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Unveiling a Hidden Driver of Online Rating Bias: The Role of Consumer Variety-Seeking Behavior

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Abstract

Variety-seeking is a fundamental motivation in consumer decision making, yet its subsequent effect on consumer behavior is not fully understood. Thus, this study aims to investigate how consumers' variety-seeking behaviors influence their subsequent ratings on online reputation platforms. We proposed a framework and constructed econometric models to validate it based on large-scale restaurant-review data from an online reputation platform. Several robustness-check methods were employed to ensure the reliability of our results. The empirical results demonstrate that consumers exhibit a positive rating bias in their reviews for variety-seeking options, compared to regular ones. Further analysis reveals that the influence of variety-seeking dynamically changes with the time-varying characteristics of consumers and restaurants. Specifically, as consumers accumulate a larger number of similar experiences and as restaurants age, the observed rating bias gradually diminishes. This study found a previously undocumented but widely prevalent factor causing rating bias on online reputation platforms, and its significant impact warrants attention. The findings also extend the theoretical application scope of variety-seeking in the field of consumer behavior and offer practical implications for managers and platform designers.

Keywords: variety-seeking; rating bias; restaurant; consumer experience; online reputation platform; consumer evaluation

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1. Introduction

Online reviews, serving as a form of consumer evaluation, play a significant role in addressing information asymmetry, thereby exerting extensive economic effects. Over the past two decades, consumer reviews on online reputation platforms, such as Yelp, TripAdvisor, and Dianping.com, have had a broad and profound influence on the product and service industry [1,2]. Numerous surveys and studies have shown that most consumers, when faced with uncertainties of online or offline consumption, refer to online reviews to aid their decision making [3–5]. Extensive research has also demonstrated that online reviews can boost the sales performance and associated metrics of hotel bookings [6,7], restaurant popularity [8,9], destination trust, and travel intention [10,11] by influencing potential consumers.

Although the importance of consumer online reviews on online reputation platforms has been widely confirmed, some scholars have indicated that multiple factors can lead to deviations between consumer online reviews and the true quality of products or services. Among the aspects that have been well-documented is review rating bias—the tendency for consumer ratings (typically a numerical rating from 1 to 5) to be excessively high or low due to internal and external factors [12,13]. For example, in studies focusing on online restaurant reviews, identified biasing factors include consumer demographics [14], cultural backgrounds [15], location-based effects [12], and the time elapsed between the experience and the review submission [16,17]. These biases and the misinformation they bring can negatively affect consumers and businesses. However, current research on rating bias predominantly concentrates on the review-authoring stage, whereas factors affecting reviews during the consumer decision-making stage have received minimal attention.

In view of this gap, the current study aims to examine the effect of variety-seeking behavior (VSB) on rating bias in online reputation platforms. VSB refers to the tendency of individuals to pursue differences from the past or diversification of categories during decision making [18,19]. For example, when choosing a restaurant, consumers often explore various options rather than returning to the same restaurants, even if they were highly satisfied previously. The desire for new experiences stems from the fact that repetitiveness can lead to boredom, whereas variety-seeking can enhance consumers' overall enjoyment [20]. Moreover, although variety-seeking shares similarities with other hedonic motivations such as novelty-seeking and sensation-seeking, they are conceptually distinct. VSB refers to deliberate switching among familiar options to avoid boredom, with consumers often switching within the same product category. In contrast, novelty-seeking focuses on exploring completely unfamiliar experiences, and sensation-seeking reflects a broader trait characterized by the desire for intense or risky stimulation. Our study specifically focuses on VSB, as it directly aligns with the predictions of OSL theory and the context of repeated consumption. Previous studies in marketing, psychology, and behavioral science have investigated the effects of variety-seeking on positioning and pricing [21], product promotion [22], and consumer retention [23]. However, the effect of VSB on subsequent consumer review behavior, particularly in the context of the tourism and hospitality industry, has not been extensively examined.

To investigate, we conducted an empirical study by collecting and analyzing restaurant-review data from an online reputation platform. Current studies have demonstrated that variety-seeking is an important motivation behind consumers' choices of food and restaurants, with consumers pursuing dining experiences that stand out from their daily life [24]. Moreover, compared to other product and service consumption scenarios, consumers demonstrate a stronger variety-seeking tendency in their food preferences [25]. In actual situations, people tend to eat local dishes regularly due to the consistent availability of certain ingredients and established culinary traditions. However, various factors such as sensory stimulation seeking, food-related knowledge, and personal taste preference can prompt people to eat at certain restaurants and explore different food varieties [26]. These experiences enable consumers to derive hedonic and utilitarian value from this exploration [27]. In this study, we considered restaurants offering local cuisine as the non-variety-seeking choice in the dining selection scenario, whereas the choice of nonlocal-cuisine restaurants by consumers is regarded as being motivated by variety-seeking. A theoretical framework was proposed and tested by analyzing consumers' online restaurant-review records. The empirical results showed that VSB significantly influences consumers' subsequent review ratings. Specifically, consumers give significantly higher ratings to variety-seeking choices (nonlocal-cuisine restaurants) than to non-variety-seeking choices (local cuisine restaurants). This process is typically automatic and not fully conscious.

Consumers driven by VSB may unknowingly inflate their ratings, as heightened emotional responses can temporarily bias their ratings, even though they are not intentionally distorting their judgments. The existence of this mechanism explains how VSB can lead to systematic rating inflation on online-review platforms. Subsequently, we examined the moderating effects of consumers' past similar experiences and restaurant age, both of which negatively moderate the rating bias introduced by VSB.

This study broadens the application of variety-seeking within the field of consumer rating behavior. It reveals that the motivations behind consumers' restaurant choices can induce bias in subsequent ratings, with the dynamic nature of this bias also being explored. These findings suggest that online reputation platforms could employ algorithms to identify and counteract the influence of this biasing factor. In addition, restaurants can improve their services to consumers motivated by variety-seeking through effective communication during the service process. Although the investigation is rooted in the restaurant sector, the insights gained are equally applicable to other tourism and hospitality domains that value online reviews.

2. Literature Review and Hypothesis Development

2.1. Online Rating Bias

In the online-review literature, numerous studies have examined rating bias in online reputation platforms from various perspectives, identifying factors that elicit positive or negative bias [28–30]. Since the early days following the emergence of online reviews, scholars employing various methods such as experimental, survey, and secondary data analysis have confirmed that average rating is a biased indicator for potential consumers in predicting product quality [30,31]. Some scholars who have approached this area from the perspective of review gathering have discovered that self-selection bias can lead to inconsistencies between online and offline reviews due to the voluntary nature of consumer review posting. Other studies have further explored the effects of consumers' cultural background [15], expertise [32], popularity [28], and demographics [14], as well as the platform-related monetary incentives [33] and weather factors [34], on online reviews. Overall, the previous research has focused more on the factors influencing the review-authoring stage, overlooking the effects during the consumer decision-making stage. This study, set within the restaurant sector, addresses this gap by examining whether variety-seeking, as a decision-making motivation, affects consumer review behavior, thereby expanding the research scope in this field.

2.2. Consumer VSB

VSB involves choosing alternatives that are different from previous selections from a range of similar options [35]. For instance, after having pasta for lunch, one might prefer a different dish for dinner. Compared to repetitive consumption, variety-based consumption enhances enjoyment and reduces boredom, thereby optimizing consumer utility [20]. VSB influences consumer decision making across products and services, encompassing packaged goods, financial services, and dining experiences [18]. This behavior also manifests within various consumption contexts in the tourism and hospitality sectors. Utilizing data from a tourism market survey, Jang and Feng (2007) discovered that variety-seeking significantly affects tourists' intentions to engage in medium-term revisits and is associated with long-term revisit intentions [36]. Kim et al. (2018) found that travelers exhibit different variety-seeking tendencies toward bundled travel product packages under varying conditions [37]. Kemperman et al. (2000) demonstrate that variety-seeking significantly influences tourists' choices of theme parks, and the extent of its influence depends on the type of park [38]. In restaurant marketing, VSB is characterized as "the tendency of consumers to seek diversity in their choice of cuisine and related experiences", and it is often considered one of the key motivations for consumers with respect to eating out and trying different restaurants [24,39]. Most consumers consider several alternative restaurants before making a choice when dining out rather than adhering to just one establishment. Consumers bored with the restaurants they have already visited are likely to patronize new establishments to alleviate boredom from repeat visits [24]. Even if consumers are satisfied with the restaurants they have frequented in the past, they still desire to experience a different establishment, because seeking new experiences is a fundamental aspect of human nature [40]. Therefore, in the existing research, VSB is often operationalized as a key decision-making variable that drives consumers to alternate among familiar restaurants and to try newly opened ones [41].

To investigate the reasons and underlying mechanisms behind consumers' VSB, scholars have conducted a series of studies. Kahn (1995) shows that internal and external factors drive individuals' VSB. Individuals' desire for novelty, surprise, and change, along with external factors such as market conditions, promotional pricing, and family dynamics, can trigger shifts in consumer goals [18,42]. In the works on mechanisms explaining VSB, optimum stimulation level (OSL) theory is the most widely adopted [43]. OSL theory proposes that individuals have an optimum level of stimulation relative to the external environment [42]. When environmental stimulation is below the optimal level, people will attempt to increase their levels of stimulation, and the converse occurs when it exceeds the optimum [43]. Accordingly, VSB is understood as a way to achieve and maintain individuals' optimal stimulation levels.

