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Booking Now or Later: Do Online Peer Reviews Matter?

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Abstract

Consumers always face a tradeoff between making a purchase decision now and continuing information searching with delayed purchase decision. This study extends extant literature by empirically investigating the effects of online peer reviews on consumers' timing of booking a restaurant using a merged data set of online peer reviews and consumer reservation records. The results show that the rating valence, rating variation, and review content richness of online peer reviews positively motivate potential consumers to book a restaurant earlier, while the time interval between successive reviews hinders consumers' booking decision. It is also found that the effects of rating valence on timing of restaurant booking depend on the different levels of rating variation and review content richness. The findings of this study help practitioners better understand consumers' purchase decision process and improve marketing strategies.

Keywords: Advance booking, timing, online reviews, restaurants

1 Introduction

Timing is one of the most important factors considered by service providers (Chen & Schwartz, 2013). The importance of timing is due partly to the perishable nature of service-oriented products, i.e., unsold items cannot be consumed beyond a given time. Accordingly, advance reservations can significantly influence service providers' revenue management (e.g., Chen & Schwartz, 2008a; Schwartz, 2006). In the context of the hospitality industry, online reservations provide useful information for restaurants in terms of cover prediction and cover turnover management. By facilitating more accurate cover projections, online reservations allow restaurants more time to better plan for food purchases, production, and staff scheduling. In contrast, lacking a reservation system or employing last-minute booking may create difficulties in restaurant operations, sales forecasting, and simultaneous management of booked customers and walk-in diners, particularly in popular restaurants.

Timing is also important for potential customers who plan to make reservations, and it is of even greater importance when making decisions in uncertain environments (Chen & Schwartz, 2008b). Consumers are often beset by deciding a rational booking time, which is a complicated problem for many consumers. This difficulty is evident by a Google search of keywords such as "booking early or late", as many related questions have been asked by consumers in online communities and Q&A websites. The major reason for customers' hesitation in making purchase decisions lies in their uncertainty about whether or not their current choice is correct, as they can obtain only insufficient or asymmetric information (Cheung et al., 2014; Money & Crotts, 2003). Consumers often hesitate to make a final decision when they are unable to collect relatively complete information about the target products or services (Liang et al., 2017a; Zhu & Zhang, 2010). Further, the experiential and dynamic nature of travel- and hospitality-related products and services is another important factor that leads to customers' hesitation (Schwartz, 2006; Chen & Schwartz, 2008a).

A few studies have addressed the importance of the timing of reservations for service providers (Chen & Schwartz, 2006; Chen & Schwartz, 2008a, 2008b, 2013; Schwartz, 2008) and have applied analytical models or survey data to examine the factors that may affect consumers' booking propensity or timing, including demand information (Chen & Schwartz, 2006), the likelihood of being offered a good deal, the sellout risk or availability (Chen & Schwartz, 2008b; Chen et al., 2011), consumers' price expectations and the price patterns observed (Chen & Schwartz, 2008a). However, there is no study empirically test the determinants of booking timing in the context of the real online environment by using real purchase/booking data. Moreover, as more and more consumers search online for information to evaluate the choice alternatives, they often have access to hundreds or thousands of reviews from peer consumers before the purchase/booking (Mudambi & Schuff, 2010). The effectiveness of online reviews for consumers' booking and/or purchase intention has been addressed by many studies (e.g., Sparks & Browning, 2011; Xie et al., 2014). However, little research has focused on the impact of online peer reviews on the timing of the purchase decision. According to the information economics theory presented by Stigler (1961), information search can influence consumers' booking timing decisions (Jayaraman & Baker, 2003; Talluri & Van Ryzin, 2005) because this search is costly and time consuming and consumers must make a trade-off between the future costs saved by stopping searching and the benefits of additional search (Stigler, 1961). It is possible that review content such as words and pictures motivates consumers to make purchase decisions by providing information on the quality of products or services (Sparks & Browning, 2011). Additionally, review volume, a widely used indication of business popularity (Gu et al., 2013), is helpful for predicting the sellout risk or the likelihood of waiting for a table.

On this basis, we use restaurant industry as our context and develop a research framework for the effects of online review characteristics, including review valence, review variation, review content richness, and review interval, as well as their interactions on the timing of restaurant booking based on information economics theory. We then empirically test the research model using a merged dataset of actual restaurant reservation records and online reviews from a leading restaurant website in China. The findings contribute to a better understanding of the factors motivating consumers' purchase and/or booking behavior from the decision process perspective and promote more explicit thinking about the customer relationship management.

2 Literature Review and Research Hypotheses

2.1 Online Reviews and Booking Decision in Hospitality

Consumers are increasingly relying on Internet as an information source when they search for hospitality products (Sparks & Browning, 2011), and the impact of online reviews on booking/purchase decision in the hospitality industry has been confirmed by the prior literature (Casaló et al., 2015; Xie et al., 2014; Zhao et al., 2015). In general, review characteristics can be classified into two types of information: structured and unstructured information (Goh et al., 2013). Prior literature mainly focused on how three structured characteristics affect consumers' purchase decisions, i.e., rating valence, variation, and volume. First, rating valence provides subsequent consumers with important information of the product/service quality (Ladhari & Michaud, 2015; Mauri & Minazzi, 2013; Ye et al., 2009). Second, rating variation captures the heterogeneity of peer evaluations and thus is also regarded as a useful source for consumers to make decisions (Park & Park, 2013; Ye et al., 2009). Third, rating volume not only determines the amount of information available for a product but also likely leads potential buyers to rationalize their decisions by telling them how popular the product is (Liang et al., 2017a; Zhang et al., 2010). However, this present study uses review time interval rather than review volume to calculate the popularity of restaurants. Review time interval is measured by the average time for a restaurant to attract a review, and thus can capture the popularity of a restaurant from the temporal perspective. For instance, assume that two restaurants each have 100 reviews, but they receive these reviews within one month and one year, respectively. In this case, the review time interval appears more appropriate than review volume for capturing the popularity level of the restaurant.

Recently, with the development of text-mining skills, the unstructured characteristics of online reviews such as textual content have attracted increasing academic attentions (Goh et al., 2013). For example, Berezina et al. (2016) used a text-mining approach to compare the differences between positive and negative reviews and found that dissatisfied customers are more likely to mention the tangible aspects of hotels in their reviews. Similarly, by applying the text-mining technique, Li et al. (2013) reported that transportation convenience, food and beverage management, convenient distance from tourist destinations, and value for money are the most important factors affecting consumers' hotel bookings. Among the unstructured characteristics, it was found that review content richness is one of the most important factors, because it represents the amount of information that subsequent consumers can obtain from review textual content (Liang et al., 2017b) and is positively related to the perceived helpfulness of the review (Mudambi & Schuff, 2010). Zhao et al. (2015) found that the comprehensiveness of online review content positively affects consumers' online hotel booking intentions.

On this basis, this study investigates the effects of rating valence, rating variation, review time interval and review content richness, and their interaction effects on consumers' timing of booking a restaurant.

2.2 Rating Valence and Booking Timing

When making booking decisions in advance, consumers often search for information online to help them predict the quality and availability of the targeted products or services (Goes et al., 2014; Sparks et al., 2013). Peer reviews are among the major sources consumers can consult online (Duan et al., 2008; Mauri & Minazzi, 2013). The credibility of online reviews is perceived to be higher than those of traditional advertising provided by product providers and of promotional messages on third-party websites (Gretzel & Yoo, 2008; Zhang et al., 2010) because consumers are more likely to believe peer-generated information (e.g. online reviews) than that posted by product providers (Chen & Xie, 2008; Zhu & Zhang, 2010).

