dimensions, namely, power distance, long-term orientation, masculinity, uncertainty avoidance, and individualism. A large body of research has suggested that the customers' cultural values, such as power distance, individualism, and uncertainty avoidance, significantly affect their perception of service quality, service evaluation, and satisfaction (Furrer, Liu, & Sudharshan, 2000; Kim & Aggarwal, 2016; Ladhari, Pons, Bressolles, & Zins, 2011; Mattila, 2000). These studies are based on survey data that merely involve hundreds of observations for few service providers and mostly rely on two-country designs (i.e., comparing the evaluations by customers from two countries or areas). However, the limitations in the data and design employed by these studies restrict the generalizability of their findings (Kim & Aggarwal, 2016).

Online reviews provide rich data that reflect the consumers' characteristics and perceptions of service satisfaction. However, only several online review studies have incorporated the cultural background of customers as a factor that determines ratings. By comparing reviews from China and the US, some studies find cultural differences in the generation and utilization of online reviews (Fang, Zhang, Bao, & Zhu, 2013; Koh, Hu, & Clemons, 2010). Based on their analysis of online review data, Hong, Huang, Burtch, and Li (2016) suggest that on average, the consumers' individualism affects their propensity to conform to the emotionality of prior opinion. King, Racherla, and Bush (2014) highlight the importance of conducting additional cross-cultural comparisons of online review generation and dissemination behavior. Therefore, investigating the influence of cultural factors on the customers' online rating behavior is essential.

Investigating this issue is particularly important in the hotel sector because the hotel industry has a high level of globalization and involves customers with diverse cultural values. Globalization facilitates the mobility of people around the world and increases the number of international customers for hotels. Therefore, the hotel industry, as well as the behavior of its customers, is very likely to be influenced by cultural factors. Moreover, globalization promotes the boom of online hotel reviews and allows one to collect service evaluation data provided by consumers from various cultural backgrounds. Thus, the online hotel review behavior of diverse customers provides an ideal context and rich data for investigating how the customers' cultural values influence their online ratings.

By considering the limitations of prior research and taking advantage of online hotel review data, this research investigates the effects of the customers' power distance on their online hotel ratings and describes how these effects are moderated by the characteristics of hotels and reviewers. Power distance reflects "the extent to which the less powerful members of organizations and institutions accept and expect that power is distributed unequally" (Hofstede et al., 2010). Conceptually, in a culture of high power distance, inequalities are generally accepted by individuals (Hofstede et al., 2010), and consumers often feel superior to service providers in the social hierarchy (Kim & Aggarwal, 2016). Therefore, they expect high service quality from service providers (Mattila, 1999) and tend to give low service evaluations (Mattila, 2000). However, other cultural factors, such as individualism and uncertainty avoidance, only reflect one's risk attitude and inconformity to group opinion (Ferguson, Megehee, & Woodside, 2017; Hong et al., 2016; Liu, 2015; Liu, Wang, & Huang, 2017a; Liu, Zhang, Keil, & Chen, 2010), both of which are insignificantly related to service satisfaction or rating. Therefore, we focus on power distance than on the other cultural dimensions.

The effects of the customers' power distance on their online hotel ratings may vary because of the heterogeneity among hotels and customers. For example, compared with independent hotels, chained hotels incorporate standard services to satisfy customers with different cultural backgrounds (Cezar & Ögüt, 2014; Schilke, Reimann, & Thomas, 2009). Reviewers with significant travel experiences also have an extensive understanding of various cultures (Banerjee & Chua, 2016). These product and reviewer characteristics may change the inclinations of reviewers with varying power distance levels to provide online ratings. Therefore, this study further explores how hotel chain brands and reviewers' travel experiences moderate the relationship between the customers' power distance and their online hotel ratings.

This study contributes to the online review literature by investigating the effect of cultural factors on online review behavior. The findings empirically show that the reviewers from countries with high power distance provide low online hotel ratings. This research also offers a new perspective to the service management literature by confirming the negative relationship between power distance and service quality or satisfaction in the online review context, by addressing the generalizability issue faced by previous studies, and by extending the results from the literature by utilizing a large sample of countries. This study also contributes new knowledge to the hotel management literature by investigating the moderating role of hotel chain brands on the relationship between power distance and hotel online ratings. We empirically reveal that the negative effect of power distance on hotel online ratings is weaker for chained hotels than for independent hotels. This research also contributes to the consumer behavior literature by examining the moderating role of consumer travel experience on the correlation between power distance and online hotel ratings. Power distance has a weak effect on online ratings for consumers with extensive travel experience. This research also offers methodological contributions by using multi-dimensional ratings to validate the robustness of its findings.

This paper is organized as follows. Section 2 presents the testable hypotheses for the subsequent empirical examinations. Section 3 describes the data and research methodology. Sections 4presents the empirical results and performs some robustness checks. Section 5 discusses the implications of our findings. Section 6 highlights the research contributions and concludes the paper.

2. Literature review and hypothesis development

Previous studies indicate that the customers' power distance significantly affects their service expectations, perceived service quality, and relationship quality (Dash, Bruning, & Acharya, 2009; Dash, Bruning, & Guin, 2006; Kim & Aggarwal, 2016; Ladhari et al., 2011; Mattila, 2000; Polsa, Fuxiang, Sääksjärvi, & Shuyuan, 2013). Therefore, this study focuses on the effects of consumers' power distance on their online hotel ratings, a topic that has been investigated inadequately in the literature.

Power distance is defined as "the extent to which a society accepts the fact that power in institutions and organizations is distributed unequally" (Hofstede et al., 2010). Individuals in a high power distance society tend to comply with a hierarchy where "everybody has a place and which needs no further justification" (Hofstede et al., 2010). In other words, inequalities are generally accepted by individuals from societies with a high power distance (Hofstede et al., 2010). The power distance level of a country can be determined through the power distance index, which measures "the extent to which power differs within the society, organization and institutions (like the family) are accepted by the less powerful members" (Hofstede, 1997).

In societies with a high power distance, a differential power

between service providers and customers exists because of the "the consumer is always right" or "the customer is king" philosophy (Hanser, 2007; Kim & Aggarwal, 2016). Customers from such societies may feel superior to service providers in the social hierarchy (Kim & Aggarwal, 2016). In the same culture, customers expect that the power distance between them and their service providers is reflected in the service processes and deliveries (Ladhari et al., 2011). As such, given the low status service of employees, customers from high power distance cultures expect services to be delivered with the highest level of quality that they deserve (Furrer et al., 2000; Ladhari et al., 2011; Mattila, 1999; Raajpoot, 2004). Given their high service expectations, consumers from high power distance societies tend to perceive the quality of a service as poor and give low evaluation scores for the service providers (Ladhari et al., 2011; Mattila, 2000). Mattila (2000) shows that the evaluation of hotels by Western customers is significantly higher than that of Asian customers with a high power distance.

In the online review context, numerical ratings quantitatively summarize a reviewer's evaluation of a hotel by using a single scale (Xie, Chen, & Wu, 2016). Therefore, consistent with the abovementioned literature conducted in the offline context, we expect that reviewers with a higher power distance tend to provide lower ratings to hotel services provided that other things are left equal.