Although many studies have explained the role of VSB as an initial motivation in consumer decision making, few have delved into the consequences of this behavior. A recent review on VSB and its effects on satiation elaborately explains how VSB can maximize individuals' utility by alleviating physiological and psychological satiation [20]. As the frequency of similar consumption experiences among consumers increases within a certain temporal interval, physiological satiety significantly increases [44]. Even if the level of stimuli from external factors remains constant, consumers' perceived subjective utility can fluctuate. When satiation occurs, consumers will seek other options, ones that potentially offer higher utility, to recover from satiation [45]. Alternatively, when individuals anticipate satiation, they might also plan VSB in advance as a preventive measure [19]. In summary, consumers' VSB can help alleviate the satiation accumulated from past consumption, thereby enhancing the enjoyment of the current experience, which may have a positive effect on consumers' subsequent rating behavior. Accordingly, we hypothesize the following:

H1: *Consumers' ratings associated with their variety-seeking choices are higher than those associated with their non-variety-seeking choices.*

2.3. Moderating Effect of Consumers' Past Similar Experiences

Consumers are inherently motivated to seek an optimal level of stimulation in their experiences, as proposed by the OSL theory. When individuals repeatedly engage with similar products or services, the novelty and complexity diminish, leading to states of satiation or boredom [43]. To restore psychological arousal and maintain interest, consumers often exhibit VSB [42]. In line with this reasoning, we further examined related factors that can serve as moderators, thereby enhancing our understanding of the underlying mechanisms. Given that the utility brought by VSB primarily arises from the perceived differentiation between the current and regular choices, a criterion which depends on consumers' subjective judgment of the attributes and features of different products or services, we posit that the time-varying characteristics of consumers and the restaurants being rated may dynamically influence this process. From the consumers' perspectives, their preference for variation results from the diminishing marginal utility for each similar consumption experience in the past [46].

The fluctuation of consumers' enjoyment of a stimulus over time may also be influenced by other discrete mechanisms [20]. From a psychological perspective, increased exposure to objects causes individuals' responses to motivated behaviors to become habitual. As individuals become habituated to an object, its effectiveness diminishes, resulting in the cessation of behaviors targeted toward the initial goal [47]. Repeated behaviors or choices solidify into consumers' knowledge and experience, and the accumulation of experiences and memories dictates the level of satiation during subsequent consumption [48]. Another stream in the literature suggests that future-preference uncertainty is also a motivation for VSB. Consumers engage in VSB in their current situations as a hedge against the uncertainty in future circumstances [49]. As consumers visit nonlocal-cuisine restaurants, their familiarity with nonlocal cuisine increases, which, in turn, reduces uncertainty when they rate restaurants. Thus, consumers accumulating more experiences with similar nonregular choices leads to a loss of novelty, and the choices are thereby turned into "new regular choices". The effect derived from VSB undergoes a diminishing marginal utility. Consequently, the rating bias brought about by VSB does not remain constant. Hence, we propose the following:

H2: *Consumers' past similar experiences negatively moderate the effect of VSB on restaurant rating bias.*

2.4. Moderating Effect of Restaurant Age

Research indicates that consumer satiation with experiences depends on the attributes of the product or service [50]. In the context of restaurants, characteristics related to food, environment, and service affect consumers' perceived differentiation and novelty, becoming key factors that contribute to experiential satiation [24]. These characteristics continue to evolve throughout a restaurant's operational life. If restaurants fail to adapt to evolving consumer expectations and mitigate experiential satiation, they risk losing competitiveness, which may contribute to high failure rates. Indeed, according to industry research, the risk of failure is consistently high in the restaurant sector, particularly for newly opened establishments [40]. Approximately 26% of independent restaurants in the US fail within their first year of operation [51], and the median lifespan of restaurants is only about 4.5 years [52]. Among the reasons for restaurant failure, internal factors are generally found to exert a stronger influence than external ones. To survive, restaurants must continuously adjust their operational strategies to maintain customer engagement and integrate into the local community [51].

From another perspective, according to evolutionary theory, aging firms often experience managerial inefficiencies and reduced motivation to innovate, resulting in decreased overall performance [53]. Specifically, in the restaurant industry, the research indicates that older restaurants tend to rely excessively on maintaining the status quo and may gradually lose their ability to deliver value to customers [51]. In contrast, younger restaurants, facing stronger competitive pressures, are generally more proactive in innovation and transformation efforts adopted in order to achieve better performance [54]. One important point is that the physical environment (also termed "atmospherics") of a restaurant tends to deteriorate as its years of operation accumulate [55]. This aspect is recognized as a pivotal element in defining the distinctiveness of restaurants [56]. For instance, decor style, lighting, and layout can significantly influence consumer experience [56] and serve as important motivations when consumers choose a new restaurant [40]. Nevertheless, as restaurants age, these environment-related elements often become outdated and fall out of fashion.

This, in turn, leads to a decline in the distinctiveness and novelty perceived by consumers. Therefore, we propose the following:

H3: *Restaurant age plays a negative moderating role in the effect of VSB on restaurant rating bias.*

A research framework is constructed to address the research questions, as shown in Figure 1:

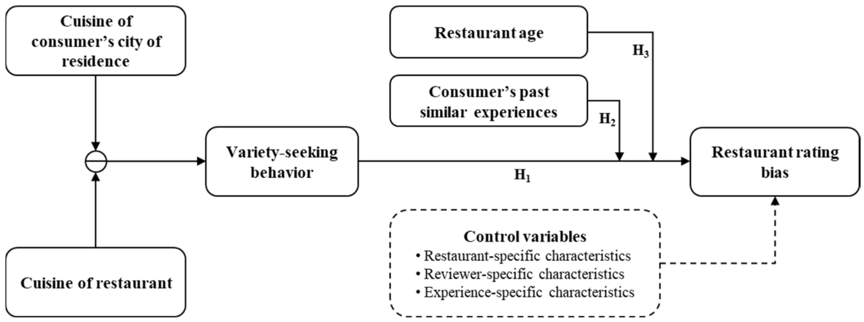

Figure 1. Research framework.

3. Methodology

3.1. Data Collection

The research data were collected from Dianping.com, China's leading online reputation platform, which allows users to rate and review local businesses such as restaurants, hotels, and entertainment venues. On this platform, consumers are required to provide an overall star rating (ranging from 1 to 5) when submitting a review, while including textual comments or images is optional. Dianping.com employs sophisticated algorithms to detect and remove fake reviews, ensuring a high level of data credibility for empirical analysis. To meet our research objectives, we considered several key factors when defining the scope of the data. First, to reduce the inherent heterogeneity in the restaurants and reviewers within the sample, we focused our data collection on a single geographic region, thereby mitigating potential biases in online reviews caused by regional variations in cultural and economic contexts [15]. Second, the selected region should ideally feature a distinctive local cuisine within its restaurant sector while also offering consumers various selections from other cuisines. Third, the quantity of online reviews in that region must be substantial enough to control for certain incidental factors. Considering these three criteria, we selected Guangzhou. As one of the largest cities in China, Guangzhou's population size and the scale of the restaurant industry meet the requirements for the sample. Moreover, Cantonese cuisine is one of the several significant regional cuisines in China. This study incorporated the most popular traditional Chinese cuisines listed on Dianping.com; they are the Anhui, Sichuan, Hunan, Shandong, Fujian, Jiangzhe, Beijing, and Cantonese cuisines. A random assortment of restaurants from each cuisine was selected, and all associated reviews were compiled. The final dataset included 651,665 reviews associated with 773 restaurants, and spanning from January 2009 to December 2019, avoiding the effect of the COVID-19 pandemic.

Figure 2 presents translated screenshots of a restaurant homepage, a consumer profile page, and a review page from the Dianping website. These screenshots provide examples of online reviews, including information on the restaurant's cuisine category, the rating, the review text, the review time, and the locations of the restaurant and the consumer, as well as the consumer-reported average spending per person.

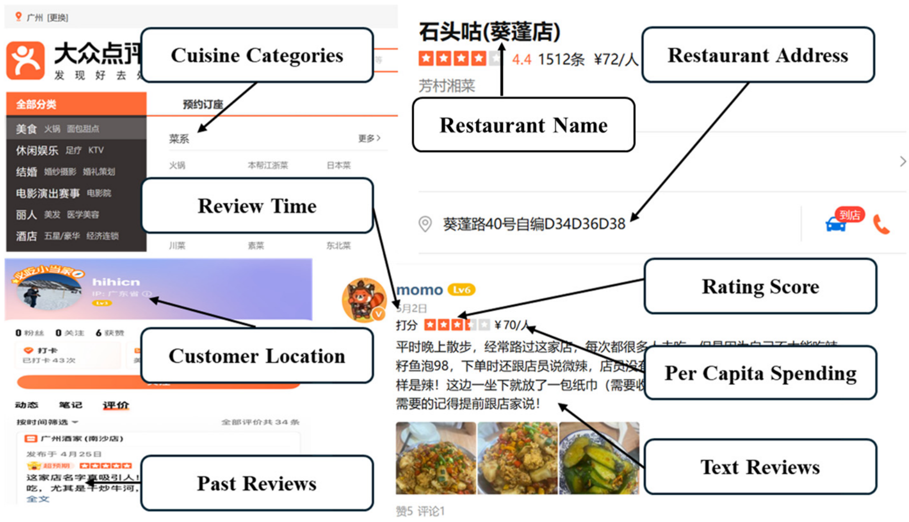

Figure 2. Sample screenshots of the restaurant, consumer, and review pages.

3.2. Variable Measurements

Dependent variables. Two measures of restaurant rating bias were adopted as the dependent variables. The first used the rating scores (Rating) as the dependent variable to test whether potential biasing factors cause a significant increase or decrease in this variable [12]. The second involved using the restaurant's average rating (Average rating) as a proxy for true quality, defining the deviation (Deviation) between the current rating and Average rating as either a positive or negative bias [15].