Consumers are often requested to provide a numerical rating when they post a review of a product (Yang & Mai, 2010). The numerical rating – or rating valence – represents an overall attitude toward or satisfaction with a consumption experience. Hence, other consumers can make a direct comparison and judgment of the service quality of targeted restaurants based on the ratings of peer consumers (Zhang et al., 2010). Rating valence has been used as a proxy for online word-of-mouth for a product or service and was found to be highly related to product quality (Sun, 2012; Clemons & Gao, 2008). Studies have documented that rating valence positively affects consumer purchase decisions and product sales (Casaló et al., 2015; Floyd et al., 2014; Mauri & Minazzi, 2013; Sparks & Browning, 2011; Xie et al., 2014). A recent study (Viglia et al., 2016) argued that rating valence is the most important dimension of online reviews, and the empirical results suggest that a one-point increase in review ratings for a hotel will lead to a 7.5% increase in the hotel's occupancy rate. Based on the above discussions, we expect that consumers will predict that a restaurant with a higher rating valence has higher quality, and thus, they will be more confident in their choice, stop searching for information and make a final decision earlier than they will for a restaurant with a lower rating valence. Therefore, we propose the following hypothesis:

Hypothesis 1: The rating valence has a positive impact on the advance booking time of restaurants.

2.3 Rating Variation and Booking Timing

Rating variation is another factor that can influence consumers' booking timing decisions. According to Sun (2012), rating variation refers to the heterogeneity of diners' evaluations of restaurants. As one of the prominent characteristics of online reviews, rating variation's influence on consumers' purchasing decisions has been examined in the previous literature. While some studies found that inconsistency in online ratings is related to a decline in service providers' sales performance (Zhu & Zhang, 2010), other studies reported a positive relationship between rating variation and consumers' purchasing decisions (Chintagunta et al., 2010; Clemons et al., 2006; Park & Park, 2013; Xie et al., 2014). Despite these inconsistent results, the studies generally agree that higher rating variation means that some consumers dislike the given product or service, while other consumers with specific personality characteristics might like it.

Unlike previous studies, this study does not consider the question of whether a consumer books a restaurant but rather how rating variation can influence consumers' booking timing. Diners must collect information to evaluate the quality of restaurants before making a decision. As a consumer can collect more complete information about a target restaurant, the likelihood he or she will make a decision quickly increases. Thus, consumers tend to book earlier at restaurants on which they can collect relatively complete information in a limited amount of time. A higher rating variation for a restaurant indicates that previous diners not only identified the merits of a restaurant but also found its shortcomings and thus provided diverse information in their ratings and textual reviews. For example, assume two restaurants with the same rating valence (e.g., 4.5) but different rating variations. Then, most ratings for the restaurant with the lower rating variation should be approximately 4.5, while more extreme positive and negative ratings are likely for the restaurant with the higher rating variation. Therefore, for the restaurant with lower variation, consumers may still be ambiguous about the restaurant's disadvantages and if they would care about them. The above argument is partly proven by studies on review helpfulness. When a product has many positive reviews, the rare negative reviews will be perceived as extremely helpful (Yin et al., 2014). Therefore, we propose the following hypothesis:

Hypothesis 2a: Rating variation has a positive impact on the advance booking time of restaurants.

Previous studies have investigated the interaction effects between rating variation and rating valence on product sales (e.g., Sun, 2012; Xie et al., 2014) but neglected their interaction effect on the purchase decision process. Negative reviews have a more salient influence than positive reviews on consumers' perceived quality (Chevalier & Mayzlin, 2006; Cui et al., 2012); therefore, for two service providers with the same rating valence but different rating variations, the service provider with the higher rating variation should have more negative reviews and thus will be perceived as lower quality (Papathanassis & Knolle, 2011). For example, for a restaurant with a rating valence of 4, a lower rating variation means that most of its ratings are distributed around the rating of 4. Diners' consistent evaluation is likely to enhance the credibility of this rating. However, if a restaurant has a higher rating variation with the same rating valence of 4, it may have received some extreme positive ratings and extreme negative ratings. Since consumers psychologically weigh negative reviews more strongly than positive reviews (Chevalier & Mayzlin, 2006; Cui et al., 2012; Papathanassis & Knolle, 2011), the rating of 4 would be underrated. In other words, the positive influence of rating valence is likely to be impaired when the rating variation is high than when it is low. Thus, we propose the following hypothesis:

Hypothesis 2b: Rating variation negatively moderates the impact of rating valence on the advance booking time of restaurants.

2.4 Review Content Richness and Booking Timing

In addition to numerical ratings, the content of the review in the form of text or pictures is an important source of information when evaluating the quality of products online (Goh et al., 2013). While online ratings provide an intuitive impression for consumers, the text and pictures that accompany the review provide more detailed information on the food and characteristics of the restaurant. When consumers aim simply to find a good restaurant without specific requirements, they can refer to numerical ratings to save searching costs and cognitive costs. However, consumers who have clear preferences for certain restaurant characteristics may benefit from reading the entire content of a review to identify these characteristics (Liang et al, 2017b).

However, not all reviews help consumers make decisions (Liu & Park, 2015). Reviews that include details on the product, retailers or available alternatives are usually perceived as high quality and helpful for consumers (Mudambi & Schuff, 2010; Park & Nicolau, 2015). In contrast, if reviews include simple words such as “It’s great!”, the details of the product remain unknown, and then, consumers must consult more information from historical reviews. According to information economics theory, consumers recognize that information search is costly and time consuming and that there are tradeoffs between effort and accuracy (Stigler, 1961). When they have collected diagnostic information – which can reduce purchase uncertainty and increase their confidence in the decision – consumers are willing to stop information search (Browne et al., 2007; Moorthy et al., 1997). In these situations, reviews with rich content that offer details such as how and where the product was used in specific contexts are diagnostic; therefore, this content richness can save consumers significant searching costs and cognitive costs and thereby facilitate the purchase decision process. This argument leads us to hypothesize the following:

Hypothesis 3a: Review content richness in terms of words and pictures has a positive *impact on the advance booking time of restaurants.*

Although many studies have examined ratings or the content of reviews in isolation, few have attempted to combine multiple sources of information. In an early study, Ganu et al. (2009) combined review text and ratings and observed that reviews often discuss multiple aspects of a restaurant and that a diner's rating depends on the importance that he or she ascribes to each aspect. They found that the inclusion of textual information results in general or personalized review score predictions that are better than predictions derived from diners' numerical ratings. McAuley and Leskovec (2013) and Ling et al. (2014) attempted to combine review text and numerical ratings to predict users' feedback on products (or services) and found that analyzing review text can help consumers better understand the latent dimensions of numerical star ratings and thus improve the accuracy of their predictions. These studies indicated that the open-ended text of a review offers additional explanation and context to supplement numerical ratings (Mudambi & Schuff, 2010; Sparks & Browning, 2011). In particular, consumers can adjust the accuracy of ratings according to the information details embedded in review text and pictures (Ludwig et al., 2013). Moreover, some other studies even found that the existence of review text is a substitute for ratings in consumers' decision-making process (Hu et al., 2014). This substitution occurs mainly because consumers can only get a general impression of product quality from numerical ratings, whereas rich information gained from review textual content gives them a relevantly comprehensive understanding of the product (Goh et al., 2013; Liang et al., 2017a). For example, an empirical study by Hu et al. (2014) stated that rating valence does not directly influence online sales but only has an indirect effect through the sentiment expressed in review text. On this basis, review content richness may weaken the impact of rating valence on booking decisions, and thus we propose the following hypothesis:

Hypothesis 3b: Review content richness in terms of words and pictures negatively *moderates the impact of rating valence on the advance booking time of restaurants*.