H1. The reviewers' power distance is negatively related to their online hotel ratings such that the reviewers from countries with higher power distance tend to provide lower online hotel ratings.

Standardized operations and openness to various cultural values may enable chained hotels to mitigate the effect of the customers' cultural factors (e.g., power distance) on their ratings. Chained hotels generally operate in multi-markets. Compared with independent hotels, chained hotels provide services for wider customer segments across national boundaries and social classes (Cezar & Ögüt, 2014; Hollenbeck, 2016). Given that employees of chained hotels have access to comprehensive knowledge on various cultural values and approaches for handling the different demands of customers, such knowledge must be exchanged to satisfy the requirements of customers from different cultures. Companies operating in multi-markets can efficiently and effectively exploit and transfer knowledge through intracorporate knowledge spillover (Dyer & Nobeoka, 2000; Gupta & Govindarajan, 2000; Zhang, Liu, Deng, & Chen, 2017). Knowledge spillover, which refers to the exchange of ideas among individuals to capture and disseminate knowledge within a firm (Carlino, 2001), enables individuals to avoid repeating mistakes and to operate intelligently. As a result, openness to various cultural values and intra-corporate knowledge spillover help chained hotels gain a better understanding of the cultural values and beliefs of different customers.

To survive and succeed in multi-markets, chained hotels have to adopt appropriate strategies and set up standardized operations to respond to the preferences of customers with different cultural values. Although hotels in the same chain group show some differences in their quality as they operate in different places and countries, they apply similar procedures and standards to meet certain quality criteria (Cezar & Ögüt, 2014). The standardized operations of chained hotels reflect their understanding of various cultural values because such hotels aim to satisfy the dissimilar requirements of consumers from different countries rather than the needs of customers in a specific region. Accordingly, the effects of the reviewers' power distance (a type of cultural value) on their online ratings are weaker for chained hotels than for independent hotels provided that other things are left equal. Therefore, we propose the following: **H2.** Hotel chain brands positively moderate the negative effect of reviewers' power distance on their online hotel ratings such that the negative effect is weaker for chained hotels than for independent hotels.

Cultural values are national-level characteristics. However, individuals within the same country may differ in terms of their personal characteristics. Thus, the cultural value and rating behavior of consumers from the same country may still vary. Previous studies show that the homogeneities in the behavior of consumers within a country can be diminished by increasing globalization (Cleveland & Laroche, 2007; Ladhari et al., 2011). Travel experience may also improve the heterogeneity in the cultural values of individuals within the same country (Hong et al., 2016).

Consumers with richer travel experiences have more opportunities to be exposed to different cultural values, which in turn may potentially increase their intercultural awareness (Hong et al., 2016). Intercultural awareness enables consumers to understand the cultural conventions of other countries and develops their capability to acknowledge and respect cultural differences (Chen & Starosta, 1996). Therefore, in the hotel context, the travel experiences of customers increase their understanding of cultural diversification. Moreover, the travel experience of consumers can facilitate general cultural adjustment (Parker & Mcevoy, 1993), which allows consumers to adapt to different cultural environments and motivates them to engage with and accept cultural differences (Klak & Martin, 2003; Selmer, 2002).

Consequently, the understanding of cultural diversification and the acceptance of cultural differences may alleviate the effects of culture on the thinking and behavior of customers. As such, not every customer from countries with a high power distance believes that s/he is superior to service providers and still submits low ratings. Based on the above analysis, travel experience can mitigate the influence of culture-related biases.

H3. The travel experience of reviewers positively moderates the negative effect of power distance on their online hotel ratings such that the negative effect becomes weaker when the travel experience becomes extensive.

3. Research methodology

3.1. Data acquisition and processing

We combined two publicly accessible datasets for the empirical study. One is the online hotel review data from TripAdvisor.com, while the other is the power distance index from "The Hofstede Centre" (geert-hofstede.com). We collected online hotel reviews from TripAdvisor, which is the largest online hotel review platform in the world that attracts over 300 million users every month. TripAdvisor aims to provide high-quality reviews and offer more than 430 million opinions and reviews that cover 7 million attractions, accommodations, and restaurants. This website has served as a data source for many previous studies (Banerjee & Chua, 2016; Duan, Yu, Cao, & Levy, 2016; Fang, Ye, Kucukusta, & Law, 2016; Gao et al., 2017; Hong et al., 2016; Li, Cui, & Peng, 2017; Liu, Teichert, Rossi, Li, & Hu, 2017; Rhee & Yang, 2015).

Fig. 1 shows the process of data acquisition and processing. First, we selected cities for this research. We limited the review data to hotels in the US. We selected "the top 20 popular USA destinations" as rated by TripAdvisor travelers in 2013 and then included the US cities listed in the "top 10 America's most-visited cities" by Murray (2010) but were not included in the list from TripAdvisor. These two lists added up to 24 cities. We focused on the most visited cities



Fig. 1. Process of data acquisition and processing.

because they attract many customers from various cultures and have greater economic importance. Such selection is consistent with the previous literature (e.g., Falk & Hagsten, 2015; Xie et al., 2016) and is unlimited with one single city.

Second, we scraped review data from TripAdvisor. In April 2014, we programmed a Python spider to collect the reviews of all hotels in the 24 selected cities. As shown in Fig. 2, for each review, we

scraped many items that fall into three categories, namely, the review-, reviewer-, and hotel-level items. The review-level items included the overall rating, six dimensional ratings (i.e., ratings for service, rooms, value, location, sleep quality, and cleanliness), text comments, rating date, and travel type. The reviewer-level items include the descriptions of reviewers, including their name, gender, age, location, nickname, number of cities visited, and contributions



Fig. 2. Data items of reviews and reviewers.

to TripAdvisor. We also collected hotel-level items, such as the hotel's name, grade (star class), and chain brand.

Third, we extracted data on the reviewers' self-reported home country. As indicated in Fig. 2, reviewers can choose whether to disclose their locations or not. Given that the location item is reported in open text form instead of standard choices, the home countries of reviewers are not ready for immediate use. To extract data on the reviewers' countries, we first built a database that contained the full and abbreviated names of each country as well as the names of big cities in each country. We also specified these names in their native language for non-English countries. Second, we developed a computer program to extract the reviewers' home countries automatically from the open text form locations by matching the locations with the items in the database. After obtaining the automated results, we randomly selected 1000 reviewers for validation. Two graduate students were recruited to identify the home countries of these 1000 reviewers. When their opinions differed, the authors intervened and made the final decision. By comparing the automatically generated names with the human-identified names, we found that 94% of these names were coherent, thereby indicating the reliability of our country name extraction procedure.

Fourth, we cleaned the extracted data. Given that this research focuses on the reviewers' cultural value, the home country of each reviewer is essential. Therefore, we dropped those reviews which authors did not disclose their locations. We also pruned those reviews written by customers whose home countries were not recognizable despite disclosing their locations. To avoid home country bias, we only retained the reviews written by non-US authors because the hotels were located in the US. As a result, 243,071 reviews were retained for the analysis.