Focal variables. We focused on consumers' ratings of variety-seeking choices. Local-cuisine restaurants were defined as non-variety-seeking options, whereas the act of consumers choosing nonlocal-cuisine restaurants was defined as a VSB. Two measures were selected to measure VSB. First, a dummy variable was established to distinguish the effect of VSB from non-VSB. Second, we aimed to examine whether the level of stimulation varies with different variety-seeking options. Cuisines that are more different from the local cuisine may provide greater stimulation. According to Zhu et al. (2013), based on a database of 8498 Chinese cuisine recipes, the similarity between cuisines primarily depends on geographical proximity rather than climatic closeness [57]. Therefore, we used the geographical distance from the place of origin of the cuisine as a proxy for the degree of similarity between cuisines and set VSB_Cont. as a continuous variable to examine the trends in the effects of variety-seeking options with different degrees of stimulation on rating bias.

Moderating variables. The first moderating variable was consumers' past similar experiences (Experience), calculated by the number of times a consumer has previously reviewed nonlocal-cuisine restaurants. The second moderating variable was the restaurant age (Restaurant age), calculated as the number of months between the time the current review was posted and the time of the restaurant's first review.

Control variables. To control for the endogenous and exogenous factors that may affect review ratings, we incorporated relevant variables by referring to previous studies on online reviews of restaurants [15], including time-varying restaurant characteristics, time-varying consumer characteristics, and review-specific characteristics. Detailed variable descriptions are provided in Table 1. Table 2 presents the statistics associated with the variables.

Table 1. Description of variables.

Variables	Description
Dependent Variables	
Rating	Rating score of the restaurant by consumers.
Focal Variable	
VSB	Dummy variable, set to 0 when reviewers rate local-cuisine restaurants, and 1 for the others.
VSB_Cont.	The geographical distance between the origin of the cuisine and the consumer's place of residence (log).
Moderators	
Experience	The number of times the reviewer has rated nonlocal-cuisine restaurants in the past.
Restaurant age	The number of months between the current review and the first review of the restaurant.
Control Variables	
Average rating	The average of all past ratings for the restaurant.
Rating num	The number of existing reviews for the restaurant.
Cuisine popularity	The popularity of the reviewed cuisine in the city, operationalized as the ratio of current cuisine reviews (log) to total cuisine reviews (log).
Highest price	The highest per capita price reported by consumers for the restaurant.
Lowest price	The lowest per capita price reported by consumers for the restaurant.
Length	The length of the consumer review text.
Weekend	Dummy variable, 0 for reviews on weekdays, and 1 for weekends.

Table 2. Statistics summary.

Variables	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Rating	651,665	4.1915	0.9654	0.5	5
VSB	651,665	0.5440	0.4981	0	1
Experience	651,665	1.7596	2.5327	0	53
Restaurant age	651,665	42.7903	47.6811	0	185
Average rating	651,007	4.0243	0.6009	0	5
Rating num	651,665	2203.3430	2733.1780	1	22,447
Cuisine popularity	651,665	0.8952	0.0710	0.0562	0.9622
Highest price	651,534	497.6870	157.6092	20	604
Lowest price	651,534	23.0520	7.0663	20	300
Length	651,665	110.8390	109.3836	0	554.3333
Weekend	651,665	0.3345	0.4718	0	1

3.3. Econometric Modeling

Empirical models were constructed to address our research hypotheses. To meet the econometric model's assumption of variable normal distribution and avoid significant magnitude differences among variables, a natural logarithm transformation was applied specifically to the variables of Experience, Restaurant age, Rating num, Highest price, and Lowest price. The specific econometric model is written as follows:

$$\begin{aligned} Rating_{ijt}/Deviation_{ijt} &= \beta_0 + \beta_1 \times VSB_{ijt} + \beta_2 \times Experience\ (log)_{ijt} + \beta_3 \times Restaurant\ age\ (log)_{ijt} + \beta_4 \times VSB_{ijt} \times Experience\ (log)_{ijt} \\ &+ \beta_5 \times VSB_{ijt} \times Restaurant\ age\ (log)_{ijt} + \beta_6 \times Average\ rating_{itj} + \beta_7 \times Rating\ num\ (log)_{ijt} + \beta_8 \times Cuisine\ popularity_{ijt} + \beta_9 \\ &\times Highest\ price\ (log)_j + \beta_{10} \times Lowest\ price\ (log)_j + \beta_{11} \times Length\ (log)_{ijt} + \beta_{12} \times Weekend_{ijt} + Consumer_i + Time_t + \varepsilon_{ijt}, \end{aligned} \quad (1)$$

where i refers to the consumer, j refers to the restaurant, t refers to the rating time, and ε_{ijt} represents the error term. We controlled for observable restaurant and consumer states that vary over time. Furthermore, research grounded in OSL theory has revealed that the tendency to seek variety varies among individuals, with some requiring more variety to achieve their optimal level of stimulation [43]. Consequently, $Consumer_i$ was included to eliminate the effects of these differences by controlling for individual fixed effects. Moreover, $Time_t$ was used to capture fixed effects associated with review-authoring year and month. Table 3 presents the correlation matrix among the variables, with all results being less than 0.7, indicating no strong correlation between the variables.

Table 3. Matrix of correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Rating	1.000										
(2) VSB	0.0371	1.000									
(3) Experience	−0.0424	0.1945	1.000								
(4) Restaurant age	−0.0443	−0.2783	−0.0817	1.000							
(5) Average rating	0.1450	0.1326	0.0794	−0.4597	1.000						
(6) Rating num	0.0266	−0.2218	−0.0884	0.3510	0.0608	1.000					
(7) Cuisine popularity	0.0047	−0.6404	−0.1236	0.1480	−0.0052	0.2215	1.000				
(8) Highest price	0.0072	−0.2801	−0.1571	0.2560	−0.0890	0.3485	0.2314	1.000			
(9) Lowest price	0.0068	0.1305	0.1016	−0.1669	0.0920	−0.2257	−0.1033	−0.0801	1.000		
(10) Length	−0.1222	−0.0162	0.3084	−0.0345	0.0193	−0.0678	0.0085	−0.1249	0.0886	1.000	
(11) Weekend	−0.0200	−0.0115	−0.0166	0.0143	0.0076	0.0007	0.0040	0.0122	−0.0042	−0.0139	1.000

4. Results

4.1. Main Estimation Results

Table 4 presents the regression results based on Equation (1), using OLS. To examine the main effect, the table begins with the more basic Model 1. The results indicated that the regression coefficient for *VSB* is positive and statistically significant (coeff. = 0.0650, $p < 0.001$), showing that consumer ratings following the selection of restaurants serving nonlocal cuisines are significantly higher than those for local-cuisine restaurants. In other words, *VSB* is associated with a positive bias in subsequent rating behavior. Hypothesis 1 was supported. Model 2 accounts for the potential confounding effects induced by moderating variables. The results presented in Column 2 reveal that the main effect persists even after factoring in consumers' past experiences and restaurant age.

Model 3 introduces interaction terms between the moderating and main variables. The coefficient of the interaction term *VSB* × *Experience (log)* is significantly negative (coeff. = −0.0634, $p < 0.001$), indicating an association in which consumers' past similar experiences may lessen the positive association. Similarly, the coefficient for the interaction term *VSB* × *Restaurant age (log)* is significantly negative (coeff. = −0.0216, $p < 0.001$), indicating that restaurant age negatively moderates the bias induced by variety-seeking, which also indirectly implies that established restaurants provide less stimulation to consumers, compared to newer ones. These results support Hypotheses 2 and 3.

Model 4 strictly adheres to the form of Equation (1), controlling for consumer fixed effects. This approach helps to reduce potential bias from unobserved consumer-specific factors and presents robust standard errors clustered by consumer ID. The results remain consistent. In Models 5 and 6, Deviation is employed as the dependent variable, and the results remain stable.

Figure 3 visually illustrates how the marginal effect of *VSB* on ratings varies across different levels of *Experience (log)*. The marginal effect curve, accompanied by a 95% confidence interval, shows a downward trend, indicating that as *Experience (log)* increases, the negative impact of *VSB* on ratings becomes stronger. This finding confirms the significant negative moderating effect of *Experience (log)* on the main effect, which is consistent with the significantly negative coefficient of the interaction term *VSB* × *Experience (log)* in the regression model. Figure 4 presents the marginal effect of *VSB* on ratings across different levels of restaurant age. Similarly, the marginal effect curve displays a downward trend, supporting the significant negative moderating effect of restaurant age on the effect of *VSB*.

Table 4. Main results.