2.5 Review Intervals and Booking Timing

Product popularity and scarcity are two factors that can influence consumers' booking decisions and timing. First, information on product popularity indicates the product's quality, as explained by signaling theory in information economics (Connelly et al., 2011). Information asymmetry often occurs in an online retail environment since consumers sometimes cannot estimate the quality of products directly (Mukherjee & Nath, 2007; Wang et al., 2004). This asymmetry leads to a gap between the information delivered by product providers and the information perceived by consumers and simultaneously results in consumers' uncertainty before purchasing (Mishra et al., 1998). Therefore, to make rational decisions, consumers often actively seek information that signals quality to compensate for this information asymmetry (Zhu & Zhang, 2010). Popularity is among the signals showing the quality of products or services. If a product has been frequently purchased by others, consumers often perceive the product as "high-quality item" since its quality has been verified by many peers (Liang et al., 2017a). Moreover, due to the herding effect, consumers will be less likely to hesitate in purchasing popular items (Cheung et al., 2014; Li et al., 2016).

Second, according to commodity theory and scarcity effects, scarce products are perceived to be more valuable and desirable (Verhallen, 1982; Verhallen & Robben, 1994). This phenomenon occurs mainly because scarcity represents either higher demand or limited supply, both of which signal high quality (Akerlof, 1970). Cialdini (1993, 2001) argued that scarce products may induce relatively thoughtless and automatic responses by consumers. Consequently, a product's value is enhanced because scarcity hinders consumers' ability to think rationally (Cialdini, 2001). As products become scarce, their likelihood of sellout increases (Chen & Schwartz, 2008a). The cost of continuing information search for products with a high sellout risk is high (Stigler, 1961) because those items may become sold out during the subsequent search process, and all efforts would therefore be in vain. In summary, scarcity can urge consumers to book earlier due to higher perceived quality and a higher sellout risk.

In the e-commerce context, companies in the hospitality industry often use statements or visual icons attached to products to inform consumers about product popularity and scarcity (Suri et al., 2007). For example, typical displays to indicate product popularity are "92 people booked this property in the last 48 hours", "164 others viewing this property right now", and "65% booked this property". Typical displays to indicate product scarcity include "only 4 deals left" and "deal of the day". In addition, online reviews have been used widely as product signals. For example, the number of peer reviews is an indication of product popularity (Zhu & Zhang, 2010) and availability (or scarcity). As the number of reviews written for a specific product increase, consumers' tendency to be aware of and to buy the product increases (Dellarocas et al., 2007; Godes and Mayzlin, 2004). Previous studies have also found that the number of reviews is positively related to the product's sales volume (e.g., Chevalier & Mayzlin, 2006; Liang et al., 2017a). However, the total review volume neglects the influence of time. A restaurant may have a large number of reviews because it has been in business for a long time or because it was popular in the past. In our research setting, we measured the average time interval between successive reviews for a restaurant by the ratio of a period of time to the number of reviews generated during this period. Since reviews are consumers' post-consumption evaluations, shorter review intervals imply more patronages to a restaurant within a fixed period. On one hand, a short average review interval is likely to lead consumers to rationalize their booking decisions, given that many other people also made their purchases in certain period (the effect of "popularity"). On the other hand, this short interval may induce consumers' perception of the risk of sellout or of waiting for a table (the effect of "scarcity"). In these situations, the average review interval can be viewed as a signal of product popularity and scarcity. Therefore, we hypothesize the following:

Hypothesis 4a: The average review interval has a negative impact on the advance booking time of restaurants.

According to the scarcity effect, product scarcity constrains an individual's ability to process information, resulting in judgments based on heuristics (Cialdini, 1993, 2001; Suri & Monroe, 2003). If consumers perceive a high sellout risk for a product, they may heuristically process information and thereby think less. In this case, online ratings can be a cost-saving source to consult. Hence, we conjecture that consumers are heavily affected by the rating valence of a restaurant with a short review interval due to their perception of scarcity. For restaurants with a large review interval (i.e., low sellout risk), consumers have less time pressure to make a decision, and they may want to collect additional information from other sources, such as textual reviews, advertising, or promotions. Therefore, a short review interval enhances the impact of rating valence on consumers' booking decisions more than a long review interval does. In addition, a shorter review interval implies that more reviews are generated during a certain period, which indicates that the rating valence of those reviews has been justified by more consumers and should be perceived as more credible. The influence of rating valence is thus enhanced by an increase in rating credibility. Accordingly, we present the following hypothesis:

Hypothesis 4b: The average review interval negatively moderates the impact of rating valence on the advance booking time of restaurants.

The conceptual framework of this study is presented in Figure 1.

---Insert Figure 1 here---

3 Methodology

3.1 Data Collection

In this study, we use the restaurant industry as our context, for two reasons. First, an increasing number of diners currently use reservation websites to book restaurants in advance. A survey of 1,115 diners showed that access to an online reservation system could influence restaurant consumers' purchasing decisions, with 36% of the participants regarding online reservation systems as among the most important technologies (Toast's annual Restaurant Technology Industry Report, 2016). Easy access to peer reviews can create a source of differentiation in reservation systems and has been adopted by several popular restaurant booking websites, such as OpenTable.com and Bookatable.com. Moreover, unlike hotels and airlines, restaurants rarely change their menus and prices; thus, restaurants provide an ideal context for us to understand the timing behavior of consumer booking by removing the influence of price.

The study collected restaurant booking and review data from Xiaomishu.com, which provides reservation services for consumers, allowing them to find available tables that meet the desired criteria for type of cuisine, price and location at a specified time. This website was chosen for three main reasons. First, Xiaomishu is a third-party platform on which consumers can make online reservations and read restaurant reviews posted by their peers. The website features an easy switch between reservation and review options on the restaurant home page. Therefore, this website design makes it convenient for bookers to consult online reviews, and it is expected that restaurant reviews are likely to affect consumer booking decisions. Second, the website uses a star rating system, thereby allowing us to easily quantify consumer word-of-mouth for restaurants on a five-point scale. Third, Xiaomishu is a leading restaurant booking website in China. By March 2014, over 3 million users had used this website to make reservations at over 2.7 million restaurants across 400 Chinese cities[1].

The city of Shanghai was selected because it was the birthplace of the Xiaomishu site and is home to the largest number of users. Over 60,000 restaurants in Shanghai were listed on the Xiaomishu site at the beginning of the data collection period. We collected booking information for these restaurants using self-compiled Java crawler tools and obtained 330,439 total bookings from September 10, 2016, to January 9, 2017. For each booking, we gathered the name of the booking customer (from which the customer's gender could be extracted, as the name was entered in the form of Mr. or Mrs. XX), booking date and time, the number of diners, and dining date and time (see Figure 2). We also collected all reviews posted prior to January 9, 2017, for the 60,000 restaurants. For each review, the time the review was posted, the review rating on a scale of 1-5 (1=poor to 5=excellent), the review text, and the number of pictures were extracted.

