International Journal of Hospitality Management 100 (2022) 103090

Contents lists available at ScienceDirect

International Journal of Hospitality Management

journal homepage: www.elsevier.com/locate/ijhm

How rainy-day blues affect customers' evaluation behavior: Evidence from online reviews

Ziqiong Zhang [a], Shuchen Qiao [a], Hengyun Li [b], Zili Zhang [a,*]

[a] School of Management, Harbin Institute of Technology, 92 West Dazhi Street, Harbin 150001, China
[b] School of Hotel and Tourism Management, The Hong Kong Polytechnic University, 17 Science Museum Road, TST-East, Kowloon, Hong Kong, China

ARTICLE INFO

Keywords:
Online review
Rainy weather
Emotion-related words
Review ratings
Review length

ABSTRACT

Although many firms deem weather conditions relevant to customers' decision making and satisfaction, firms often struggle to quantify the impact of weather on customers' online evaluation behavior. By combining hourly weather data and online review data from an online booking platform, this study found distinct review-related effects of rainy weather on customers' numerical review ratings versus textual review content. Specifically, customers' ratings and engagement in textual reviews were lower when reviews were written while it was raining. Also, rainy weather had second-order interactive effects on customers' consumption experiences: favorable experiences weakened the negative effects of rainy weather on ratings, whereas unfavorable experiences mitigated customers' unwillingness to post longer textual reviews in rainy weather. Compared with review ratings, textual reviews were less likely to be influenced by rainy weather as indicated by the emotional intensity of reviews. Theoretical and practical implications of these findings are also discussed.

1. Introduction

Weather is an ever-present force in consumers' daily lives. People often check the weather 3–4 times per day to assess the conditions and modify their behavior accordingly (Suddath, 2014). Weather-related factors have been found to correlate with individual psychological and physical states such as mood, health effects, emotional well-being, and overall behavior (Baylis et al., 2018; Connolly, 2013; Hsiang et al., 2013). Firms have thus increasingly begun to consider the weather to boost business; scholars in marketing, psychology, and economics have demonstrated that weather affects individuals and their consumption patterns (Buchheim and Kolaska, 2016; Busse et al., 2015; Li et al., 2017; Schlager et al., 2020).

Although weather is typically considered an external environmental factor, it has started to attract managers' and scholars' interest in the hospitality industry (Bujisic et al., 2019; He et al., 2020). Practically, managers may notice poor evaluations on certain days versus others, and such feedback may have nothing to do with product or service quality (Bujisic et al., 2019). By analyzing comment cards and questionnaire data, Bujisic et al. (2019) investigated how the weather while dining (e.g., temperature, precipitation, barometric pressure, humidity) affected customers' ratings. The authors found that diners' moods and affective experiences mediated the relationship between perceived weather and word-of-mouth (WOM). In many cases, however, customers do not post evaluations immediately after consumption (Li et al., 2020). Weather conditions at the comment stage may thus play a role in their evaluations. Customers' online evaluations can ultimately be influenced by weather at two stages: the consumption stage and the comment stage. Among the several empirical studies illustrating how rainy weather at the comment stage affects online ratings (Bakhshi et al., 2014; He et al., 2020), none appears to have considered weather conditions at the consumption stage concurrently.

Moreover, customer online reviews represent crucial electronic WOM (eWOM) for firms, online platforms, and potential patrons (Bai et al., 2020; Chen et al., 2018; Ho et al., 2017; Liu et al., 2019). Numerical review ratings are generic scores directly reflecting the quality of products and services, while textual reviews offer specific descriptions of an experience. The drafting of online textual reviews is considered a form of information processing that requires high customer engagement (Liu et al., 2019; Wei et al., 2013). Customers' judgment and decisions can be influenced by online reviews, and weather may serve as an environmental factor affecting customers' online review biases and behavior (Buchheim and Kolaska, 2016; Chen et al., 2018; Li et al., 2017; Tian et al., 2018). However, it remains largely underexplored (a)

* Corresponding author.
E-mail addresses: ziqiong@hit.edu.cn (Z. Zhang), qiaoshch@hit.edu.cn (S. Qiao), neilhengyun.li@polyu.edu.hk (H. Li), zilizhang@hit.edu.cn (Z. Zhang).

https://doi.org/10.1016/j.ijhm.2021.103090
Received 7 January 2021; Received in revised form 26 September 2021; Accepted 15 October 2021
Available online 27 October 2021
0278-4319/

whether evaluation biases manifest in online textual reviews and (b) whether and how rainy weather influences customers' numerical review ratings compared with textual review content.