DV	(1) Rating	(2) Rating	(3) Rating	(4) Rating	(5) Deviation	(6) Deviation
VSB	0.0650 *** (0.0032)	0.0737 *** (0.0033)	0.1952 *** (0.0080)	0.0414 *** (0.0094)	0.2617 *** (0.0040)	0.0936 *** (0.0053)
Experience (log)		−0.0136 *** (0.0022)	0.0091 *** (0.0025)	−0.0003 (0.0048)	−0.0264 *** (0.0014)	−0.0042 (0.0027)
Restaurant age (log)		0.0061 *** (0.0014)	0.0178 *** (0.0017)	0.0190 *** (0.0019)	0.0498 *** (0.0009)	0.0536 *** (0.0011)
VSB × Experience (log)			−0.0634 *** (0.0038)	−0.0128 ** (0.0042)	−0.0832 *** (0.0021)	−0.0288 *** (0.0025)
VSB × Restaurant age (log)			−0.0216 *** (0.0020)	−0.0156 *** (0.0022)	−0.0330 *** (0.0010)	−0.0217 *** (0.0012)
Average rating	0.2171 *** (0.0029)	0.2234 *** (0.0034)	0.2223 *** (0.0034)	0.1389 *** (0.0038)	−0.1484 *** (0.0013)	−0.2265 *** (0.0019)
Rating num (log)	0.0116 *** (0.0011)	0.0081 *** (0.0013)	0.0077 *** (0.0013)	−0.0061 *** (0.0015)	−0.0239 *** (0.0006)	−0.0354 *** (0.0008)
Cuisine popularity	0.3136 *** (0.0220)	0.3197 *** (0.0221)	0.3269 *** (0.0221)	0.2100 *** (0.0244)	0.2987 *** (0.0111)	0.1666 *** (0.0134)
Length (log)	−0.1651 *** (0.0014)	−0.1625 *** (0.0014)	−0.1614 *** (0.0014)	−0.1137 *** (0.0026)	−0.0794 *** (0.0007)	−0.0318 *** (0.0013)
Highest price (log)	0.0157 *** (0.0033)	0.0162 *** (0.0033)	0.0173 *** (0.0033)	0.0417 *** (0.0036)	0.0149 *** (0.0017)	0.0267 *** (0.0020)
Lowest price (log)	0.0402 *** (0.0058)	0.0381 *** (0.0058)	0.0391 *** (0.0058)	0.0722 *** (0.0060)	−0.0274 *** (0.0030)	−0.0168 *** (0.0034)
Weekend	−0.0462 *** (0.0025)	−0.0464 *** (0.0025)	−0.0467 *** (0.0025)	−0.0209 *** (0.0029)	−0.0142 *** (0.0012)	−0.0054 *** (0.0016)
Constant	3.7941 *** (0.0433)	3.7781 *** (0.0433)	3.7085 *** (0.0435)	3.4323 *** (0.0392)	1.0126 *** (0.0167)	1.4209 *** (0.0216)
Consumer FE	Not	Not	Not	Yes	Not	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	651,014	651,014	651,014	450,858	651,014	450,858
R^2	0.0547	0.0548	0.0553	0.4757	0.0864	0.4693

Note: For Models (1)–(3) and (5): robust standard errors are in parentheses; for Models (4) and (6): consumer clustered robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

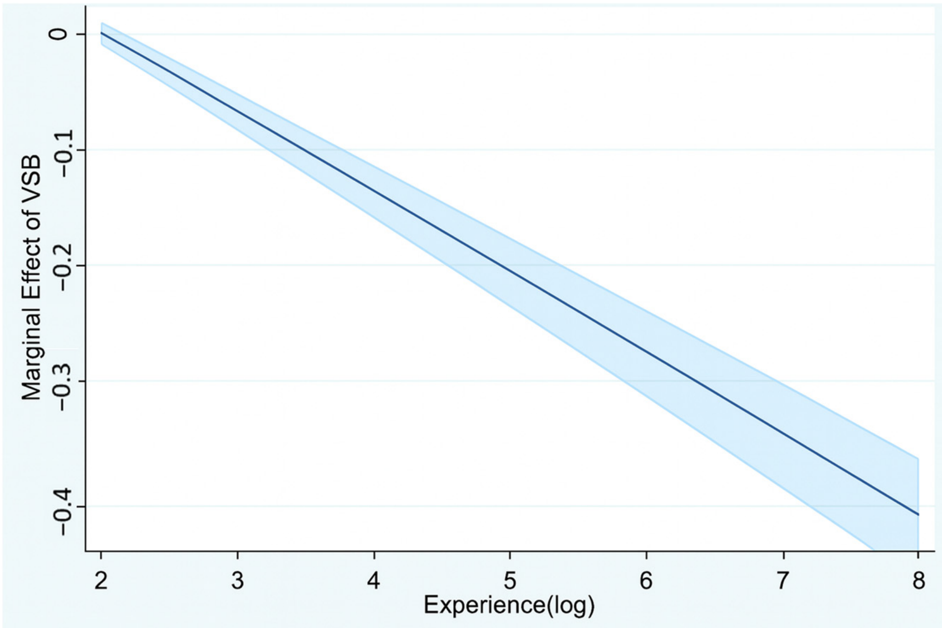

Figure 3. As consumer experience increases, the effect of VSB on rating bias decreases.

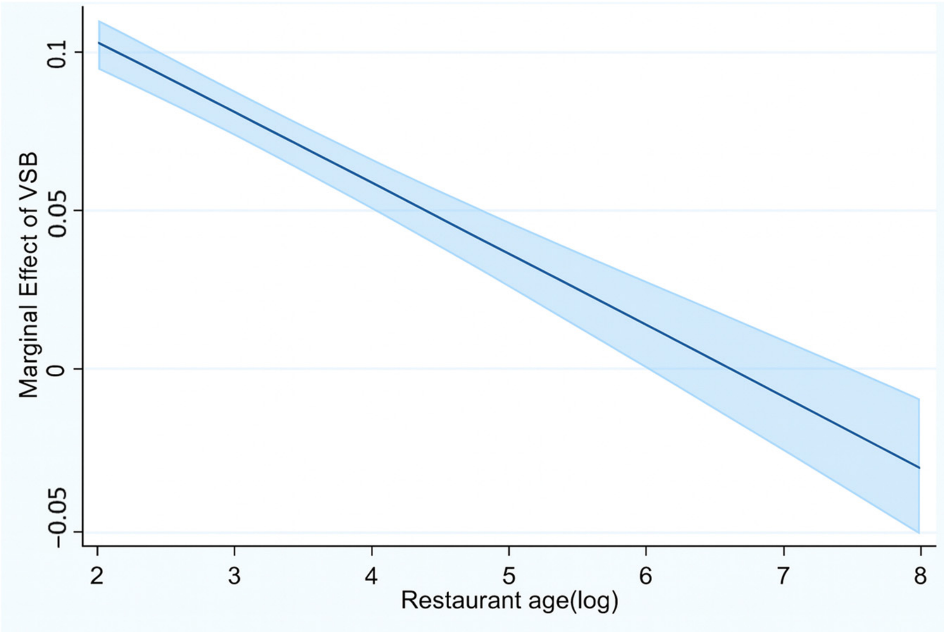

Figure 4. As restaurant age increases, the effect of VSB on rating bias decreases.

To further confirm the effect of our variety-seeking construct, we tested whether cuisines that differ more significantly from the local cuisine provide greater utility to consumers. We used the geographical distance between the consumer's residence and the place associated with the nonlocal cuisine (data obtained from Gaode Map) as a proxy for cuisine differences, resulting in the continuous variable VSB_Cont. Table 5 presents the regression results using the alternative independent variable. The coefficient of VSB_Cont is significantly positive, indicating that restaurant choices with greater differences from local cuisine are associated with more positively biased consumer ratings. These findings further support the behavioral foundation of our VSB construct and reinforce the robustness of our main results.

Table 5. Alternative measure of VSB (*VSB_Cont.*).

DV	(1) Rating	(2) Rating	(3) Deviation	(4) Deviation
VSB_Cont.	0.0271 ***	0.0062 ***	0.0367 ***	0.0136 ***
	(0.0011)	(0.0013)	(0.0006)	(0.0007)
Experience (log)	0.0094 ***	−0.0012	−0.0268 ***	−0.0053 *
	(0.0025)	(0.0048)	(0.0014)	(0.0027)
Restaurant age (log)	0.0184 ***	0.0191 ***	0.0504 ***	0.0538 ***
	(0.0017)	(0.0019)	(0.0009)	(0.0011)
VSB_Cont. × Experience (log)	−0.0088 ***	−0.0017 **	−0.0116 ***	−0.0040 ***
	(0.0005)	(0.0006)	(0.0003)	(0.0003)
VSB_Cont. × Restaurant age (log)	−0.0031 ***	−0.0022 ***	−0.0047 ***	−0.0031 ***
	(0.0003)	(0.0003)	(0.0001)	(0.0002)
Average rating	0.2225 ***	0.1387 ***	−0.1483 ***	−0.2267 ***
	(0.0034)	(0.0038)	(0.0013)	(0.0019)
Rating num (log)	0.0074 ***	−0.0061 ***	−0.0243 ***	−0.0354 ***
	(0.0013)	(0.0015)	(0.0006)	(0.0008)
Cuisine popularity	0.3104 ***	0.2196 ***	0.2934 ***	0.1790 ***
	(0.0219)	(0.0242)	(0.0110)	(0.0133)
Length (log)	−0.1616 ***	−0.1137 ***	−0.0795 ***	−0.0318 ***
	(0.0014)	(0.0026)	(0.0007)	(0.0013)

Table 5. *Cont.*

Highest price (log)	0.0159 ***	0.0421 ***	0.0137 ***	0.0270 ***
	(0.0033)	(0.0036)	(0.0017)	(0.0020)
Lowest price (log)	0.0402 ***	0.0717 ***	−0.0265 ***	−0.0174 ***
	(0.0058)	(0.0060)	(0.0030)	(0.0034)
Weekend	−0.0468 ***	−0.0209 ***	−0.0142 ***	−0.0054 ***
	(0.0025)	(0.0029)	(0.0012)	(0.0016)
Constant	3.7298 ***	3.4217 ***	1.0228 ***	1.4087 ***
	(0.0433)	(0.0390)	(0.0165)	(0.0215)
Consumer FE	Not	Yes	Not	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
N	651,014	450,858	651,014	450,858
R^2	0.0553	0.4757	0.0866	0.4694

Note: For Models (1) and (3): robust standard errors are in parentheses; for Models (2) and (4): consumer clustered robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2. Robustness Checks

4.2.1. Propensity Score Matching (PSM) Analysis

To further assess the robustness of our main findings and address potential selection bias in consumers' VSB, we employed a propensity score matching (PSM) approach. Specifically, we matched reviews of consumers who selected nonlocal-cuisine restaurants (VSB = 1) with those who chose local cuisine (VSB = 0), based on a set of covariates including gender, consumer spending level, restaurant rating, brand status, and whether the review was posted on a weekend. The matching was performed using nearest-neighbor matching with one-to-one pairing and a caliper of 0.03. We then conducted post-matching balance tests using the *pstest* command in Stata 18. As shown in Figure 5, the treated and control groups exhibited a substantial overlap in the mid-range of propensity scores (approximately 0.4 to 0.7), supporting the feasibility of matching. Some divergence in the tails was observed, suggesting limited common support at the extremes, which were excluded by the caliper restriction. Overall, the distribution indicates a balanced matched sample suitable for causal inference.