Fifth, we obtained the score of power distance index of each country from the "The Hofstede Centre," which forms the power distance dataset for this work. Given that both datasets include country items, we linked these two datasets by country name to form the final dataset for our empirical work. In our sample, the 243,071 reviews for 3081 hotels in 24 cities spanned the years 2002–2013 and were written by reviewers from 92 countries. As such, our empirical work utilizes a sample ideal for cultural research in terms of size and cultural diversity.

3.2. Research variable

3.2.1. Dependent and independent variables

The dependent variable is the rating of each review, an integer ranging from 1 to 5. On TripAdvisor, the reviewer not only leaves an overall rating but also rates the hotels on six aspects, including service, rooms, value, location, sleep quality, and cleanliness. To check the robustness of our results, we also used these six product attribute ratings as dependent variables.

The main independent variable is the reviewers' power distance, which is denoted as *Power_Dist*. To investigate the moderating role of hotel chain brands as stated in H2, we added the indicator *Chain* to the model. This indicator is equal to 1 if the hotel belongs to a hotel chain and equal to 0 otherwise. To empirically test H3, we need a measure for the consumers' travel experience. Following Hong et al. (2016) and Ma et al. (2013), we used the number of cities that a customer visited as the measure for one's travel experience.

3.2.2. Control variables

Following previous literature (Forman et al., 2008; Gao et al., 2017; Hong et al., 2016; Ma et al., 2013; Sridhar & Srinivasan, 2012), we added a set of control variables to capture the confounding effects caused by the reviewer, review, and hotel.

The specific effects of the reviewer-level items are mostly

captured by the identity, age, gender, travel experience, and contributions of the reviewers to TripAdvisor. On TripAdvisor, reviewers can decide whether to disclose their personal information, including their location, age, and gender. Given that identity disclosure may affect the reviewers' online ratings (Forman et al., 2008; Gao et al., 2017), we used a dummy variable, No_Identity_-Disc, to denote whether the reviewers disclosed their gender and age. This variable is equal to 1 if such information is not disclosed and is equal to 0 otherwise. Following the literature (Gao et al., 2017; Ma et al., 2013), we further captured the effects of the reviewer's age and gender. We used a dummy variable, Women (which is equal to 1 for women and equal to 0 for men), for the gender effect. TripAdvisor classified the reviewers according to their age into six groups, namely, above 65 years, 51-65 years, 36-50 years, 26-35 years, 18-25 years, and below 18 years. As such, we used a set of dummies to capture the effects of each age group. Given that the reviewers' rating behavior may vary as their online experience increases (Goes, Lin, & Au Yeung, 2014; Janze & Siering, 2015), we also controlled their online experience. Consistent with the literature (Gao et al., 2017; Hong et al., 2016), we used the Contributions of the reviewer to TripAdvisor to reflect his/her online experience. This variable represents the sum of photos, forum posts, and reviews posted by the reviewers, thereby reflecting their participation and efforts on TripAdvisor.

The review-level control variables include the hotels' review volume and average rating as observed by the reviewer as well as the reviewers' travel type. The observed review volume and average rating refer to the number of reviews and average rating of the hotel at the time when a reviewer posted his/her review. respectively. Both these variables vary as the reviewer enters the system and posts his/her reviews at different periods. Therefore, we must calculate these two variables based on the full rating history of each hotel that we scraped from TripAdvisor. TripAdvisor uses a half-star rating system for the values of the observed average ratings. As such, we rounded the average rating to the closest half star after obtaining its raw value. The observed average rating is the most common factor and is controlled in many studies for online rating because of its ability to capture the effects of social influence (Gao et al., 2017; Hong et al., 2016; Ma et al., 2013; Sridhar & Srinivasan, 2012). The observed review volume must also be controlled according to attention-grabbing theory (Shen et al., 2015), which contends that reviewers tend to deviate from the average rating when the review volume of product is large. When submitting a review on TripAdvisor, the reviewer can choose to disclose their travel type (i.e., on business, with family, with friends, solo, and couple). Given that rating patterns vary across reviewers by travel type (Banerjee & Chua, 2016), we developed a set of dummy variables to capture the effect of travel type.

The rating patterns of customers may also vary across different hotel grades and geographical locations (Gao et al., 2017; Hong et al., 2016; Liu, Teichert, Rossi, Li, & Hu, 2017b). Therefore, we added two sets of dummies, namely, *Star_Class* and *City*, to capture the fixed effect of hotel grades and cities, respectively.

The key variables of the empirical model, their descriptive statistics, and their correlations are shown in Tables 1–3, respectively. Table 2 shows that the minimum and maximum scores of the power distance indices of reviewers from 92 countries are 11 and 100, respectively, thereby ensuring cultural diversity. Around 45% of the reviews are for chained hotels, while 55% are for independent hotels. The ratings exhibit a clear L-shaped pattern as half of them are over 4 (Hu, Pavlou, & Zhang, 2017). The review volume of hotels is skewed to the right because the mean is two times larger than the median. Around 40% of the reviews are written by reviewers who did not disclose their gender and age, while 29% and 31% of the reviews are written by females and males, respectively. Both the

Table 1	
Description	of variables.

Variable	Description
Power_Dist	Hofstede power distance value for a reviewer.
Chain	Equals to one if a hotel belongs to a hotel chain, and zero otherwise.
Rating	Online rating posted for a hotel by a reviewer.
Obs_Avg_Rating	A hotels' average rating at the time just before a reviewer posted the review.
Obs_Rev_Volume	The review volume of a hotel that the reviewer observed when he/she posted a review.
Travel_Type	Reviewer self-reported travel type for the focal review. Fall in these categories: business, family, couple, with friends, solo, and not disclosed.
No_Identity_Disc	Equal to one if a reviewer didn't disclose gender and age, and zero otherwise.
Women	Equal to one if a reviewer's gender is female, and zero otherwise.
Age	Represents reviewers' age as categorical variables, including older than 65 years, 51–65 years, 36–50 years, 26–35 years, 18–25 years, and less than 18
	years.
Contributions	Sum of the total number of reviews, ratings, forum posts, and photos that a reviewer has posted on TripAdvisor.
Experience	Measured by the number of cities that a reviewer has visited.
Hotel_Grade	The diamond star of a hotel that indicates the grade of hotels, ranging from 1 to 5.

contributions and travel experiences of reviewers are highly dispersed and skewed to the right. Thus, in the empirical analysis, we took the logarithmic values of these two variables. Table 3 indicates that the correlations among the variables are very small as most of them are less than 0.05.

3.3. Empirical model

The ordinary least squares estimates are biased because the dependent variable, online rating (integer value ranging from 1 to 5), is an ordered and censored data. Consistent with the literature, we employed the ordinal logistic model (Gao et al., 2017; Hu & Li, 2011; Ma et al., 2013; Sridhar & Srinivasan, 2012), of which details are presented in Agresti (2012) and Harrell (2015). We specified the following ordinal logistic model by accommodating the nonlinear effects of the independent variables on U_{ij} , a latent variable representing reviewer *i*'s evaluation on hotel *j*.

power distance index score of the reviewer's home country, $Chain_j$ indicates whether the focal hotel belongs to a hotel chain, and *Experience_i* denotes the travel experience of the reviewer. This research focuses on β_1 , β_2 , and β_3 , which capture the main effect of power distance and the moderating roles of *Chain* and *Experience*.