In addition, an individual's experience affects their satisfaction and evaluation behavior (Bai et al., 2020; Ho et al., 2017; Tang and Yu, 2021). The consumption experience has been considered an antecedent to emotional arousal and response (Dellarocas and Narayan, 2006; Li et al., 2020; Mano and Oliver, 1993; Phillips and Baumgartner, 2002). When customers evaluate products online, favorable consumption experiences generate satisfactory emotions which may weaken the effects of negative emotions evoked by rainy weather (Bujisic et al., 2019; Dehaan et al., 2017; Li et al., 2017; Tian et al., 2018). Unfavorable consumption experiences lead to unsatisfactory emotions, potentially strengthening the adverse impacts of rainy weather. Yet few studies have investigated how the consumption experience, together with weather-related factors, can shape customers' online evaluation behavior.

As an early effort, this study explores a specific manifestation of rainy weather effects in the online evaluation context: when customers post online ratings and textual reviews. Although weather cannot be managed, the development of modern weather forecasting technology allows individuals to obtain weather data for a given area in advance. To assess the spectrum of customers' evaluation behavior and provide a comprehensive understanding of evaluation biases related to rainy conditions, this study examines the effects of rainy weather while posting a review on customers' overall and attribute ratings, emotion-related words used in textual reviews, and review length. In addition to these main effects, we consider the second-order interaction effects of rainy weather and customers' consumption experiences on their numerical review ratings and textual review content. Resultant insight should help managers capitalize on weather-related effects to reduce customers' evaluation biases and promote eWOM.

The remainder of this paper is organized as follows. First, a theoretical background and review of literature related to weather effects are presented to contextualize our research hypotheses. Next, studies testing these hypotheses are described in detail, including the data, methodology, and econometric analysis. Theoretical and managerial implications of the findings are then discussed. Finally, limitations and directions for future research are presented.

2. Theoretical background and literature review

2.1. Effects of weather on customer psychology and behavior

Research in marketing, psychology, and economics has shown that weather can substantially influence customers' thoughts, moods, and judgment (Buchheim and Kolaska, 2016; Busse et al., 2015; Li et al., 2017; Schlager et al., 2020; Tian et al., 2018). Human senses receive stimulation from various weather characteristics. For example, sunlight can lead the brain to produce more serotonin, making people feel happier (Lambert et al., 2002). Serotonin production is inhibited during rainy days, which can lead to sadness and negative emotions such as anxiety, tension, and stress (Hsiang et al., 2013). Even without being directly exposed to outside weather conditions, people have been found to exhibit a certain degree of tension, anxiety, and sadness when viewing information about rainy weather (Reser and Swim, 2011). The influences of weather on individuals' cognition are mainly reflected in memory and information processing: people tend to engage in more heuristic and less systematic information processing on sunny and warm days than on cloudy and cool days (Keller et al., 2005). Forgas et al. (2009) further indicated that negative emotions sparked by the weather can improve memory, as evidenced by individuals recalling more goods in a shopping scene.

Researchers have particularly explored how cloudy and rainy weather negatively influences customers' evaluations of overall life satisfaction (Connolly, 2013; Lucas and Lawless, 2013) and consumption satisfaction, including via online ratings (Bakhshi et al., 2014; He et al., 2020) and complaints reported on feedback cards (Bujisic et al., 2019). The effects of weather conditions on customer behavior are also reflected in product sales (Buchheim and Kolaska, 2016), shopping modes (Busse et al., 2015; Tian et al., 2018), and financial investment (Dehaan et al., 2017).