---Insert Figure 2 here---

In summary, our dataset includes two parts: daily restaurant reservation records (e.g., booking and dining times) and consumer restaurant review information (e.g., review ratings and review text). The disparate data types were then compiled to create one comprehensive dataset. Specifically, each record consists of a booking record and the review information accumulated prior to the booking of a specific restaurant.

3.2 Variable Operationalization

The dependent variable is the duration (in days) between the booking time and the dining time as provided in the booking record (*BookDineDiff*). The explanatory variables include the review information accumulated prior to a specific booking, including the rating valence (*RatingAvg*), rating variation (*RatingVar*), content richness (*ReviewText* and *ReviewPic*), and average time interval (*ReviewInterval*) of previous reviews. Since it is very likely that recent

[1] http://www.xiaomishu.com/about/aboutus/

reviews have a stronger impact on consumer booking decisions than more distant reviews (Sahin & Robinson, 2002), we used the two hundred most recent reviews before each booking record to measure the review effects in the main test; that is, *ReviewInterval* was calculated as the average time interval of the two hundred most recent reviews prior to a reservation. We also conducted several robustness checks by estimating the most recent one hundred reviews, the reviews posted in the previous year, and the reviews posted in the previous two years, and the results remain robust. We also controlled for certain characteristics of the booked meal, including the dining date (*DineDay* and *DineHoliday*), the sex of the booking customer (*CustSex*) – as the previous literature suggests that females are more risk averse in decision-making than males (e.g., Eckel & Grossman, 2008) – and the number of diners (*Diners*). Please note a small number of booking records do not list all the information, therefore there exist missing values for a few variables (e.g., *CustSex* and *Diners*). After screening out the samples with missing values, our final analysis is restricted to 321,973 bookings. Table 1 presents the definitions of all variables included in this research.

---Insert Table 1 here---

Table 2 presents descriptive statistics for all the variables. As shown in Table 2, the standard deviations of *BookDineDiff*, *ReviewText*, *ReviewPic* and *ReviewInterval* are relatively high; therefore, we used the logarithm of the four variables in the model to slow the fluctuation of the sample data and to encourage the normal distribution of the data. The average time interval between the booking time and dining time for each diner is 6.144 days (SD=14.124). Regarding the review characteristics, the rating valence of the 200 most recent reviews before booking is 4.108 (SD=0.243) with a variation of 0.645 (SD=0.228). The number of text characters and pictures for these 200 reviews are 4832.735 (SD=2836.463) and 43.319 (SD=39.342), respectively, on average. The average time to publish one review on a restaurant is 20.638 (SD=38.212) days, which shows that the average speed at which the website generates a review is relatively slow and highlights the need to consider only recent reviews rather than all historical reviews in our analysis. Among all reservations, 34.0% and 16.6% were booked for meals on weekends and holidays, respectively, and 48.6% and 51.4% are booked by female and male, respectively. The average number of diners for each reservation is 7.930 (SD=6.118).

---Insert Table 2 here---

The Pearson's correlation matrix is shown in Table 3. The results indicate that the correlations among the explanatory variables (including the independent variables and control variables) in this study are weak. Moreover, we also reported the variation inflation factor (VIF) and tolerance values of the explanatory variables (see Table 4). The results show that all VIF values are less than 10, and the values of tolerance are over 0.1, indicating that multicollinearity is not a problem in our model estimation.

---Insert Table 3 here---

---Insert Table 4 here---

3.3 Econometric Specifications

In our econometric model, the dependent variable $LnBookDineDiff_{ij}$ represents the time elapsed between the booking time and the dining time for reservation *i* of restaurant *j*. The explanatory variables are the characteristics of reviews posted before reservation *i* of restaurant *j*, including $RatingAvg_{ij}$, $RatingVar_{ij}$, $LnReviewText_{ij}$, $LnReviewPic_{ij}$ and $LnReviewInterval_{ij}$. We also controlled the factors related to the characteristics of bookers and booked meals (i.e., $DineDay_{ij}$, $DineHoliday_{ij}$, $CustSex_{ij}$, and $Diners_{ij}$ are denoted by $Control_{ij}$). Specifically, the econometric model is as follows:

$$LnBookDineDiff_{ij} = \beta_0 + \beta_1 RatingAvg_{ij} + \beta_2 RatingVar_{ij} + \beta_3 LnReviewText_{ij} + \beta_4 LnReviewPic_{ij} + \beta_5 LnReviewInterval_{ij} + \chi Control_{ij} + \varepsilon_{ij} \quad (1)$$

To test Hypotheses 2b, 3b and 4b, several interaction terms were introduced into Model (1). The vector $Interaction_{ij}$ includes the interaction terms between $RatingAvg_{ij}$ and other four explanatory variables (i.e., $RatingVar_{ij}$, $LnReviewText_{ij}$, $LnReviewPic_{ij}$ and $LnReviewInterval_{ij}$). Moreover, to control for the restaurant heterogeneity effects coming from factors such as restaurant location and price and to control for temporal heterogeneity effects (e.g., external shocks may occur at certain months), we also included the restaurant fixed effects (R_j) and dining month fixed effects (M_t) in our model. Then we reach Model (2):

$$LnBookDineDiff_{ij} = \beta_0 + \beta_1 RatingAvg_{ij} + \beta_2 RatingVar_{ij} + \beta_3 LnReviewText_{ij} + \beta_4 LnReviewPic_{ij} + \beta_5 LnReviewInterval_{ij} + \chi Control_{ij} + \lambda Interaction_{ij} + R_j + M_t + \varepsilon_{ij} \qquad (2)$$

4 Results

4.1 Estimation Results

Table 5 shows the estimation results using a robust standard deviation. Model 1 and Model 2 provide the main results, with review effects measured by the two hundred most recent reviews before a reservation is made. The results of Model 1 are estimated based on Equation 1 and show that the coefficient of *RatingAvg* is positive and statistically significant (coeff=0.0802, p<0.001), which means that as the rating valence increases, customers book a restaurant earlier, supporting our Hypothesis 1. The coefficient of *RatingVar* is positive, suggesting that this variable has a positive impact on the time of an advance restaurant reservation (coeff=0.138, p<0.001). High variation communicates to consumers that a restaurant is loved by some consumers but not others. Heterogeneity in previous diners' opinions may provide more complete information to people, especially those with less prior knowledge, and positively affects the interval between booking time and dining time. Therefore, Hypothesis 2a is supported. The coefficients of *LnReviewText* (coeff=0.00926, p<0.001) and *LnReviewPic* (coeff=0.00423, p<0.05) are both positive and significant, indicating that rich content in previous reviews is likely to help consumers make a booking decision. Therefore, Hypothesis 3a is supported. The average time interval between reviews has a negative influence on the interval between booking time and dining time (coeff=-0.147, $p<0.001$), supporting Hypothesis 4a.