In Equation (1), we also control the factors of review, reviewer, and hotel levels. All terms are described in Table 1. We treat the age and travel type of the reviewers as well as the hotel grade and location as categorical variables. and are two vectors that reflect the effects of the age and travel type of reviewers on their value ratings. Vectors and θ_2 control the fixed effects of hotel grade and hotel location, respectively, by including dummies for hotel grade (1- to 5-star rating) and hotel location (*CityID*). We estimated the intercepts λ_k (k = 2-5), which capture the range of distribution associated with U_{ij} .

In Equation (1), the dependent variable, *Rating*_{ij}, refers to the overall rating. On TripAdvisor, a reviewer not only leaves an overall rating to the hotels but also rates the hotel on six dimensions (i.e.,

$U_{ii} = \beta_0 + \beta_1 Power_Dist_i + \beta_2 Power_Dist_i \times Chain_i + \beta_3 Power_Dist_i \times Experience_i + \beta_3 Power_Dist_i \times Chain_i + \beta_3 Power_Dist_i + \beta_3$	
β_4 Obs_Avg_Rating _{ij} + β_5 Obs_Avg_Volume _{ij} + β_6 No_Identity_Disc _i + β_7 Women _i +	(1)
β_8 Contributions _i + β_9 Experiecne _i + β_{10} Chain _i + γ_1 'Age _i + γ_2 'Travel_Type _{ii} + θ_1 'Hotel_Grade _i + θ_2 'CityID _i + ε_{ii}	

The observed variable $Rating_{ij}$ is determined from U_{ij} using the following rule:

$$Rating_{ij} = k = \begin{cases} 1 \text{ if } \lambda_1 \le +\infty \\ 2, 3, 4 \text{ if } \lambda_k < U_{ij} \le \lambda_{k-1} \\ 5 \text{ if } -\infty < U_{ij} \le \lambda_4 \end{cases}$$

In the above model, k denotes the realized value of the rating posted by reviewers, and λ_1 to λ_4 are the cutoff parameters that determine the intervals for each rank of the ratings. The probability of an observed outcome *Rating*_{ij} corresponds to the region of probability distribution where U_{ij} falls between λ_k and λ_{k-1} . The predicted probability is computed as follows:

$$ln\!\left[\!\frac{Pr\!\left(Rating_{ij} \geq k\right)}{1 - Pr\!\left(Rating_{ij} \geq k\right)}\!\right] = U_{ij} - \lambda_{k-1}, k \!\in\! \{2, 3, 4, 5\}$$

We investigated the effects of the reviewers' power distance on their rating behavior as well as the moderating roles of hotel chain brand and travel experience. In Equation (1), i and j denote the reviewer and hotel, respectively. *Power_Dist_i* indicates the Hofstede

rooms, service, location, value, cleanliness, and sleep quality) as shown in Fig. 1. Both the overall rating and these six dimensional ratings reflect the reviewers' attitude toward and preferences for hotels. Therefore, to check the robustness of our findings, after obtaining the benchmark results using overall rating as the dependent variable, we changed the dependent variable to these six dimensional ratings and repeated the analysis. Through this procedure, we can validate whether the proposed hypotheses still hold for the dimensional ratings, thereby strengthening the robustness of our results.

4. Results

4.1. Hypothesis testing

We implemented the ordinal logistic model of Equation (1) using the "Irm" procedure of R language. Table 4 shows the results of our empirical analysis. Column (1) of Table 4 is the baseline model without the two interaction terms, while Column (2) of Table 4 is the full model that includes both the main effects of *Power_Dist* and the moderating effects of *Chain* and *Experience*. The

 Table 2

 Descriptive statistics of variables.

Statistic	Mean	Standard deviation	Min	Median	Max
Power	43.89	15.05	11	38	100
Chain	0.45	0.50	0	0	1
Rating	4.05	0.97	1	4	5
Obs_Avg_Rating	4.00	0.46	1.00	4.00	5.00
Obs_Rev_Volume	1001.09	1339.82	2	525	11,475
No_Identity_Disc	0.40	0.49	0	0	1
Women	0.29	0.46	0	0	1
Contributions	94.53	492.24	1	30	52,904
Experience	70.20	110.32	1	32	4996

results of each model are consistent.

Table 4 shows that the coefficient of *Power_Dist* with rating is significantly negative (p < 0.001), thereby suggesting that the reviewers' power distance is negatively related to their online hotel ratings. The reviewers with higher power distance tend to leave lower ratings to the hotels. Thus, H1 is supported.

Column (2) of Table 4 reveals that the coefficients of the two interaction terms are both positive and significant at the 0.001 significance level. Given that the main effect of power distance is negative and that the interaction of *Power_Dist* × *Chain* is positive, the negative effect of the reviewers' power distance on their online ratings is much smaller for chained hotels (*Chain* = 1) than for independent hotels provided that other things are equal. Therefore, the effects of the reviewers' power distance on their online ratings are moderated by whether a hotel belongs to a hotel chain, and the negative effect is weaker for chained hotels than for independent hotels. Thus, H2 is supported.

Similarly, the main effect of power distance is negative and the coefficient of *Power_Dist* × *Experience* is positive, thereby indicating that as the travel experience of reviewers increases, the negative influences of power distance on the reviewers' ratings decrease. Therefore, the negative relationship between the reviewers' power distance and their online hotel ratings is moderated by their travel experience. The ratings of reviewers who travel frequently are slightly affected by their cultural values because they have been exposed to many different cultures. Therefore, H3 is supported.

For the review-level control variables, the coefficient of Obs_Avg_Rating is significantly positive (p < 0.001), while that of Obs_Rev_Volume is not significant. Therefore, the ratings of reviewers are affected by social influence, such as the previous average rating (Ma et al., 2013; Sridhar & Srinivasan, 2012). Table 4 also presents the results for the reviewer-level control variables. Those reviewers who did not disclose their gender or age ($No_Identity_Disc = 1$) tend to submit higher ratings than those who disclose such information. Women generally rate the hotels higher compared with men. The coefficients of *Contribution* and *Experience* are negative, thereby indicating that reviewers tend to submit lower ratings as their online experience and physical travel experience increase. *Age*, *Trav_Type*, *Hotel_Grade*, and *City* are coded as sets of dummies. The results of these variables were not reported

Tab	le	3	

V	aria	ble	corre	lations.
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		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	Rating	1								
2	Obs_Avg_Rating	0.37	1							
3	Obs_Rev_Volume	0.04	0.05	1						
4	No_Identity_Disc	-0.01	0.01	0.02	1					
5	Women	0.03	-0.01	-0.004	-0.53	1				
6	Contributions	-0.001	-0.01	-0.01	-0.05	0.02	1			
7	Experience	-0.02	-0.01	-0.04	-0.17	0.01	0.22	1		
8	Chain	0.005	0.02	-0.09	-0.02	-0.03	0.01	0.04	1	
9	Power	-0.04	-0.04	0.02	-0.03	-0.03	0.02	0.02	0.05	1
7 8 9	Experience Chain Power	-0.02 0.005 -0.04	-0.01 0.02 -0.04	-0.04 -0.09 0.02	-0.17 -0.02 -0.03	-0.03 -0.03	0.22 0.01 0.02	0.04 0.02		1 0.05