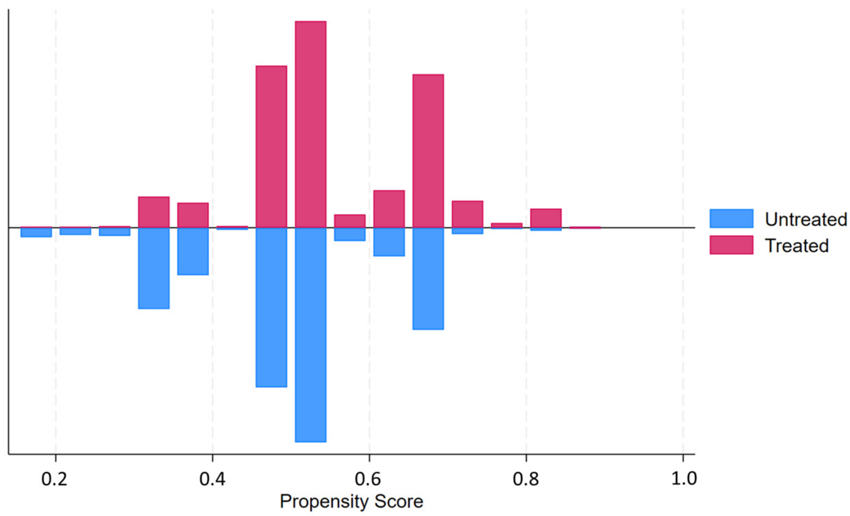

Figure 5. Distribution of propensity scores after matching (treated vs. untreated groups).

Subsequent regression analyses on the matched sample further confirm the robustness of our results. As shown in Table 6, the effect of VSB on consumer ratings remains positive and statistically significant. This provides additional support for the main conclusion that consumers' VSB significantly influences their restaurant ratings, even after controlling for potential confounding through matching.

Table 6. Regression results based on matched sample (PSM).

DV	(1) Rating	(2) Rating	(3) Deviation	(4) Deviation
VSB	0.9069 ***	0.6403 **	0.2724 ***	0.2353 **
	(0.2278)	(0.3031)	(0.0792)	(0.1178)
Experience (log)	0.4634 ***	0.3213 **	0.1165 ***	0.1120 **
	(0.1124)	(0.1407)	(0.0367)	(0.0542)
Restaurant age (log)	0.2375 ***	0.2134 ***	0.0644 ***	0.0818 ***
	(0.0564)	(0.0726)	(0.0190)	(0.0273)
VSB × Experience (log)	−0.5395 ***	−0.3565 **	−0.2040 ***	−0.1377 **
	(0.1124)	(0.1406)	(0.0368)	(0.0541)
VSB × Restaurant age (log)	−0.2174 ***	−0.1901 ***	−0.0426 **	−0.0518 *
	(0.0564)	(0.0725)	(0.0190)	(0.0273)
Average rating	0.2733 ***	0.2114 ***	−0.1550 ***	−0.2318 ***
	(0.0059)	(0.0070)	(0.0024)	(0.0036)
Rating num (log)	−0.0049 **	−0.0163 ***	−0.0188 ***	−0.0275 ***
	(0.0020)	(0.0025)	(0.0010)	(0.0014)
Cuisine popularity	0.2589 ***	0.1347 ***	0.2440 ***	0.1469 ***
	(0.0255)	(0.0295)	(0.0135)	(0.0165)
Length (log)	−0.1549 ***	−0.0953 ***	−0.0865 ***	−0.0314 ***
	(0.0022)	(0.0041)	(0.0011)	(0.0021)
Highest price (log)	0.0248 ***	0.0517 ***	0.0007	0.0085 ***
	(0.0047)	(0.0054)	(0.0024)	(0.0030)
Lowest price (log)	0.0133 *	0.0390 ***	−0.0285 ***	−0.0121 **
	(0.0079)	(0.0087)	(0.0043)	(0.0051)
Weekend	−0.0330 ***	−0.0130 ***	−0.0129 ***	−0.0050 *
	(0.0039)	(0.0047)	(0.0020)	(0.0026)
Constant	2.9126 ***	2.6254 ***	1.0998 ***	1.3595 ***
	(0.2346)	(0.3096)	(0.0816)	(0.1224)
Consumer FE	Not	Yes	Not	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
N	254,743	173,500	254,743	173,500
R^2	0.0620	0.4985	0.0846	0.4968

Note: For Models (1) and (3): robust standard errors are in parentheses; for Models (2) and (4): consumer clustered robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.2. Construct Validation for VSB

To further validate the behavioral basis of the VSB construct, we created an alternative indicator derived from consumers' historical review patterns. Following prior research linking behavioral switching to variety-seeking tendencies [20,42], we constructed a sequence-based switching indicator (*Switch Prop.*) to capture consumers' tendency to diversify their dining choices. Specifically, we first sorted each consumer's review history in chronological order and compared the cuisine types between each consecutive pair of reviews. For each transition, we created a binary variable indicating whether the consumer switched cuisine types. We then calculated a cumulative switching rate for each consumer, reflecting the proportion of reviews in which the consumer switched to a different cuisine type relative to their overall review history.

To ensure the reliability of the sequence-based switching indicator, we further restricted the sample based on consumers' review history. Since the construction of this indicator requires a sufficient number of review records to meaningfully capture switching behavior, we conducted the analysis using two sub-samples. The first sub-sample included consumers with at least five reviews, while the second included those with at least ten reviews. This filtering step helps exclude low-activity users whose limited review history may introduce noise and weaken the validity of the switching measure. We incorporated this sequence-based measure as an alternative operationalization of VSB in our regression models. As shown in Table 7, the results remained consistent with the main analysis, further supporting the robustness of our findings.

Table 7. Regression results using the sequence-based switching indicator.

	(1)	(2)	(3)	(4)
Subsample	Reviews ≥ 5		Reviews ≥ 10	
DV	Rating	Deviation	Rating	Deviation
Switch Prop.	0.2481 ***	0.1547 ***	0.3146 ***	0.2125 ***
	(0.0403)	(0.0228)	(0.0878)	(0.0492)
Experience (log)	0.0294 ***	0.0085	0.0633 ***	0.0248 **
	(0.0092)	(0.0052)	(0.0179)	(0.0104)
Restaurant age (log)	0.0287 ***	0.0532 ***	0.0400 ***	0.0553 ***
	(0.0057)	(0.0032)	(0.0110)	(0.0064)
Switch Prop. × Experience (log)	−0.0897 ***	−0.0576 ***	−0.0856 **	−0.0547 ***
	(0.0170)	(0.0098)	(0.0333)	(0.0195)
Switch Prop. × Restaurant age (log)	−0.0200 **	−0.0177 ***	−0.0296	−0.0233 **
	(0.0095)	(0.0053)	(0.0181)	(0.0104)
Average rating	0.1490 ***	−0.3217 ***	0.1834 ***	−0.3734 ***
	(0.0075)	(0.0034)	(0.0130)	(0.0064)
Rating num (log)	−0.0206 ***	−0.0438 ***	−0.0277 ***	−0.0476 ***
	(0.0028)	(0.0016)	(0.0045)	(0.0026)
Cuisine popularity	0.1459 ***	0.1020 ***	0.1794 ***	0.1414 ***
	(0.0434)	(0.0254)	(0.0684)	(0.0410)
Length (log)	−0.0444 ***	−0.0169 ***	0.0147 **	0.0170 ***
	(0.0032)	(0.0018)	(0.0057)	(0.0033)
Highest price (log)	0.0422 ***	0.0381 ***	0.0586 ***	0.0535 ***
	(0.0060)	(0.0035)	(0.0092)	(0.0056)
Lowest price (log)	0.0686 ***	−0.0111 *	0.0382 **	−0.0324 ***
	(0.0100)	(0.0060)	(0.0156)	(0.0096)
Weekend	−0.0165 ***	−0.0039	−0.0187 **	−0.0037
	(0.0050)	(0.0029)	(0.0081)	(0.0048)
Constant	3.2316 ***	0.8172 ***	2.8205 ***	0.5429 ***
	(0.1248)	(0.0383)	(0.2173)	(0.0640)
Consumer FE	Not	Not	Not	Not
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
N	122,573	122,573	44,830	44,830
R^2	0.0199	0.0897	0.0190	0.0938

Note: Robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.3. Alternative Independent Variable Operationalizations

Furthermore, to address the concern that geographical distance might influence consumers' restaurant choices through other confounding factors, we followed the approach of Zhu et al. (2013) [57]. Their study, based on large-scale data from a Chinese online recipe platform, developed a regional cuisine evolution model using 8498 recipes and 2911 ingredients and cooking methods, and calculated a similarity index between major Chinese cuisines. We obtained this index and computed a cuisine dissimilarity score (*CDS*) by taking its inverse. We argue that consumers who choose restaurants offering cuisines with greater dissimilarity from their local food culture are exhibiting stronger VSB. Table 8 presents the regression results using *CDS* measures, which are consistent with the main findings, thereby confirming the robustness of our VSB construct.