Our research further complements the literature on the association between weather and user-generated content. On social platforms, extreme weather can influence individuals' tweets, retweet frequency, and content categories (i.e., information, humor, and emotions) (Lin et al., 2016). Similarly, sentiment analyses of Facebook and Twitter posts revealed rainfall and cloud coverage to be significantly related to individuals' emotional expression (Baylis et al., 2018): positive emotions declined during rainy or cloudy weather while negative emotions were more prevalent. With respect to online reviews in particular, the present study extends prior work by understanding how rainy weather influences customers' emotional expression and online reviews at the consumption stage and at the comment stage.

2.2. Effects of emotions

Previous research has illustrated the informative function of emotions, which can influence individuals' judgment and decisions (Pham et al., 2012; Schwarz and Clore, 1983). People expressing positive emotions tend to positively assess their environment and make productive decisions (Tian et al., 2018). For instance, customers in pleasant moods often evaluate products more positively and are more likely to accept promotions (Li et al., 2017). Isen (2001) found that people pay more attention to non-negative information when in a good mood because they are unwilling to be exposed to negative information and seek to maintain their happiness. On the contrary, people in a bad mood focus more on negative information because they are vigilant and accept such information more readily.

One's emotional state has been found to mediate weather-related factors and consumer behavior according to the stimulus-organism-response (S-O-R) model (Mehrabian and Russel, 1974). For example, Bujisic et al. (2019) and He et al. (2020) noted that customers' moods mediated the association between perceived weather and WOM. Furthermore, a number of studies have uncovered significant relationships between weather-induced emotions and stock market trading (Dehaan et al., 2017; Lu and Chou, 2012), retail sales (Murray et al., 2010), variety seeking (Tian et al., 2018), and responses to promotions (Li et al., 2017).

3. Hypothesis development

3.1. Impact of rainy weather on emotional expression

The effects of weather-related factors can manifest through people's behavior with emotional states as a mediator (Mehrabian and Russel, 1974). Generally, rainy weather elicits negative moods, and one's emotional state can affect their judgment and information processing (Bakhshi et al., 2014; Forgas et al., 2009; Keller et al., 2005). As mentioned in the literature review, a person's mood is a source of information with which to evaluate life satisfaction (Schwarz and Clore, 1983) and product satisfaction (Bujisic et al., 2019): people are likely to rate a product or service more favorably when in a pleasant mood and less favorably when in an unpleasant mood. For instance, customers' purchase responses to mobile promotions are lower and slower when in a bad mood during rainy weather relative to cloudy conditions (Li et al., 2017). This pattern is consistent with the psychological theory of "affect as information" (Pham et al., 2012; Schwarz and Clore, 1983). One's emotional state at a given time increases their likelihood of recalling events that evoked similar feelings, which then leads customers to overestimate the incidence of such events and generates rating biases (Tversky and Kahneman, 1973). In particular, individuals are more

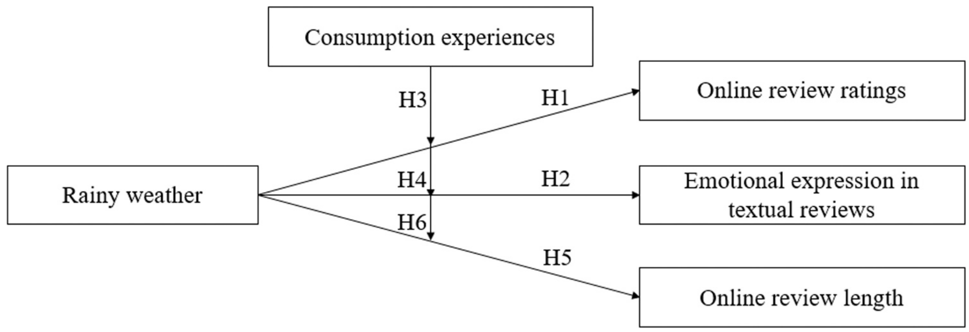

Fig. 1. Impact of rainy weather on customers' online evaluations.