$\begin{tabular}{ c c c c c c c } \hline Rating & & & & & & & & & & & & & & & & & & &$		Dependent variable:	
$\hline \hline (1) (2) \\ \hline (1) \hline (1) \\ \hline (1) \\ \hline (1) \hline (1) \hline (1) \\ \hline (1) \hline (1$		Rating	
Power_Dist -0.0019^{***} -0.0021^{***} Power_Dist ×Chain 0.0016^{***} 0.0005) Power_Dist ×Experience 0.0006^{***} (0.0005) Power_Dist ×Experience 0.0006^{***} (0.0001) Obs_Avg_Rating 1.6615^{***} 1.6600^{***} (0.0001) Obs_Rev_Volume 0.0070 0.0071 (0.0047) No_Identity_Disc 0.0752^{***} 0.0749^{***} (0.0098) Women 0.1334^{***} 0.1339^{***} (0.0107) Contributions -0.0141^{***} -0.0144^{***} (0.0037) Experience -0.0601^{***} -0.0597^{***} (0.0037) Intercept-2 -2.5580^{***} -2.5540^{***} -3.6288^{***} (0.0620) (0.0620) (0.0620) Intercept-3 Intercept-4 -5.1068^{***} -5.1027^{***} (0.0617) Intercept-5 -7.0852^{***} -7.0812^{***} (0.0626) Age YES YES YES YES Star_Class YES YES YES		(1)	(2)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Power_Dist	-0.0019***	-0.0021***
Power_Dist ×Chain 0.0016^{***} Power_Dist ×Experience 0.0006^{***} 0.0000^{***} (0.0005) Power_Dist ×Experience (0.0001) $0bs_Avg_Rating$ 1.6615^{***} 1.6600^{***} (0.0109) (0.0109) (0.0109) Obs_Rev_Volume 0.0070 0.0071 (0.0047) (0.0047) (0.0047) $No_Identity_Disc$ 0.0752^{***} 0.0749^{***} (0.0098) (0.0098) (0.0098) Women 0.1334^{***} 0.1339^{**} (0.0107) (0.0107) (0.0107) Contributions -0.0141^{***} -0.0144^{***} (0.0037) (0.0037) (0.0034) Chain -0.0444^{***} -0.0443^{**} (0.0082) (0.0082) (0.0082) Intercept-2 -2.5580^{***} -3.6288^{**} (0.0617) (0.0617) (0.0617) Intercept-4 -5.1068^{***} -5.1027^{***} (0.0626) (0.0626) (0.0626) Intercept-5 -7.0852^{***} -7.0		(0.0002)	(0.0002)
Power_Dist \times Experience(0.0005) (0.0001)Obs_Avg_Rating1.6615***1.6600***(0.0109)(0.0109)(0.0109)Obs_Rev_Volume0.00700.0071(0.0047)(0.0047)(0.0047)No_Identity_Disc0.0752***0.0749***(0.0098)(0.0098)(0.0098)Women0.1334***0.1339***(0.0107)(0.0107)(0.0107)Contributions-0.0141***-0.0144***(0.0037)(0.0037)(0.0037)Experience-0.0601***-0.0597***(0.0034)(0.0034)(0.0034)Chain-0.0444***-0.0443***(0.0620)(0.0620)(0.0620)Intercept-3-3.6288***-3.6288***(0.0617)(0.0615)(0.0615)Intercept-4-5.1068***-5.1027***(0.0617)(0.0617)(0.0617)Intercept-5-7.0852***-7.0812***(0.0626)(0.0626)(0.0626)AgeYESYESTravel_TypeYESYESStar_ClassYESYESCityYESYESObservations243.071243.071R ² 0.17790.1780chi ² 43.347.76***43.375.44***	Power_Dist ×Chain		0.0016***
Power_Dist \times Experience 0.0006" 0bs_Avg_Rating 1.6615*** 1.6600*** (0.0001) (0.0001) (0.0001) 0bs_Rev_Volume 0.0070 0.0071 (0.0047) (0.0047) (0.0098) No_Identity_Disc 0.0752*** 0.0749*** (0.0098) (0.0098) (0.0098) Women 0.1334*** 0.1339*** (0.0107) (0.0107) (0.0107) Contributions -0.0141*** -0.0144*** (0.0037) (0.0037) (0.0034) Chain -0.044*** -0.0444*** (0.0082) (0.0082) (0.0082) Intercept-2 -2.5580*** -2.5540*** (0.0620) (0.0620) (0.0615) Intercept-3 -3.6328*** -3.6288*** (0.0617) (0.0617) (0.0617) Intercept-4 -5.1068*** -5.1027*** (0.0626) (0.0626) (0.0626) Age YES YES Tavel_Type YES			(0.0005)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	<i>Power_Dist</i> × <i>Experience</i>		0.0006
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Ola Ann Bating	1 001 5***	(0.0001)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Obs_Avg_kating	1.6615	1.6600
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Oha Day Valuma	(0.0109)	(0.0109)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Obs_Rev_volume	0.0070	0.0071
No_identity_Disc 0.0752 0.0749 (0.0098) (0.0098) Women 0.1334^{**} 0.1339^{***} (0.0107) (0.0107) Contributions -0.0141^{***} -0.0144^{***} (0.0037) (0.0037) Experience -0.0601^{***} -0.0597^{***} (0.0034) (0.0034) Chain -0.0444^{***} -0.0444^{***} (0.0082) (0.0082) Intercept-2 -2.5580^{***} -2.5540^{***} (0.0620) (0.0620) Intercept-3 -3.6228^{***} -3.6288^{***} (0.0615) (0.0615) Intercept-4 -5.1068^{***} -5.1027^{***} (0.0617) (0.0617) (0.0626) Age YES YES Travel_Type YES YES Star_class YES YES City YES YES Observations 243.071 243.071 R ² 0.1779 0.1780 chi ² 43.347.76*** 43.375.44***	No Identity Disc	(0.0047)	(0.0047)
Women (0.0058) (0.0058) (0.0058) (0.0058) (0.0058) (0.017) (0.0107) (0.0107) (0.017) (0.0107) (0.0107) (0.0037) (0.0037) (0.0037) $Experience$ -0.0601^{***} -0.0597^{***} (0.0034) (0.0034) (0.0034) $(Chain$ -0.0444^{***} -0.0443^{***} (0.0082) (0.0082) (0.0082) Intercept-2 -2.5580^{***} -2.5540^{***} (0.0620) (0.0620) (0.0620) Intercept-3 -3.6328^{***} -3.6288^{***} (0.0615) (0.0615) (0.0615) Intercept-4 -5.1068^{***} -5.1027^{***} (0.0617) (0.0617) (0.0617) Intercept-5 -7.0852^{***} -7.0812^{***} (0.0626) (0.0626) (0.0626) AgeYESYESTravel_TypeYESYESStar_ClassYESYES $City$ YESYESObservations243.071243.071R ² 0.1779 0.1780 chi ² 43.347.76^{***}43.375.44^{***}	No_Identity_Disc	0.0752	0.0749
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Women	(0.0098)	(0.0098)