---Insert Table 5 here---

Model 2 in Table 5 shows the estimation results of interaction effects. The coefficients of interaction terms *RatingAvg×RatingVar* (coeff=-0.533, $p<0.001$), *RatingAvg×LnReviewText* (coeff=-0.285, $p<0.001$), and *RatingAvg×LnReviewPic* (coeff=-0.151, $p<0.01$) are negative and significant, indicating that both rating variation and content richness of previous reviews negatively moderate the influence of average rating on advance booking time. Specifically, the impact of average rating on advance booking time is weaker when the rating variation and content richness of previous reviews are high compared with when they are low, and vice versa. These results support Hypothesis 2b and Hypothesis 3b. However, the interaction effect between *RatingAvg* and *LnReviewInterval* is insignificant, and thus Hypothesis 4b is not supported.

4.2 Robustness Check

4.2.1 Alternative Measurement of Review Content Richness

Although the number of words and pictures can capture the content richness of reviews in many situations, it is possible that some reviews with long text or many pictures only refer to one or two aspects of the reviewed restaurants, and thus readers cannot grasp an all-rounded assessment of the restaurant. In contrast, readers could obtain richer information if a review mentions more topics of a reviewed restaurant, therefore, we use the number of topics as an alternative measurement of review content richness in this robustness check. Following the study of Xiang et al. (2017), we used the Latent Dirichlet Allocation (LDA) model to iteratively infer the topics mentioned in each review (please refer to Appendix for details).

Then we re-estimated our econometric models by replacing original review content richness indicators (*LnReviewText* and *LnReviewPic*) with the new variable *LnReviewTopic*, which denotes the number of topics mentioned in the latest two hundred reviews before a reservation. The results reported in Table 6 are highly consistent with those shown in Table 5.

---Insert Table 6 here---

4.2.2 Different Cutoff Points of Previous Reviews

To avoid the arbitrary choice of online review data, we checked the sensitivity of our empirical results by using online review data with different cutoff points. Specifically, in Model 1 of Table 7, we modelled the timing of advance booking based on one hundred most recent reviews before a reservation, while Model 2 and Model 3 were modelled based on reviews posted in past one and two years, respectively, prior to each reservation. As shown in Table 7, the re-estimation results are highly consistent with those in Table 5. Further, assuming that all reviews can have effects on the product life cycle, many product- or service-level studies (such as Chevalier & Mayzlin, 2006; Xie et al., 2014) measured review characteristics based on all historical product or service reviews. However, this study investigates the determinants of consumers' booking decision and assumes that a consumer most likely pays attention to recent and real-time reviews rather than all historical reviews before making a decision to save searching costs and ensure the instantaneity of information they collect. We confirmed this argument by re-calculating review characteristics using all historical reviews for a restaurant prior to a booking and rerunning Equation 2. The results in Model 4 show that the coefficients of all explanatory variables except for rating valence (i.e., *RatingVar*, *LnReviewText*, *LnReviewPic*, *and LnReviewInterval*) are insignificant. The rating valence of all reviews plays a role in consumers' booking decision because it is equivalent to the overall star rating in a restaurant profile on the website and can be seen directly when consumers browse restaurant review pages. This finding supports our assumption of recency effects, i.e., a consumer is more likely to see recent and real-time reviews than reviews posted long time ago before making a booking. Moreover, this finding is consistent with the study of Filieri and McLeay (2014), which reported that information timeliness is a strong predictor of consumers' adoption of online accommodation reviews. This finding is also consistent with Zhao et al. (2015), which found a significantly positive relationship between timeliness of online reviews and online hotel booking intentions.

---Insert Table 7 here---

5 Discussion and Implications

5.1 Discussion

This study collected detailed data on consumers' restaurant reservations and combined them with a review dataset to analyze the impact of online review characteristics on consumers' booking timing. The literature on information economics theory and online reviews is summarized and discussed to formulate the theoretical framework. According to information economics theory, consumers always face a tradeoff between stopping and continuing an information search (Browne et al., 2007; Moorthy et al., 1997). Online reviews affect the stopping time by exposing consumers to information on restaurant quality through numerical ratings, text and pictures. This exposure saves significant searching costs and helps consumers make decisions (Huang et al., 2009; Zhu & Zhang, 2010). Moreover, a high frequency of generated reviews signals a restaurant's popularity and high risk of sellout. In the case of a high sellout risk, the cost of continuing the information search is high, which places pressure on consumers and motivates them to stop the information search and make a decision.

We provide empirical evidence that is consistent with theoretical predictions. The results show that high rating valence helps consumers make a decision with less hesitation due to the positive relationship between rating valence and perceived quality (Sparks & Browning, 2011). Similar results are reported that online ratings have a positive impact on product sales (e.g., Xie et al., 2014; Zhu & Zhang, 2010), consumers' booking intentions (Casaló et al., 2015), and the size of online reservation transaction (Torres et al., 2015). Large rating variation means heterogeneous peer reviews that likely provide potential consumers with comprehensive information compared with consistent peer reviews. Consumers may have a better understanding of the advantages and disadvantages of a restaurant and thus are able to make bookings more quickly, when they are exposed to heterogeneous reviews. In addition to ratings, detailed review content in the form of texts and pictures is also important information that can help consumers make booking decisions, which highlights the value of textual and graphic content in online reviews. This finding is consistent with previous studies suggesting that the comprehensiveness of online review content positively affects consumers' online hotel booking intentions (Zhao et al. 2015). Finally, the average time interval between successive reviews affects consumers' restaurant booking behavior. Specifically, due to the effect of "scarcity," if consumers observe that a restaurant frequently attracts reviews, they tend to make a booking with less hesitation because they perceive that this restaurant is popular and has a high sellout risk. This result is consistent with prior studies showing the positive impact of review volume on sales (e.g., Xie et al., 2014; Zhu & Zhang, 2010) and booking intention (Zhao et al. 2015).

We further examined whether there exist interaction effects among the review characteristics on booking time. Interestingly, we found that the impact of rating valence depends on the level of rating variation and the content richness of reviews. Specifically, the impact of rating valence is weaker when the average variation and content richness are high than when they are low. These findings indicate that consumers tend to refer to multisource information before making decisions, and information from multiple sources can complement each other in the consumers' decision-making process.

5.2 Theoretical and Practical Implications

5.2.1 Theoretical Implications

This study makes three theoretical contributions to the literature. First, this study contributes to the hospitality management literature. Reservation systems are widely used in the hospitality industry, and previous studies on reservation systems have acknowledged the importance of booking timing due to the perishable nature of service-oriented products (Chen & Schwartz, 2008a, 2013). However, given the difficulties in obtaining data in the decision-making process, limited studies provided the direct empirical evidence of the determinants of booking timing in the hospitality industry. This study fills in this research gap under the context of online restaurant reservations. To our best knowledge, it is one of the first empirical studies to examine the determinants of timing of restaurant booking based on real booking data.

Second, it also contributes to the literature on e-commerce by confirming the impact of online reviews on timing of purchase decision. Although prior studies have confirmed the business value of online reviews, (e.g., their effects on product sales or consumer purchase intention), few studies pay attention to the role of online reviews in the process of decision-making. Our study reveals that both structured and unstructured characteristics (i.e., numerical ratings and textual content) of online reviews can affect the timing of consumer booking/purchase decision. Therefore, this study would help better understand the mechanism in which online reviews affect potential consumers.

Third, we ground the timing of restaurant booking in theory by linking it to the concept of information economics. This study thus helps extend the literature on information economics in the context of online reviews. Our findings suggest that the characteristics of online reviews and their interactions can affect the timing of stopping information searching.