Table 8. Robustness check: Alternative measure of VSB (*CDS*).

DV	(1) Rating	(2) Rating	(3) Deviation	(4) Deviation
CDS	0.0075 ***	0.0026 ***	0.0101 ***	0.0043 ***
	(0.0003)	(0.0004)	(0.0002)	(0.0002)
Experience (log)	0.0178 ***	−0.0025	−0.0188 ***	−0.0049
	(0.0028)	(0.0052)	(0.0015)	(0.0029)
Restaurant age (log)	0.0155 ***	0.0190 ***	0.0480 ***	0.0530 ***
	(0.0018)	(0.0020)	(0.0009)	(0.0011)
CDS × Experience (log)	−0.0027 ***	−0.0004 *	−0.0037 ***	−0.0012 ***
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
CDS × Restaurant age (log)	−0.0008 ***	−0.0009 ***	−0.0012 ***	−0.0010 ***
	(0.0001)	(0.0001)	(0.0000)	(0.0001)
Average rating	0.2132 ***	0.1288 ***	−0.1462 ***	−0.2270 ***
	(0.0035)	(0.0040)	(0.0013)	(0.0020)
Rating num (log)	0.0116 ***	−0.0045 **	−0.0210 ***	−0.0328 ***
	(0.0014)	(0.0016)	(0.0007)	(0.0009)
Cuisine popularity	0.2129 ***	0.2890 ***	0.2574 ***	0.1954 ***
	(0.0282)	(0.0334)	(0.0143)	(0.0184)
Length (log)	−0.1617 ***	−0.1120 ***	−0.0802 ***	−0.0305 ***
	(0.0015)	(0.0028)	(0.0007)	(0.0014)
Highest price (log)	−0.0026	0.0264 ***	0.0071 ***	0.0243 ***
	(0.0035)	(0.0038)	(0.0018)	(0.0022)
Lowest price (log)	0.0398 ***	0.0715 ***	−0.0223 ***	−0.0145 ***
	(0.0063)	(0.0066)	(0.0032)	(0.0038)
Weekend	−0.0456 ***	−0.0216 ***	−0.0133 ***	−0.0047 **
	(0.0026)	(0.0031)	(0.0013)	(0.0017)
Constant	3.9268 ***	3.4759 ***	1.0677 ***	1.3789 ***
	(0.0477)	(0.0458)	(0.0188)	(0.0253)
Consumer FE	Not	Yes	Not	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
N	589,609	398,675	589,609	398,675
R^2	0.0556	0.4804	0.0845	0.4744

Note: For Models (1) and (3): robust standard errors are in parentheses; for Models (2) and (4): consumer clustered robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.4. Alternative Measures of Consumers' Past Similar Experiences

To mitigate potential endogeneity concerns regarding the endogeneity of the moderator "consumers' past similar experiences", we replaced it with a time-varying measure: the diversity of consumers' prior dining experience (*Experience diversity*). This variable was constructed by analyzing each reviewer's review history prior to the focal review and calculating the number of distinct cuisine types they had experienced. A higher diversity score reflects a broader prior exposure to different cuisines, which can attenuate the novelty effect of new cuisine experiences and thus reduce the strength of VSB. This revised moderator is not only more granular and theoretically grounded—consistent with variety-seeking theory, which posits that consumers with richer prior experience seek novelty differently [24,43]—but also alleviates simultaneity concerns by relying on temporally lagged information. We re-estimated the interaction effect between VSB and this diversity index on consumer ratings.

As shown in Table 9, the interaction term *VSB* × *Experience diversity* remains significantly negative, confirming that consumers with higher prior cuisine diversity exhibit a weaker positive association between VSB and ratings. This robustness check reinforces the validity of our original findings and supports the conceptual logic behind the moderating role of consumer experience.

Table 9. Robustness check: Alternative measure of consumers' past similar experiences.

DV	(2) Rating	(3) Rating	(5) Deviation	(6) Deviation
VSB	0.1970 *** (0.0081)	0.0472 *** (0.0100)	0.2240 *** (0.0041)	0.0922 *** (0.0057)
Experience diversity	0.0059 *** (0.0017)	-0.0004 (0.0027)	-0.0183 *** (0.0009)	-0.0002 (0.0016)
Restaurant age (log)	0.0178 *** (0.0017)	0.0191 *** (0.0019)	0.0496 *** (0.0009)	0.0535 *** (0.0011)
VSB × Experience diversity	−0.0371 *** (0.0021)	−0.0091 *** (0.0026)	−0.0377 *** (0.0012)	−0.0150 *** (0.0015)
VSB × Restaurant age (log)	−0.0216 *** (0.0020)	−0.0157 *** (0.0022)	−0.0329 *** (0.0010)	−0.0216 *** (0.0012)
Average rating	0.2218 *** (0.0034)	0.1389 *** (0.0038)	−0.1491 *** (0.0013)	−0.2266 *** (0.0019)
Rating num (log)	0.0079 *** (0.0013)	−0.0061 *** (0.0015)	−0.0233 *** (0.0006)	−0.0353 *** (0.0008)
Cuisine popularity	0.2822 *** (0.0222)	0.1978 *** (0.0245)	0.2174 *** (0.0111)	0.1450 *** (0.0134)
Length (log)	−0.1601 *** (0.0014)	−0.1136 *** (0.0026)	−0.0783 *** (0.0007)	−0.0317 *** (0.0013)
Highest price (log)	0.0176 *** (0.0033)	0.0416 *** (0.0036)	0.0153 *** (0.0017)	0.0267 *** (0.0020)
Lowest price (log)	0.0392 *** (0.0058)	0.0721 *** (0.0060)	−0.0274 *** (0.0030)	−0.0171 *** (0.0034)
Weekend	−0.0468 *** (0.0025)	−0.0209 *** (0.0029)	−0.0142 *** (0.0012)	−0.0054 *** (0.0016)
Constant	3.7338 *** (0.0435)	3.4432 *** (0.0395)	1.0958 *** (0.0167)	1.4371 *** (0.0218)
Consumer FE	Not	Yes	Not	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
N	651,014	450,858	651,014	450,858
R^2	0.0555	0.4757	0.0875	0.4693

Note: For Models (1) and (3): robust standard errors are in parentheses; for Models (2) and (4): consumer clustered robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.5. Alternative Model Specifications

Given that the two dependent variables (*Rating* and *Deviation*) in this study are essentially ordinal in nature, to ensure that our results are not driven by model specification, we re-estimated the main regression models using an ordinal logistic regression approach, which is more appropriate for handling ordered categorical outcomes. Table 10 presents the estimation results based on this model specification. The direction and statistical significance of the coefficients for both the main effect of VSB and the interaction terms remain consistent with the OLS results reported in the main analysis. These findings further reinforce the robustness of our results across different modeling assumptions.

Table 10. Estimation results with ordinal logit regression.

DV	(1) Rating	(2) Rating	(3) Deviation	(4) Deviation
VSB	0.7115 *** (0.0160)		1.1518 *** (0.0179)	
VSB (Cont.)		0.0990 *** (0.0022)		0.1614 *** (0.0025)
Experience (log)	−0.0876 *** (0.0049)	−0.0871 *** (0.0049)	−0.1113 *** (0.0059)	−0.1129 *** (0.0059)

Table 10. *Cont.*

Restaurant age (log)	0.0429 *** (0.0034)	0.0450 *** (0.0034)	0.1913 *** (0.0039)	0.1941 *** (0.0039)
VSB × Experience (log)	−0.2347 *** (0.0075)		−0.3584 *** (0.0094)	
VSB (Cont.) × Experience (log)		−0.0327 *** (0.0011)		−0.0500 *** (0.0013)
VSB × Restaurant age (log)	−0.0652 *** (0.0039)		−0.1454 *** (0.0045)	
VSB (Cont.) × Restaurant age (log)		−0.0094 *** (0.0006)		−0.0206 *** (0.0006)
Average rating	0.4421 *** (0.0063)	0.4425 *** (0.0063)	−0.8795 *** (0.0085)	−0.8792 *** (0.0085)
Rating num (log)	0.0030 (0.0026)	0.0019 (0.0026)	−0.0852 *** (0.0030)	−0.0870 *** (0.0030)
Cuisine popularity	0.8917 *** (0.0439)	0.8447 *** (0.0436)	1.3488 *** (0.0501)	1.3212 *** (0.0497)
Length (log)	−0.3681 *** (0.0029)	−0.3686 *** (0.0029)	−0.3546 *** (0.0031)	−0.3549 *** (0.0031)
Highest price (log)	0.0501 *** (0.0066)	0.0451 *** (0.0066)	0.0575 *** (0.0075)	0.0523 *** (0.0074)
Lowest price (log)	0.0869 *** (0.0116)	0.0906 *** (0.0116)	−0.1006 *** (0.0130)	−0.0966 *** (0.0130)
Weekend	−0.0764 *** (0.0050)	−0.0765 *** (0.0050)	−0.0645 *** (0.0056)	−0.0645 *** (0.0056)
Consumer FE	Not	Not	Not	Not
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
N	651,014	651,014	651,014	651,014
Pseudo R^2	0.0310	0.0309	0.0703	0.0704

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

To facilitate a more intuitive comparison of the key results across different estimation approaches, we present a summary table that reports the effect estimates of VSB on rating bias derived from OLS, PSM, and ordinal logit models. While these models differ in their underlying assumptions and interpretations—particularly regarding the scale of the coefficients—they consistently demonstrate a positive and significant association between VSB and rating bias. Table 11, below, summarizes these results and illustrates the robustness of our findings.