$\begin{array}{c ccccc} (0.0107)^{***} & -0.0144^{***} \\ -0.0141^{***} & -0.0144^{***} \\ (0.0037) & (0.0037) \\ Experience & -0.0601^{***} & -0.0597^{**} \\ (0.0034) & (0.0034) \\ Chain & -0.0444^{***} & -0.0443^{***} \\ (0.0082) & (0.0082) \\ Intercept-2 & -2.5580^{***} & -2.5540^{***} \\ (0.0620) & (0.0620) \\ Intercept-3 & -3.6328^{***} & -3.6288^{***} \\ (0.0615) & (0.0615) \\ Intercept-4 & -5.1068^{***} & -5.1027^{***} \\ (0.0617) & (0.0617) \\ Intercept-5 & -7.0852^{***} & -7.0812^{***} \\ (0.0626) & (0.0626) \\ \hline Age & YES & YES \\ Star_Class & YES & YES \\ City & YES & YES \\ $	women	(0.0107)	(0.0107)
$\begin{array}{cccc} 0.00371 & 0.00371 \\ (0.0037) & (0.0037) \\ (0.0037) & (0.0037) \\ (0.0037) & (0.0037) \\ (0.0034) & (0.0034) \\ (0.0082) & (0.0082) \\ (0.0082) & (0.0082) \\ (0.0620) & (0.0620) \\ (0.0620) & (0.0620) \\ (0.0615) & (0.0615) \\ (0.0615) & (0.0615) \\ (0.0615) & (0.0615) \\ (0.0617) & (0.0617) \\ (0.0617) & (0.0617) \\ (0.0626) & (0.0626) \\ \hline \\ Age & YES & YES \\ Travel_Type & YES & YES \\ Travel_Type & YES & YES \\ Star_Class & YES & YES \\ City & YES & $	Contributions	0.01/11***	0.0107)
Experience -0.0601^{***} -0.0597^{***} (0.0034) (0.0034) (0.0034) Chain -0.0444^{***} -0.0443^{***} (0.0082) (0.0082) (0.0082) Intercept-2 -2.5580^{***} -2.5540^{***} (0.0620) (0.0620) (0.0620) Intercept-3 -3.6328^{***} -3.6288^{***} (0.0615) (0.0615) (0.0615) Intercept-4 -5.1068^{***} -5.1027^{***} (0.0617) (0.0617) (0.0617) Intercept-5 -7.0852^{***} -7.0812^{***} (0.0626) (0.0626) (0.0626) AgeYESYESTravel_TypeYESYESCityYESYESObservations243.071243.071R ² 0.1779 0.1780 chi ² 43.347.76^{***}43.375.44^{***}	contributions	(0.0037)	(0.0037)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Experience	-0.0601***	-0.0597***
$\begin{array}{c cccc} (0.0034)^{**} & (0.0034)^{**} & -0.0443^{***} \\ (0.0082) & (0.0082) \\ \text{Intercept-2} & -2.5580^{***} & -2.5540^{***} \\ (0.0620) & (0.0620) \\ \text{Intercept-3} & -3.6238^{***} & -3.6238^{***} \\ (0.0615) & (0.0615) \\ \text{Intercept-4} & -5.1068^{***} & -5.1027^{***} \\ (0.0617) & (0.0617) \\ \text{Intercept-5} & -7.0852^{***} & -7.0812^{***} \\ (0.0626) & (0.0626) \\ \hline \\ $	Experience	(0.0034)	(0.0034)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Chain	-0.0444***	-0.0443***
$\begin{tabular}{ c c c c c c } \hline (0.062) & (0.0622) & (0.0622) & (0.0622) & (0.0620) & (0.0620) & (0.0620) & (0.0613) & (0.0615) & (0.0615) & (0.0615) & (0.0615) & (0.0615) & (0.0617) & (0.0617) & (0.0617) & (0.0617) & (0.0617) & (0.0626) &$	Chuin	(0.0082)	(0.0082)
Intercept 2 (0.0620) (0.0620) Intercept-3 -3.6328^{***} -3.6288^{***} (0.0615) (0.0615) (0.0615) Intercept-4 -5.1068^{***} -5.1027^{***} (0.0617) (0.0617) (0.0617) Intercept-5 -7.0852^{***} -7.0812^{***} (0.0626) (0.0626) (0.0626) AgeYESYESTravel_TypeYESYESStar_ClassYESYESCityYESYESObservations243,071243,071R ² 0.1779 0.1780 chi ² 43,347.76^{***}43,375.44^{***}	Intercent-2	-2 5580***	(0.0082)
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	intercept 2	(0.0620)	(0.0620)
$\begin{array}{c ccccc} & & & & & & & & & & & & & & & & &$	Intercept-3	-3 6328***	-3 6288***
$\begin{tabular}{ c c c c c c c } \hline Intercept-4 & -5.1068^{***} & -5.1027^{***} \\ & (0.0617) & (0.0617) \\ Intercept-5 & -7.0852^{***} & -7.0812^{***} \\ & (0.0626) & (0.0626) \\ \hline \hline Age & YES & YES \\ \hline Travel_Type & YES & YES \\ \hline Star_Class & YES & YES \\ \hline City & YES & YES \\ Observations & 243,071 & 243,071 \\ R^2 & 0.1779 & 0.1780 \\ chi^2 & 43,347.76^{***} & 43,375.44^{***} \\ \hline \end{tabular}$	intercept o	(0.0615)	(0.0615)
	Intercept-4	-5.1068***	-5.1027***
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$		(0.0617)	(0.0617)
$\begin{array}{c cccc} (0.0626) & (0.0626) \\ \hline Age & YES & YES \\ Travel_Type & YES & YES \\ Star_Class & YES & YES \\ City & YES & YES \\ Observations & 243,071 & 243,071 \\ R^2 & 0.1779 & 0.1780 \\ chi^2 & 43,347.76^{***} & 43,375.44^{***} \\ \end{array}$	Intercept-5	-7.0852***	-7.0812***
Age YES YES Travel_Type YES YES Star_Class YES YES City YES YES Observations 243,071 243,071 R ² 0.1779 0.1780 chi ² 43,347.76*** 43,375.44***		(0.0626)	(0.0626)
Travel_Type YES YES Star_Class YES YES City YES YES Observations 243,071 243,071 R ² 0.1779 0.1780 chi ² 43,347.76*** 43,375.44***	Age	YES	YES
Star_Class YES YES City YES YES Observations 243,071 243,071 R ² 0.1779 0.1780 chi ² 43,347.76*** 43,375.44***	Travel Type	YES	YES
City YES YES Observations 243,071 243,071 R ² 0.1779 0.1780 chi ² 43,347.76*** 43,375.44***	Star Class	YES	YES
$\begin{array}{llllllllllllllllllllllllllllllllllll$	City	YES	YES
$\begin{array}{cccc} R^2 & 0.1779 & 0.1780 \\ chi^2 & 43,347.76^{***} & 43,375.44^{***} \end{array}$	Observations	243,071	243,071
chi ² 43,347.76*** 43,375.44***	R ²	0.1779	0.1780
	chi ²	43,347.76***	43,375.44***