5.2.2 Practical Implications

Customer relationship management through the temporal lens appears to be imperative for modern firms operating in markets where the volume and speed of change are high (Plakoyiannaki & Saren, 2006). Marketers must move from business models that adopt a static understanding of customers and markets to practices that perceive customers in a dynamic, changing environment (Lemon et al., 2002). In this regard, the practical implications of this study are two-fold. First, our findings show that a high rating valence and a high frequency of posted reviews can motivate potential consumers to make purchase decisions earlier emphasizes the importance to managers of improving and maintaining a strong and substantial online reputation. More interestingly, the finding that rating variation and review content richness provide information in addition to rating valence implies that it would be effective to provide more complete information to consumers to reduce their uncertainty, e.g., by encouraging detailed reviews (with more words and pictures), offering multidimensional ratings and asking consumers to rate products in multiple dimensions.

Second, this study also confirmed the ineffectiveness of historical reviews for purchase decisions, as the results estimated with all historical reviews are not significant in contrast to the estimations based on recent reviews. This finding is reasonable since consumers are unlikely to check and refer to reviews posted a long time ago. Thus, for a restaurant, a strong past reputation is not always effective in influencing present consumers. To consistently earn bookings, restaurants should continually provide high-quality services and thereby attract positive reviews.

5.3 Limitations and Further Directions

Although this study has important theoretical and practical implications, it is also subject to a few limitations, which can be addressed in the future studies. First, the research context of this study is the restaurant industry, where pricing effects can be well controlled as restaurants are less likely to change their menus frequently. Therefore, the results may not be applicable to other industries, such as the hotel or airline industries, where dynamic pricing strategies are commonly used to motivate consumers to make reservations. On this basis, future studies can further test the findings of our study by collecting data from hotel and airline industries. Second, using a Chinese website (Xiaomishu) may limit the generalizability of our results. In other words, the findings and implications should be applied primarily to restaurant reservation websites in China. Given the prevalence of online restaurant reservation systems in many regions in the world, further studies can extend the samples to other regions and cultures, to check the generalizability of the empirical findings from our study. Third, this study used restaurant fixed effects to control for restaurant-level heterogeneity, therefore, it is hard to detect the specific effects of different restaurant features. A possible direction for future studies is to introduce restaurant-level variables (e.g., price, location, scale, etc.) into the models and to examine how booking timing is affected by different restaurant features. Fourth, although we controlled for several important customer characteristics (e.g., gender), other customer-level variables, which may also influence the customer's booking timing, are not controlled in our models due to the data unavailability. It would be interesting for future studies to include customers' historical bookings in the model and investigate the effect of customers' habits (e.g., repeat booking) on customers' booking timing. Finally, given that we collected data from only one reservation website, it is difficult to test the influence of website design on booking timing. Examining how website design can influence consumers' booking timing could be another interesting direction for future research.

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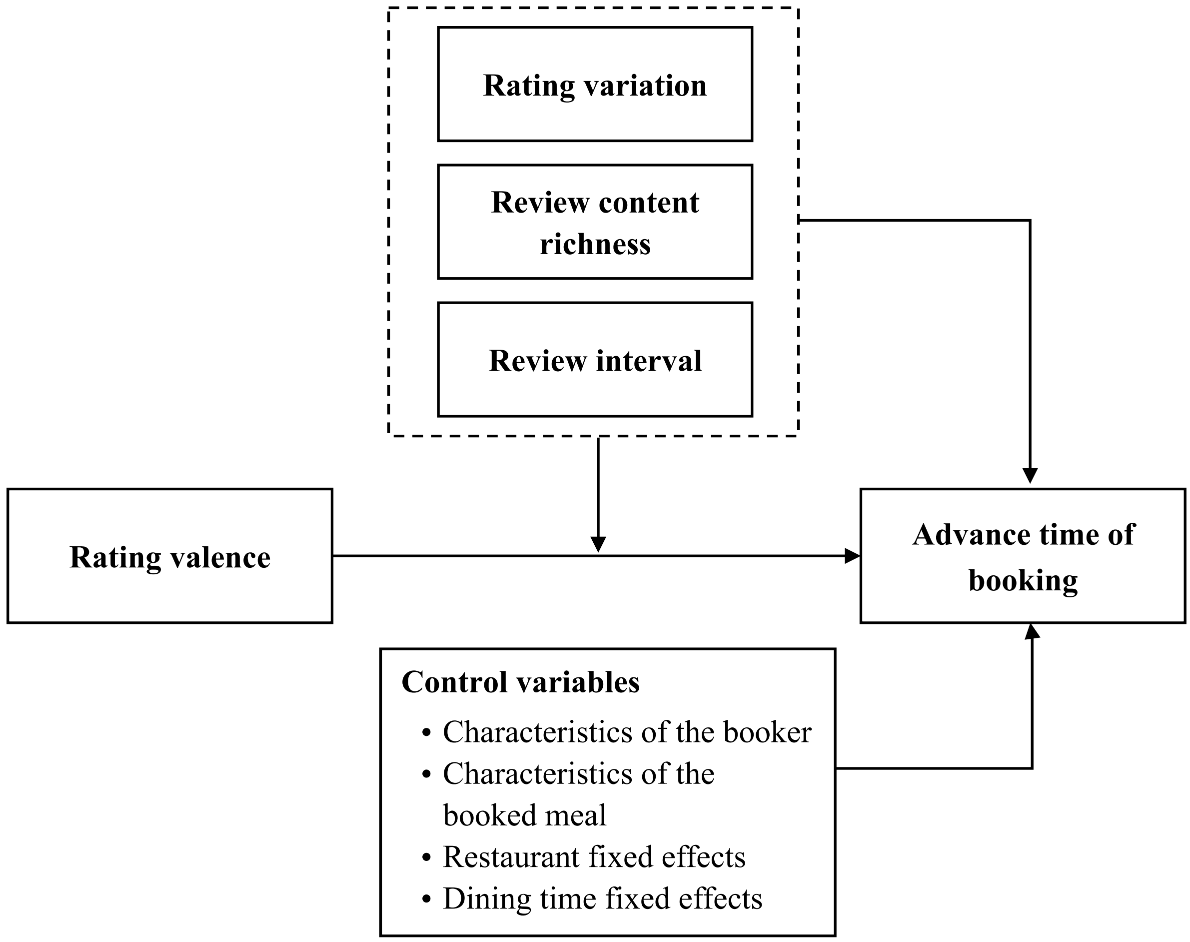