Table 11. Summary of effect estimates across models.

Estimation Method	Effect Estimate	Effect Interpretation
OLS	0.0414 ***	Linear effect on rating bias (continuous measure)
PSM	0.6403 **	Average treatment effect on treated (ATT)
Ordinal Logit	0.7115 ***	Log-odds effect on rating categories (ordinal)

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.2.6. Subgroup Analysis

In order to address concerns regarding potential bias caused by demographic heterogeneity, we conducted a sub-sample analysis focusing on consumers with more stable residential profiles. Specifically, we first restricted the sample to consumers whose registered residence was within Guangzhou, ensuring that all selected consumers were based in the same city. Next, we identified long-term active consumers by calculating the time interval between their first review and the focal review. We then created three sub-samples, in which the time gap exceeded 1 year, 3 years, and 5 years, respectively. This approach allowed us to focus on consumers with relatively stable living conditions and sustained reviewing behavior on the platform, a factor which has been used in the prior literature as an indicator of user stability.

We re-estimated the main regression models using these sub-samples. The results, as shown in Table 12, remained consistent with the main findings in terms of direction and statistical significance, confirming the robustness of our results even after accounting for potential demographic heterogeneity.

Table 12. Regression results for sub-samples based on time interval since first review.

	(1)	(2)	(3)	(4)	(5)	(6)
Time Interval	1 Year		3 Years		5 Years	
DV	Rating	Deviation	Rating	Deviation	Rating	Deviation
VSB	0.1079 ***	0.1633 ***	0.1482 ***	0.1632 ***	0.1715 ***	0.1576 ***
	(0.0157)	(0.0084)	(0.0244)	(0.0132)	(0.0448)	(0.0242)
Experience (log)	0.0010	−0.0196 ***	−0.0104 *	−0.0281 ***	0.0283 ***	−0.0087
	(0.0041)	(0.0022)	(0.0058)	(0.0032)	(0.0109)	(0.0058)
Restaurant age (log)	0.0212 ***	0.0522 ***	0.0328 ***	0.0555 ***	0.0430 ***	0.0539 ***
	(0.0029)	(0.0015)	(0.0043)	(0.0024)	(0.0078)	(0.0043)
VSB × Experience (log)	−0.0310 ***	−0.0468 ***	−0.0378 ***	−0.0448 ***	−0.0609 ***	−0.0503 ***
	(0.0065)	(0.0036)	(0.0093)	(0.0051)	(0.0169)	(0.0092)
VSB × Restaurant age (log)	−0.0125 ***	−0.0220 ***	−0.0159 ***	−0.0217 ***	−0.0200 **	−0.0208 ***
	(0.0034)	(0.0018)	(0.0052)	(0.0028)	(0.0096)	(0.0051)
Average rating	0.1945 ***	−0.2573 ***	0.2047 ***	−0.2829 ***	0.2034 ***	−0.2688 ***
	(0.0065)	(0.0028)	(0.0104)	(0.0045)	(0.0179)	(0.0076)
Rating num (log)	−0.0110 ***	−0.0383 ***	−0.0155 ***	−0.0433 ***	−0.0275 ***	−0.0413 ***
	(0.0024)	(0.0013)	(0.0038)	(0.0020)	(0.0065)	(0.0035)
Cuisine popularity	0.2211 ***	0.2051 ***	0.2874 ***	0.2111 ***	0.1521	0.1396 **
	(0.0375)	(0.0206)	(0.0580)	(0.0319)	(0.1060)	(0.0594)
Length (log)	−0.1070 ***	−0.0570 ***	−0.0774 ***	−0.0383 ***	−0.1039 ***	−0.0442 ***
	(0.0025)	(0.0013)	(0.0041)	(0.0021)	(0.0075)	(0.0039)
Highest price (log)	0.0415 ***	0.0282 ***	0.0418 ***	0.0338 ***	0.0324 **	0.0229 ***
	(0.0055)	(0.0030)	(0.0081)	(0.0045)	(0.0157)	(0.0086)
Lowest price (log)	0.0602 ***	−0.0180 ***	0.0647 ***	−0.0179 **	0.0807 ***	−0.0219
	(0.0092)	(0.0051)	(0.0136)	(0.0077)	(0.0260)	(0.0151)
Weekend	−0.0330 ***	−0.0098 ***	−0.0305 ***	−0.0091 **	−0.0242 *	−0.0078
	(0.0045)	(0.0024)	(0.0069)	(0.0037)	(0.0126)	(0.0068)
Constant	3.4845 ***	0.9948 ***	2.9562 ***	0.8995 ***	2.7492 ***	1.1183 ***
	(0.0855)	(0.0307)	(0.1547)	(0.0479)	(0.4580)	(0.1442)
Consumer FE	Not	Not	Not	Not	Not	Not
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
N	179,685	179,685	74,233	74,233	21,271	21,271
R^2	0.0282	0.0873	0.0258	0.0928	0.0287	0.1089

Note: Robust standard errors are in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To further verify the robustness of our main findings, we conducted a gender-based subgroup analysis. Specifically, we divided the sample into male and female consumer groups and separately estimated the effect of VSB on restaurant ratings, along with the moderating effects of consumer experience and restaurant age within each group. As shown in Table 13, the results for both male and female subgroups remain consistent with the main analysis in terms of direction and significance. This suggests that the positive relationship between VSB and consumer ratings, as well as the moderating effects of consumer experience and restaurant age, are stable across gender segments.

Table 13. Gender-based subgroup regression.

DV Gender	(1) Rating Female	(2) Male	(3) Female	(4) Male	(5) Deviation Female	(6) Male	(7) Female	(8) Male
VSB	0.1608 ***	0.1707 ***	0.0381 ***	0.0058	0.2117 ***	0.2284 ***	0.0919 ***	0.0753 ***
	(0.0100)	(0.0201)	(0.0111)	(0.0235)	(0.0054)	(0.0100)	(0.0064)	(0.0130)
Experience (log)	−0.0355 ***	0.0133 **	−0.0067	0.0020	−0.0351 ***	−0.0251 ***	−0.0075 **	−0.0008
	(0.0030)	(0.0062)	(0.0057)	(0.0118)	(0.0017)	(0.0033)	(0.0031)	(0.0065)
Restaurant age (log)	0.0164 ***	0.0168 ***	0.0201 ***	0.0093 **	0.0530 ***	0.0441 ***	0.0563 ***	0.0477 ***
	(0.0021)	(0.0042)	(0.0022)	(0.0046)	(0.0011)	(0.0021)	(0.0013)	(0.0025)
VSB × Experience (log)	−0.0491 ***	−0.0496 ***	−0.0123 **	−0.0055	−0.0635 ***	−0.0745 ***	−0.0276 ***	−0.0312 ***
	(0.0046)	(0.0094)	(0.0049)	(0.0104)	(0.0026)	(0.0052)	(0.0029)	(0.0061)
VSB × Restaurant age (log)	−0.0125 ***	−0.0293 ***	−0.0132 ***	−0.0173 ***	−0.0265 ***	−0.0304 ***	−0.0213 ***	−0.0193 ***
	(0.0025)	(0.0049)	(0.0026)	(0.0054)	(0.0013)	(0.0023)	(0.0015)	(0.0029)
Average rating	0.1800 ***	0.2047 ***	0.1374 ***	0.1178 ***	−0.1789 ***	−0.1623 ***	−0.2299 ***	−0.2341 ***
	(0.0042)	(0.0079)	(0.0045)	(0.0089)	(0.0016)	(0.0030)	(0.0023)	(0.0044)
Rating num (log)	0.0017	0.0135 ***	−0.0086 ***	0.0040	−0.0312 ***	−0.0221 ***	−0.0381 ***	−0.0323 ***
	(0.0016)	(0.0032)	(0.0018)	(0.0036)	(0.0008)	(0.0015)	(0.0010)	(0.0020)
Cuisine popularity	0.3429 ***	0.3017 ***	0.2151 ***	0.1449 **	0.2820 ***	0.2675 ***	0.1636 ***	0.1276 ***
	(0.0276)	(0.0556)	(0.0288)	(0.0607)	(0.0148)	(0.0270)	(0.0161)	(0.0321)
Length (log)	−0.1518 ***	−0.1469 ***	−0.1048 ***	−0.0950 ***	−0.0757 ***	−0.0646 ***	−0.0312 ***	−0.0185 ***
	(0.0018)	(0.0036)	(0.0031)	(0.0065)	(0.0009)	(0.0017)	(0.0016)	(0.0031)
Highest price (log)	0.0220 ***	0.0128	0.0408 ***	0.0415 ***	0.0207 ***	0.0195 ***	0.0253 ***	0.0313 ***
	(0.0041)	(0.0080)	(0.0043)	(0.0085)	(0.0022)	(0.0040)	(0.0024)	(0.0047)
Lowest price (log)	0.0511 ***	0.0663 ***	0.0691 ***	0.1061 ***	−0.0307 ***	−0.0230 ***	−0.0181 ***	−0.0087
	(0.0070)	(0.0145)	(0.0070)	(0.0148)	(0.0039)	(0.0073)	(0.0041)	(0.0082)
Weekend	−0.0335 ***	−0.0519 ***	−0.0152 ***	−0.0308 ***	−0.0099 ***	−0.0146 ***	−0.0026	−0.0101 ***
	(0.0031)	(0.0062)	(0.0034)	(0.0073)	(0.0016)	(0.0030)	(0.0019)	(0.0038)
Constant	3.6809 ***	3.5680 ***	3.4350 ***	3.3306 ***	1.0313 ***	0.9445 ***	1.4542 ***	1.3652 ***
	(0.0520)	(0.0993)	(0.0462)	(0.0957)	(0.0220)	(0.0401)	(0.0260)	(0.0512)
Consumer FE	Not	Not	Yes	Yes	Not	Not	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	374,259	108,862	303,616	77,084	374,259	108,862	303,616	77,084
R^2	0.0499	0.0497	0.4471	0.4885	0.0965	0.0870	0.4504	0.4770