Notes: 1. Asymptotic standard errors robust to heteroskedasticity are reported in parenthesis. The null hypothesis that each coefficient is equal to zero is tested using robust standard errors. 2. *, **, and *** indicate significance at the 0.05, 0.001, and 0.001 level, respectively. 3. All estimates control for the fixed effects of reviewers' age, travel type, hotel grade and city.

in this paper due to the page limit.

4.2. Robustness check

Using overall rating as a dependent variable, the above results support our three hypotheses. Aside from overall rating, TripAdvisor also provides a multi-dimensional rating system that allows consumers to leave ratings on six dimensions of their hotel stay experiences (Liu, Chen, & Hong, 2014). These dimensions include rooms, service, cleanliness, sleep quality, location, and value. Intuitively, if the results above are robust enough, then the hypotheses are likely to hold for the six product attribute ratings. As

Table 4

Effects of power distance on ratings.

such, to test the robustness of our results, we replaced the dependent variable of overall rating with the six product attribute ratings and re-executed the ordinal regression model indicated in Equation (1). Table 5 presents the results.

In Table 5, the dependent variables include the ratings for service, rooms, value, cleanliness, sleep quality, and location as reflected in Columns (1) to (6), respectively. On TripAdvisor, reviewers can observe the average ratings for these six product features. When they submit a rating for one of these features, social influence is also activated (Ma et al., 2013; Sridhar & Srinivasan, 2012). However, in this study, social influence is denoted by the average rating of the focal feature rather than by the average overall rating. Therefore, for each product feature rating, we calculated the corresponding observed average rating for each review by using all previous ratings for that product feature. In Columns (1) to (6) of Table 5, *Obs_Avg_Rating* refers to the average rating with regard to the dependent variables. Accordingly, we also re-formulated the observed volume of each review for each dimension.

Columns (1) to (4) of Table 5 indicate that the coefficients of *Power_Dist* are negative and significant at the 0.001 significance level and that the coefficients of *Power_Dist* × *Experience* and *Power_Dist* × *Chain* are positive and significant. Therefore, the three hypotheses still hold for the ratings on these four dimensions.

However, the results for the other two columns are different. In Columns (5) and (6), the coefficients of power distance are positive

instead of negative, thereby indicating that the ratings on these two dimensions do not decrease when the reviewers' power distance is high. Based on its definition, power distance describes the tolerance for inequality among people (Hofstede et al., 2010). Therefore, this dimension can influence the customers' evaluation of those hotel service aspects that involve the activities of hotel staff. The customers' ratings for location and sleep quality, however, are primarily determined by the physical features and conditions of hotels and are not closely related to the interactions of customers with the hotel staff. As such, the negative relationship between the customers' power distance and their online ratings (H1) is not supported for the dimensions of location and sleep quality.

Our data include different cities and various grades of hotels. Although we controlled for city and hotel grade heterogeneity by introducing two sets of dummies following the literature (Abrate, Fraquelli, & Viglia, 2012; Liu et al., 2017b; Öğüt & Taş, 2012; Sridhar & Srinivasan, 2012), we are still interested in whether the effects of power distance on hotel ratings differ among various cities and hotel grades. We performed Chow's test to answer these questions (Chow, 1960; Wooldridge, 2013). Our analysis shows that the effects of the consumers' power distance on their online hotel ratings are significantly different for some cities but insignificantly different for other cities. Therefore, we found no consistent patterns for the differences among cities. The analysis on hotel grades also reveals that the effects of the consumers' power distance on

Table 5

Results of	power	distance	on	multi-	-dim	iensional	rating	items
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	Dependent variable:							
	Service	Rooms	Value	Cleanliness	Sleep quality	Location		
	(1)	(2)	(3)	(4)	(5)	(6)		
Power_Dist	-0.0078***	-0.0014^{***}	-0.0043***	-0.0067***	0.0010***	0.0006*		
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)		
Power_Dist ×Chain	0.0012*	0.0016**	0.0019****	0.0019***	0.0016**	0.0041***		
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)		
Power_Dist × Experience	0.0008***	0.0002*	0.0008***	0.0005***	-0.0001	-0.0001		
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)		
Obs_Avg_Rating	1.4403***	1.6212***	1.1619***	1.5627***	1.1961***	0.5510***		
	(0.0110)	(0.0111)	(0.0109)	(0.0114)	(0.0114)	(0.0116)		
Obs_Rev_Volume	-0.0333***	-0.0553***	-0.0175***	-0.0493***	-0.0100*	0.2197***		
	(0.0048)	(0.0048)	(0.0048)	(0.0050)	(0.0050)	(0.0051)		
No_Identity_Disc	0.0738***	0.0813***	0.0529***	0.0341**	0.0420***	0.0349**		
_ •	(0.0101)	(0.0102)	(0.0100)	(0.0105)	(0.0107)	(0.0110)		
Women	0.1199***	0.1724***	0.1210***	0.0987***	0.1544***	0.0853***		
	(0.0110)	(0.0111)	(0.0108)	(0.0114)	(0.0116)	(0.0120)		
Contributions	-0.0245***	0.0024	-0.0106**	-0.0062	0.0075	0.0051		
	(0.0038)	(0.0038)	(0.0037)	(0.0039)	(0.0040)	(0.0041)		
Experience	-0.0583***	-0.0522***	-0.0475***	-0.0349***	-0.0381***	-0.0382***		
	(0.0035)	(0.0035)	(0.0034)	(0.0036)	(0.0037)	(0.0038)		
Chain	-0.0410***	0.0905* ^{***}	-0.0909***	0.0059	0.1118***	-0.1915***		
	(0.0085)	(0.0085)	(0.0082)	(0.0088)	(0.0089)	(0.0092)		
Intercept-2	-1.8992***	-2.1346***	-0.4987***	-1.7391***	-0.8975***	1.6252***		
•	(0.0634)	(0.0636)	(0.0630)	(0.0655)	(0.0661)	(0.0709)		
Intercept-3	-2.7962***	-3.3425***	-1.5960***	-2.7520****	-1.8600****	0.3452***		
	(0.0629)	(0.0629)	(0.0624)	(0.0647)	(0.0655)	(0.0679)		
Intercept-4	-4.2213***	-5.0523***	-3.1298***	-4.2015****	-3.2761***	-1.3420****		
	(0.0631)	(0.0632)	(0.0624)	(0.0648)	(0.0655)	(0.0671)		
Intercept-5	-5.8234***	-6.7881***	-4.7752***	-5.9657***	-4.9135****	-3.0017***		
	(0.0637)	(0.0640)	(0.0629)	(0.0655)	(0.0660)	(0.0673)		
Age	YES	YES	YES	YES	YES	YES		
Travel_Type	YES	YES	YES	YES	YES	YES		
Star_Class	YES	YES	YES	YES	YES	YES		
City	YES	YES	YES	YES	YES	YES		
Observations	229,632	228,896	229,082	229,939	214,503	230,006		
R ²	0.1394	0.2020	0.0926	0.1713	0.1284	0.1017		
$chi^2 (df = 65)$	31,485***	47,151***	20,517***	38,577***	26,601***	21,036***		

Notes: 1. Asymptotic standard errors robust to heteroskedasticity are displayed in parenthesis. The null hypothesis that each coefficient is equal to zero is tested using robust standard errors. 2. *, **, and *** indicate significance at the 0.05, 0.001, and 0.001 level, respectively. 3. All estimates control for the fixed effects of reviewers' age, travel type, hotel grade and city.

their online hotel ratings do not significantly differ among different grades of hotels.