Figure 1 Research framework

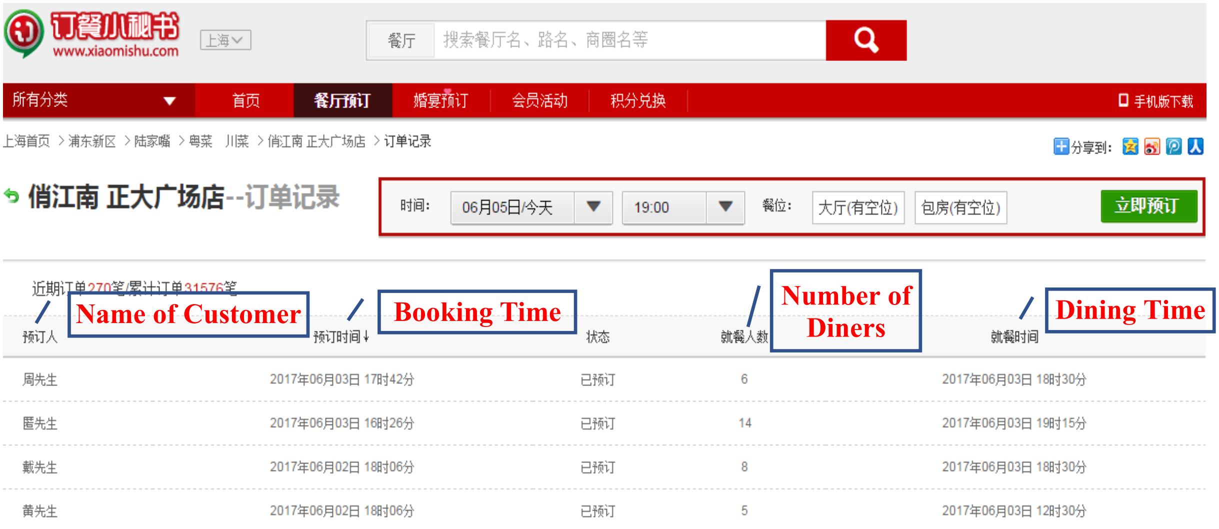

Figure 2. A screenshot of a restaurant’s booking records on Xiaomishu

Table 1 The definitions of variables

Variable	Definition
BookDineDiff	The interval between booking time and dining time in the unit of day
RatingAvg	The average rating of the latest two hundred reviews before a reservation
RatingVar	The rating variation of the latest two hundred reviews before a reservation
ReviewText	The total length of content (in characters) in the latest two hundred reviews before a reservation
ReviewPic	The total number of pictures in the latest two hundred reviews before a reservation
ReviewInterval	The average time interval (in days) between two successive reviews for the latest two hundred reviews
DineDay	Whether the reservation is for a weekend meal, coded as 1 for a weekend meal (Saturday or Sunday) and 0 otherwise
DineHoliday	Whether the reservation is for a statutory holiday meal, coded as 1 if the meal day is a statutory holiday and 0 otherwise
CustSex	The gender of the booking customer, coded as 1 for female and 0 for male
Diners	The number of diners indicated in a reservation

Table 2 Statistical description of variables

Variable	Obs	Mean	Std. Dev.	Max	Min
BookDineDiff	321,973	6.144	14.212	273.264	0.001
RatingAvg	321,973	4.108	0.243	5	1.6
RatingVar	321,973	0.645	0.228	2.889	0
ReviewText	321,973	4832.735	2836.463	21229	7
ReviewPic	321,973	43.319	39.342	291	0
ReviewInterval	321,973	20.638	38.212	1286.064	0
DineDay	321,973	0.340	0.474	1	0
DineHoliday	321,973	0.166	0.372	1	0
CustSex	321,973	0.486	0.500	1	0
Diners	321,973	7.930	6.118	1500	1

Table 3 Correlation analysis

Variable	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1. RatingAvg	—								
2. RatingVar	-0.507	—							
3. ReviewText	-0.051	0.219	—						
4. ReviewPic	0.161	-0.084	0.441	—					
5. ReviewInterval	-0.027	-0.065	-0.430	-0.269	—				
6. DineDay	-0.031	0.022	0.009	-0.007	-0.003	—			
7. DineHoliday	-0.062	0.038	0.010	-0.032	-0.005	0.066	—		
8. CustSex	0.010	-0.012	-0.004	0.016	-0.002	0.011	0.013	—	
9. Diners	-0.045	0.037	0.033	-0.023	-0.022	0.032	0.020	0.014	—

Table 4 The collinearity diagnostics test

Variable	VIF	Tolerance value
RatingAvg	1.39	0.720151
RatingVar	1.51	0.662243
ReviewText	2.55	0.392618
ReviewPic	1.83	0.545658
ReviewInterval	1.97	0.507879
DineDay	1.02	0.984812
DineHoliday	1.17	0.858051
CustSex	1	0.998712
Diners	1.02	0.98515

Table 5 Main results

	Model 1	Model 2
	200	200
RatingAvg	0.0802***	1.499***
	(0.0087)	(0.2920)
RatingVar	0.138***	1.963***
	(0.0097)	(0.4588)
LnReviewText	0.00926***	1.050***
	(0.0025)	(0.1737)
LnReviewPic	0.00423*	0.399*
	(0.0020)	(0.2018)
LnReviewInterval	-0.147***	-0.647**
	(0.0028)	(0.2138)
DineDay	0.235***	0.198***
	(0.0038)	(0.0036)
DineHoliday	0.666***	0.457***
	(0.0048)	(0.0051)
CustSex	0.0740***	0.0544***
	(0.0036)	(0.0031)
Diners	0.0274***	0.0185***
	(0.0003)	(0.0033)
RatingAvg×RatingVar		-0.533***
		(0.1161)
RatingAvg×LnReviewText		-0.285***
		(0.0405)
RatingAvg×LnReviewPic		-0.151**
		(0.0487)
RatingAvg×LnReviewInterval		0.0434
		(0.0502)
Restaurant FE		Yes
Dine Month FE		Yes
Constant	0.596***	-1.321
	(0.0443)	(1.2594)
Observations	321,973	321,973
Adjusted R-Squared	0.377	0.377
F-Test	4639.4	5248.1

Note: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6 The results of alternative measurement of review content richness

	Model 1	Model 2
	200	200
RatingAvg	-0.4709***	0.6663***
	(0.0632)	(0.1918)
RatingVar	-0.1204**	1.4240***
	(0.0530)	(0.4639)
LnReviewTopic	-0.9376***	0.9491***
	(0.0362)	(0.1790)
LnReviewInterval	-0.3945***	-0.5295***
	(0.0225)	(0.1626)
DineDay	0.1975***	0.1973***
	(0.0033)	(0.0033)
DineHoliday	0.4557***	0.4554***
	(0.0045)	(0.0045)
CustSex	0.0545***	0.0544***
	(0.0030)	(0.0030)
Diners	0.0185***	0.0185***
	(0.0003)	(0.0003)
RatingAvg×RatingVar		-0.3785***
		(0.1186)
RatingAvg×LnReviewTopic		-0.4421***
		(0.0414)
RatingAvg×LnReviewInterval		0.0268
		(0.0396)
Restaurant FE	Yes	Yes
Dine Month FE	Yes	Yes
Observations	321,973	321,973
Adjusted R-Squared	0.378	0.378
F-Test	7602.65	6412.06

Note: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7 The results of different cutoff points