Note: For Models (1), (2), (5), and (6): robust standard errors are in parentheses; for Models (3), (4), (7), and (8): consumer clustered robust standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Discussion and Implications

5.1. Main Findings and Discussion

This study examined the influence of VSB on online rating bias, as well as the moderating roles of consumer and restaurant characteristics. Using 651,665 restaurant data points on an online reputation platform, we identified consumer rating behavior toward variety-seeking choices and developed a research framework. The results highlight several notable findings. First, the results demonstrated that in online restaurant reviews, compared to regular choices, consumer ratings of variety-seeking choices show a positive bias. This positive bias stems from the utility generated by the reduction in boredom and the increase in enjoyment caused by VSB. Explained by the OSL theory, such exploratory behavior allows individuals to achieve an optimal state. Different from previous research on VSB in the restaurant context, studies by Ha and Jang (2013) and Ha (2020) focus on the effects of various factors, such as overall boredom, satisfaction, and involvement, on the intention to seek variety in restaurants, emphasizing the antecedents of VSB [24,41]. This finding validates the intrinsic link between consumer motivation for choosing restaurants and subsequent rating behavior, focusing on the consequences caused by VSB.

Second, as consumers increasingly experience similar variety-seeking choices, the bias associated with VSB diminishes. Previous studies on the effect of repeat purchases on satisfaction and evaluation have explained this phenomenon from the perspective of consumer familiarity. Scholars have argued that increased familiarity from multiple consumption experiences reduces uncertainty about quality and preference [4,58,59], altering consumers' information processing and expectation judgments and thus affecting consumer choices and subsequent behaviors. However, the theoretical framework of this study explains this phenomenon from the perspective of consumer motivation, providing new insights.

Third, as the years of operation increase, the potential changes in restaurant characteristics also play a negative moderating role. Previous research has shown that external factors, similar to internal factors, can trigger consumers' VSB [18,42]. When changes occur in the external environment, consumers react to these changes. This result suggests that compared to newer restaurants, older restaurants may not provide the level of stimulation consumers anticipate due to the natural aging of environmental stimulus cues. In such cases, consumers do not achieve the anticipated utility brought about by VSB, thereby mitigating the bias in review ratings.

5.2. Theoretical Contributions

Our study's theoretical contributions are as follows. First, this study identifies a new source of rating bias on online reputation platforms. Previous research on bias has discussed consumer characteristics, social norms, and influences from platforms [12,15,60]. Conversely, the bias captured in this study originates from consumers' motivations and exhibits dynamism. An accumulation of such reviews on a platform can influence the overall rating and ranking of a business. This is a valuable extension to research in the online reputation management area.

Second, this study extends the theoretical application of VSB beyond the purchase decision stage. Prior studies primarily focused on how VSB influences product selection and brand-switching behaviors. Some have examined its impact on post-purchase behaviors such as repurchase intention or loyalty, yet the evaluation stage—where consumers generate public feedback—remains largely underexplored. By demonstrating that VSB continues to influence evaluative behavior even after consumption, our work enriches the scope of VSB theory.

Third, according to the literature review, to date, the research methods most utilized relative to VSB have been laboratory designs, followed by surveys and modeling. The limitations of these methods have led to the current focus of variety-seeking research on the consumer decision-making stage. This study measures variety-seeking-related utility variables in large-scale online-review data, which can reflect real, dynamic consumer VSB patterns in real-world situations, infusing new insights into the methodology of research in this field. Furthermore, although the research context is set in the restaurant sector, the theoretical framework and methods employed can be extended to other areas that offer unique experiences to consumers, such as customized travel, hotels, and other entertainment projects.

5.3. Managerial Implications

Our findings offer crucial management implications for online reputation platforms and restaurants on such platforms. In practice, platforms collect and display consumer reviews based on an aggregation algorithm, and the design of the aggregation algorithm significantly affects the overall rating and ranking of restaurants, thereby influencing consumer choices. Taking Dianping.com as an example, its official rules for displaying reviews mention that the calculation of a restaurant's aggregate score considers the authenticity of reviews, the quality of reviews, the time of posting, and the cumulative number of reviews for the restaurant. Different weights are assigned to different aspects; for example, more recent reviews have higher weights than older ones.

The findings of this study indicate that the existing algorithms have certain discrete flaws. For instance, a restaurant that markets itself as serving nonlocal cuisines is more likely to attract consumers motivated by VSB. A disproportionately high percentage of reviews from these consumers can significantly elevate the restaurant's overall rating compared to other restaurants of similar quality and price. Therefore, platforms should consider implementing more nuanced review-weighting systems that account for consumer variety-seeking tendencies. Specifically, algorithms could identify users with high variety-seeking propensities—such as those who frequently switch among different cuisine types or regularly visit newly opened restaurants—based on their historical review behavior. Ratings submitted by such users could be assigned adjusted weights to reduce VSB-induced inflation and ensure the reliability of aggregate scores. Moreover, platforms might incorporate restaurant age—such as the number of years since establishment—as an additional contextual factor in review weighting or recommendation algorithms. Although the precise lifecycle stage of a restaurant may be difficult to determine, restaurants with longer operational histories may exhibit different consumer appeal patterns, particularly regarding perceived novelty. Adjusting for such temporal dynamics can improve the accuracy and fairness of consumer-facing evaluations.

In addition, platforms recommend restaurants based on consumers' historical search behaviors. According to our research findings, consumers' past similar experiences negatively affect the utility of their current choices. By recognizing this aesthetic fatigue, platforms could lower the recommendation weights for restaurants that consumers have repeatedly visited or searched for within a short time span. This adjustment could improve consumer satisfaction and engagement. Furthermore, platforms may also consider incorporating reflective prompts in the review submission process to encourage users to evaluate their experiences more objectively. For example, before submitting a review, users could be prompted to consider whether their rating genuinely reflects overall service quality, and whether they believe their evaluation is sufficiently objective rather than driven by emotional excitement.

From the perspective of businesses, VSB can be used to segment consumers. For example, in the context of restaurants, special dishes can be recommended to new consumers through menu design or service communication. In the operation of restaurants, the needs of these consumers must be fully considered, and the recommended dishes should be changed regularly. Particularly for long-established restaurants, their uniqueness must be maintained to keep a sense of freshness. Restaurants may also monitor whether their appeal to variety-seeking consumers is increasing or declining and adjust their marketing strategies or environment updates accordingly to sustain novelty.

6. Limitations and Further Directions

Although this study has confirmed that consumers' VSB affects subsequent restaurant ratings, providing relevant new insights into the existing literature and managerial implications, some limitations still remain. First, in terms of research methodology, we relied on secondary data, and the research design was limited by the information displayed on the platform. Future work could consider employing survey research or longitudinal study methods to further explore the dynamic effect of consumers' variety-seeking tendencies on reviews.

Second, our dataset focuses exclusively on restaurants and consumers located in Guangzhou, China—a highly diverse and urbanized setting. While this allows for rich variation in consumer behavior, it may also limit the generalizability of our findings to other regions with different socio-demographic compositions. Prior studies have shown that variety-seeking tendencies and reviewing behavior can vary across cultural and regional contexts [15,61]. Although we addressed this concern by incorporating CDS to capture deviations from local food culture, future research is encouraged to replicate our analyses in other cities and countries to validate the broader applicability of the observed effects.

Third, although we employed several strategies to address endogeneity concerns, including controlling for time-varying characteristics related to restaurants and consumers, applying fixed effects, using a diversity index, and conducting subgroup analyses, the risk of omitted variable bias cannot be fully eliminated. In particular, unobserved consumer characteristics—such as personality traits, psychological tendencies, or deep-seated consumption motives—may still influence both VSB and rating outcomes. Moreover, our measure of rating bias primarily relies on consumer-reported online ratings, which may be subject to review self-selection or platform design effects. This limitation is inherent in observational studies using secondary data, in which such latent factors are difficult to measure. Future research could benefit from further validation using independently measured quality benchmarks in controlled behavioral experiments.

Finally, in this study, we distinguished consumers' variety-seeking choices based on the primary characteristic of the restaurant's cuisine. However, some studies have indicated that other attributes of restaurants, such as service and ambiance-related features, also affect consumers' VSB [24]. Whether VSB prompted by these attributes has a different effect on reviews is also worth further exploration. Additionally, we used the restaurant age as a proxy for novelty, aiming to examine its moderating effect on the relationship between variety-seeking and ratings. While this operationalization is grounded in the prior literature, it is important to note that the relationship between restaurant age and perceived novelty may not be strictly monotonic. Some long-established restaurants may retain or even enhance their distinctiveness due to historical significance, cultural value, or strong brand identity. Future research could consider more nuanced or subjective proxies for novelty, such as consumer-perceived innovation reflected in reviews, the frequency of menu updates, or changes in brand image.

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