5. Discussions and implications

This study attempts to investigate the collective influences of cultural, hotel, and consumer characteristics on the consumers' online ratings by using online hotel review data for the 24 most visited cities collected from TripAdvisor. Four critical findings are obtained. First, consumers from countries with high power distance provide low ratings to hotels; this finding is consistent with those of previous studies that use survey data (Kim & Aggarwal, 2016; Ladhari et al., 2011; Mattila, 2000). Second, the negative effect of power distance on hotel rating is weaker for chained hotels than for independent hotels. Third, power distance has a weak negative effect on online hotel rating when reviewers have extensive travel experience. Fourth, these results are not only applicable for overall rating but are also robust for the multi-dimensional product feature ratings involving staff interactions, such as service, value, rooms, and cleanliness. These findings highlight the negative effect of power distance on the online rating behavior of customers as well as the moderating roles of hotel chain brands and travel experience of reviewers in the hotel sector, both of which contribute to the design of customer-oriented service strategies and the consumers' choice of hotels.

5.1. Theoretical implications

This study provides theoretical contributions in several ways. First, this research generalizes the effects of the customers' power distance on their evaluations of hotel service. Although previous studies have investigated this relationship (Kim & Aggarwal, 2016; Ladhari et al., 2011; Mattila, 2000), their data and design limitations restrict the generalizability of their findings (Kim & Aggarwal, 2016). By contrast, this work uses a unique hotel review dataset from TripAdvisor. The data for this research include over 243,000 reviews for 3000 hotels in 24 US cities that span more than 10 years and involve more than 100,000 customers from over 100 countries. The diversity of customers with various cultural backgrounds and the hotels of different grades from many cities can enhance the generalizability of the effects of power distance on service evaluation. This study also provides new evidence regarding the influence of power distance from the online perspective. This work also provides novel knowledge by examining online rating behavior from the perspective of power distance, a cultural dimension that has rarely been investigated in the online review domain.

Second, this research contributes to the hotel management and consumer behavior literature by identifying the effects of product and customer heterogeneity on the negative relationship between the customers' power distance and their online ratings. Previous studies (e.g., Rhee & Yang, 2015) failed to consider the moderating roles of product categories and consumer characteristics on the relationship between power distance and service evaluation or online hotel ratings because of data limitations. By contrast, we provide solid evidence to prove that the chained hotels operating in multi-markets mitigate the negative effects of power distance. The findings also advance the extant literature, which argue that consumer characteristics affect the perceived value of online reviews (Fang et al., 2016; Ladhari et al., 2011), by exploring the moderating effect of the travel experience of reviewers (a specific consumer characteristic).

Third, this study performed a robustness check by using multidimensional ratings, which differs from traditional methods (e.g., survey). Such method outperforms the conventional approaches in terms of efficiency and comprehensiveness because conventional methods, such as surveys, require additional measurement design and data collection. The method employed in this research also advances previous studies by demonstrating that the results are valid not only for overall hotel ratings but also for the ratings on the four aspects of hotel service that involve hotel staff activities (i.e., service, rooms, value, and cleanliness). In this way, this work provides additional insights regarding the influence of power distance, hotel chain, and reviewer's travel experience.

5.2. Practical implications

This research offers practical implications for hotel managers, consumers, and managers of online review platforms. Given that power distance has a negative effect on the online ratings of hotels, hotel managers must not focus merely on the online reviews from consumers with a high power distance. Instead, these managers must synthesize the online ratings provided by reviewers from countries with various levels of power distance to gain accurate and objective feedback from consumers. They must also recognize the differences between the management of chained and independent hotels. Hotel services must have a high cultural adaptability to satisfy consumers from different cultural backgrounds because hotel chain brands weaken the negative effect of power distance on online ratings. For independent hotels, managers should capitalize their advantages over chained hotels to attract consumers.

Consumers must focus on the country of reviewers when they read online reviews. They must also avoid relying on a single review because reviewers from countries with a high power distance provide low online ratings of hotels. Before booking hotels or submitting an online rating themselves, consumers must evaluate previous ratings and reviews based on the reviews from different countries or cultures, which can be used as objective and comprehensive references for their decision-making.

Online review platform managers can recommend the ratings and reviews from the same country or countries with a similar power distance to their readers and potential consumers considering that the online ratings given by consumers from countries with high and low power distance differ from one another. These ratings and reviews may be helpful for those consumers which cultural backgrounds and perceptions are similar to those of the reviewer. Managers can also prioritize the reviews of consumers with rich travel experience to overcome the negative influence of power distance on online ratings. Managers can also develop forums for consumers from countries with high and low power distance and those with high and low travel experiences as a venue for open discussion with consumers from the same background and with the same preferences.

6. Conclusions

This study contributes to the literature by examining the cultural influences on online ratings in the hotel sector and by exploring the joint effects of cultural-, hotel-, and consumer-related factors on online rating behavior. The consumers from countries with a high power distance provide low online hotel ratings. This finding addresses the generalizability issue being faced by previous studies by extending the results from a limited sample to a large sample of customers from various countries and from the offline context to the online review context. Our study also bridges the existing research gaps by showing that hotel and consumer heterogeneity (i.e., hotel chain and consumer travel experience) weakens the negative effect of power distance on online hotel ratings. Therefore, to improve the consumer satisfaction or online ratings for a certain product, one must consider the features of the product and the cultural background of the consumers. Several directions can be explored for future research. First, some authors may examine whether our model can be applied in other online review platforms (e.g., hotel.com) or review behavior (e.g., online recommendations in hiring) to generate additional insights on the management of review and hotels. Second, future research can apply and extend our data analysis and robustness check methods to other review sites or online review issues. Third, other factors that are related to culture or power distance (e.g., hotel brand and consumer age) may also moderate the effect of power distance on online ratings. Therefore, additional moderators can be added into our model to enrich our findings.

Authors' contribution

Dr. Baojun Gao is in charge of this research. He made substantial contributions on the research design, econometric analysis, manuscript writing and revision, and responding to the comments. Mr. Xiangge Li contributed to this paper on the data acquisition and processing and econometric analysis. Dr. Shan Liu is the corresponding author of this paper. He contributed this paper in theory development, drafting and revising the manuscript, and responding to the comments. Dr. Debin Fang participated in the model development and revision of this paper.

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