	Model 1	Model 2	Model 3	Model 4
	100	12 months	24 months	All
RatingAvg	1.213***	0.386*	2.378***	0.900**
	(0.3015)	(0.1575)	(0.4332)	(0.2841)
RatingVar	1.401**	0.589***	0.847**	0.369
	(0.4447)	(0.1372)	(0.2670)	(0.4433)
LnReviewText	0.718***	1.365***	1.737***	0.322
	(0.1609)	(0.1237)	(0.1978)	(0.2021)
LnReviewPic	0.423*	0.311***	0.323***	-0.175
	(0.1793)	(0.0588)	(0.0889)	(0.2097)
LnReviewInterval	-0.454*	-0.274*	-0.728**	-0.140
	(0.2147)	(0.1320)	(0.2257)	(0.2044)
DineDay	0.198***	0.194***	0.201***	0.198***
	(0.0036)	(0.0037)	(0.0037)	(0.0036)
DineHoliday	0.457***	0.524***	0.447***	0.457***
	(0.0051)	(0.0056)	(0.0052)	(0.0051)
CustSex	0.0545***	0.0541***	0.0546***	0.0545***
	(0.0031)	(0.0032)	(0.0032)	(0.0031)
Diners	0.0185***	0.0181***	0.0184***	0.0185***
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
RatingAvg×RatingVar	-0.406***	-0.177***	-0.285***	-0.0850
	(0.1116)	(0.0345)	(0.0668)	(0.1124)
RatingAvg×LnReviewText	-0.206***	-0.135***	-0.325***	-0.173***
	(0.0374)	(0.0294)	(0.0466)	(0.0469)
RatingAvg×LnReviewPic	-0.110*	-0.082***	-0.0547*	-0.0278
	(0.0433)	(0.0142)	(0.0216)	(0.0503)
RatingAvg×LnReviewInterval	-0.0408	-0.0559	-0.0710	-0.0316
	(0.0509)	(0.0316)	(0.0539)	(0.0481)
Restaurant FE	Yes	Yes	Yes	Yes
Dine Month FE	Yes	Yes	Yes	Yes
Constant	-0.338	-0.903	-8.454***	3.078*
	(1.2957)	(0.6633)	(1.8381)	(1.2400)
Observations	321,973	296,951	306,534	321,973
Adjusted R-Squared	0.378	0.391	0.383	0.377
F-Test	5279.3	5569.3	5352.6	5254.5

Note: Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix

Topics Identification Using Latent Dirichlet Allocation

We identified the main topics in consumers' restaurant reviews using Latent Dirichlet Allocation (LDA), a machine learning technique that has been widely used for topic discovery tasks across diverse collections of documents. LDA allows to discover the hidden topic structure of a review based on the words used in the review. It is a three-level hierarchical Bayesian model, in which each word of a collection is modeled as a finite mixture over an underlying set of topics. Each topic is, in turn, modeled as an infinite mixture over an underlying set of topic probabilities. In the context of review modeling, the topic probabilities provide an explicit representation of a review (Blei et al., 2003)[1]. The process of using LDA to discover review topics includes four steps: (1) data pre-processing; (2) topic learning; (3) topic naming; and (4) topic assignment.

In English and many other languages using the form of Latin alphabet, the space is a good approximation of a word divider (word delimiter). However, the equivalent to the word space character is not found in Chinese language. Hence, we used an open-source Chinese natural language processing platform, i.e., LTP (Language Technology Platform)[2], to convert a review text into words. We selected LTP because of its high accuracy in the processing of word segmentation (Che et al., 2010)[3]. Stop words were filtered out after word segmentation. Stop words usually refer to the most common words which appear to be of little value in helping select documents to match a user's need and are excluded from the vocabulary entirely. There is no single universal list of stop words used by all natural language processing tools, while this study applied one of the most popular stop word lists to process

[1] Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of machine Learning research*, *3*, 993-1022.
[2] https://github.com/HIT-SCIR/ltp
[3] Che, W., Li, Z., & Liu, T. (2010). Ltp: A Chinese language technology platform. *In Proceedings of the 23rd International Conference on Computational Linguistics: Demonstrations (pp. 13-16). Association for Computational Linguistics*.

Chinese online reviews[4].

Using the GENSIM python software package, we generated a bag-of-words representation of review text. A review is represented as the bag (multiset) of occurrence counts of words, disregarding grammar and even word order but keeping multiplicity. As there are no strict rules for optimal number of clusters, we learned four different topic models, each model corresponding to a fixed number of topics (k=5,…,8). All the reviews were used in the learning phase. For each topic, GENSIM outputs a list of most identifying words, and we named each topic based on a combination of those words.

Then the four learned models were applied to each review, and we got a vector of 1 to k topic assignment scores for each review from GENSIM. Each topic assignment score indicates the posterior probability of the review belonging to that topic; given that LDA is a mixed‑model, a review can belong to more than one topic. For example, if k=5, a review receives five non‑zero scores, indicating that the review includes all five topics.

These four models were then assessed in terms of the precision, recall, and indistinct clusters that a model can produce. Based on these criteria, we selected the 5‑topic model, and named each topic which was shown in Table A1. In Table A1, the numeric value is the weight associated with the topic (to save space, only the top 30 words are presented here).

[4] https://github.com/goto456/stopwords

Table A1 Review topics and top identifying words

Topic 1		Topic 2		Topic 3		Topic 4		Topic 5	
Value		Restauratnt environment		Dishes		Service		Restauratnt amenities	
去	0.036	餐厅	0.031	好吃	0.020	去	0.022	小	0.017
价格	0.035	特色	0.016	点	0.016	点	0.016	大	0.013
贵	0.022	口味	0.016	喜欢	0.014	次	0.016	包房	0.011
口味	0.020	家	0.014	大	0.008	服务员	0.015	元	0.011
朋友	0.015	感觉	0.011	最	0.007	说	0.015	点	0.011
小	0.014	喜欢	0.010	元	0.006	上	0.014	地方	0.008
实惠	0.013	上海	0.008	牛肉	0.005	感觉	0.009	适合	0.007
点	0.012	少	0.007	里面	0.005	店	0.007	有点	0.006
适合	0.012	好吃	0.007	汤	0.005	小	0.006	菜品	0.006
高	0.012	特别	0.007	去	0.005	这家	0.006	去	0.006
店	0.010	总体	0.006	感觉	0.005	态度	0.005	性价比	0.006
性价比	0.010	相当	0.006	新鲜	0.005	才	0.005	高	0.005
新鲜	0.010	菜式	0.006	肉	0.005	第一	0.005	消费	0.005
下次	0.009	正宗	0.006	上	0.004	大	0.005	无	0.005
再	0.009	上	0.006	做	0.004	再	0.005	坐	0.005
聚会	0.009	地道	0.006	嫩	0.004	想	0.005	里面	0.005
这家	0.008	菜肴	0.006	鱼	0.004	差	0.004	商务	0.005
家	0.008	装修	0.006	里	0.004	朋友	0.004	楼	0.005
菜品	0.008	适合	0.006	特别	0.004	觉得	0.004	免费	0.004
喜欢	0.007	精致	0.006	小	0.004	知道	0.004	中午	0.004
聚餐	0.007	位置	0.005	口感	0.004	慢	0.004	折	0.004
东西	0.007	做	0.005	虾	0.004	看	0.004	位	0.004
值得	0.007	大	0.005	份	0.004	好吃	0.004	大厅	0.004
次	0.007	店	0.005	辣	0.004	家	0.004	套餐	0.004
地方	0.007	量	0.004	推荐	0.004	真	0.004	订	0.004
推荐	0.006	情调	0.004	爱	0.003	已经	0.003	上	0.004
算	0.006	风味	0.004	店	0.003	送	0.003	宴请	0.004
经常	0.006	包房	0.004	赞	0.003	有点	0.003	里	0.004
好吃	0.006	菜品	0.004	这家	0.003	里	0.003	喜欢	0.004
方便	0.006	小	0.004	家	0.003	少	0.003	感觉	0.004