likely to recall unpleasant events when in a bad mood (Isen, 2001; Tian et al., 2018) and thus express more negative emotions or less positive emotions when evaluating. Therefore, we posit that negative moods derived from rainy weather when writing online reviews compromise individuals' emotional expression in two review patterns as follows:

H1. *Rainy weather when writing a review negatively influences customers' online review ratings.*

H2. *Rainy weather when writing a review negatively influences customers' emotional expression in online textual reviews.*

Studies have demonstrated that individuals' experiences can affect their customer satisfaction (Tang and Yu, 2021), online ratings (Bai et al., 2020; Ho et al., 2017), and effort devoted to posting online reviews (Dellarocas and Narayan, 2006; Li et al., 2020). The consumption experience can also be viewed as an antecedent of emotional arousal and responses which subsequently affect evaluations of satisfaction (Li et al., 2020; Mano and Oliver, 1993; Phillips and Baumgartner, 2002). In this context, positive moods are evoked when customers evaluate favorable consumption experiences online (Li et al., 2020; Phillips and Baumgartner, 2002). The informative function of emotions leads individuals' emotional states to consistently affect their judgment and decisions (Tian et al., 2018): people exhibiting positive moods tend to make more positive decisions. Specifically, a sense of satisfaction generated from pleasant consumption experiences induces positive emotions that may lessen the effects of negative emotions triggered by rain on online reviews. Customers' available time and energy to generate evaluations are limited—but positive customers' minds have already been made up, and no trigger exists to prompt them to recall disappointing details. Negative emotions influenced by rainy weather should thus be alleviated when posting reviews. Similarly, negative moods resulting from unfavorable consumption experiences will exacerbate the adverse impact of rainy weather. The following hypotheses are proposed accordingly:

H3. *Favorable consumption experiences weaken the negative impact of rainy weather when writing a review on customers' online review ratings.*

H4. *Favorable consumption experiences weaken the negative impact of rainy weather when writing a review on customers' emotional expression in online textual reviews.*

3.2. Impact of rainy weather on review length

Weather-related factors influence human senses and affect physiological states (Hsiang et al., 2013; Lambert et al., 2002). The senses are stimulated by numerous aspects of weather: without sufficient sunlight, the brain produces less serotonin, which leads to lower happiness and energy (Lambert et al., 2002) and stronger feelings of sadness, fatigue, and exhaustion (Hsiang et al., 2013). For this reason, rainy weather influences people's moods and can easily lead to fatigue.

Negative feelings also diminish people's information processing abilities. When browsing webpages, customers engage in information collection and processing. Limited information processing due to negative emotions leads to greater costs associated with such processing (Li et al., 2017). When customers browse online, semantically code textual reviews (Macinnis and Price, 1987), and even post reviews themselves, if the cost of their review process increases in rainy weather, then the effort they devote to writing reviews should be lower. Moreover, the length of customers' textual reviews can signify their effort (Liu et al., 2019). In rainy weather, customers are likely to expend less effort and to write shorter reviews:

H5. *Rainy weather when writing a review decreases customers' review length.*

In rainy weather, people may become lazy due to limited action mobility and information processing (Hsiang et al., 2013; Keller et al., 2005; Lambert et al., 2002). The length of their online reviews may also be shorter as the effort required to write increases. However, expressing dissatisfaction with a product or service is a key motivation behind customers' decisions to post online reviews (Hennig-Thurau et al., 2004). Customers consider the average ratings of prior peer reviews when developing expectations of product and service quality (Chen et al., 2018). As such, when individuals' ratings are lower than the average of prior ratings (i.e., their consumption experience failed to meet their expectations), these customers become disappointed and unsatisfied. Studies have shown that emotional arousal enhances individuals' likelihood of communicating, including by sharing personal information and public news, because they are physically and mentally stimulated (Deckert et al., 2020). In this case, the arousal of negative emotions spurs customers to act, which could increase their motivation and cognitive capacity to write longer reviews (i.e., effectively diminishing their laziness). That is, individuals who have had unfavorable consumption experiences might overcome negative emotional states even under rainy conditions and actively post about their experience as a means of self-expression or in hopes of gaining compensation. Therefore, when dissatisfied customers' ratings are lower than prior ratings, these customers tend to overcome the negative effect of rainy weather and devote more effort to composing textual reviews:

H6. *Unfavorable consumption experiences weaken the negative impact of rainy weather when writing a review on customers' review length.*

Our hypotheses concerning the effects of rainy weather on customers' online evaluations are summarized in Fig. 1.

4. Methodology

4.1. Data

In this study, we gathered online review and weather data from two sources. Hourly weather data were collected from Wunderground Weather Stations via AmbientWeather.com. Online review data were obtained from *Xiaomishu* (http://www.xiaomishu.com/), a leading restaurant reservation and review platform in China. This website is

Table 1
Variable descriptions.

Variable	Description
Dependent variables	
Overall	Overall rating
Taste	Rating for taste of meal
Environ	Rating for restaurant environment
Service	Rating for restaurant service
TextLen	Number of characters in a review
Posemo	Proportion of words expressing positive emotions among total words in a review
Negemo	Proportion of words expressing negative emotions among total words in a review
Anx	Proportion of words expressing anxiety among total words in a review
Anger	Proportion of words expressing anger among total words in a review
Sad	Proportion of words expressing sadness among total words in a review
Independent variable	
RevRainy	Dummy variable denoting whether it was raining or snowing at the review hour (1 = yes, 0 = no)
Moderators	
Experience	Dummy variable for consumption experience, referring to a favorable experience if the overall/attribute rating of a restaurant review was not lower than the average overall/attribute rating of prior reviews and an unfavorable experience otherwise
Control variables	
(1) Weather characteristics	
RevTemp	Temperature (in Celsius) at the review hour
RevWind	Wind-speed scale from 0 to 17 at the review hour
RevPress	Atmospheric pressure (in hPa) at the review hour
DineRainy	Coded as 1 if it was raining or snowing at the dining hour and 0 otherwise
DineTemp	Temperature (in Celsius) at the dining hour
DineWind	Wind-speed scale from 0 to 17 at the dining hour
DinePress	Atmospheric pressure (in hPa) at the dining hour
(2) Review and restaurant characteristics	
RevNum	Number of reviews prior to the review time
AvgRating	Average overall/attribute rating of reviews prior to the review time
VarRating	Variance of review overall/attribute ratings prior to the review time
AvgText	Average number of characters in reviews prior to the review time
VarText	Variance of review length prior to the review time
AvgPrice	The restaurant's per capita consumption
Interval	Temporal interval (in days) between the dining time and review time
Weekend	Dummy variable denoting whether a review was posted on a weekend (1 = yes, 0 = no)
RevTime	Dummy variable denoting the time of day that a review was posted (0 = morning, 1 = noon, 2 = afternoon, 3 = evening and night)

particularly well suited to our analysis, as it records the time when customers dined and posted corresponding reviews. These data allowed for careful exploration of the impact of rainy weather on customers' evaluations while controlling for other factors. Shanghai, China was chosen as the focal city in this study. Shanghai is the birthplace of *Xiaomishu* and has the largest number of users and sales revenue from restaurant and catering businesses. All customer reviews for restaurants in Shanghai were collected in September 2016 using an automatic webpage crawler.

We then merged online reviews and weather information by the hour of customers' review posting and dining from November 8, 2008 to September 7, 2016. Multiple types of data provided us with an opportunity to understand customers' behaviors more comprehensively than ever before (Wang et al., 2020). We retained restaurants with more than 30 reviews to ensure a sufficiently large sample per restaurant (Ahn et al., 2017; Chaves et al., 2012) and ultimately kept 149,388 observations across 1106 restaurants and 42,007 customers for analysis. Each observation in our dataset included the restaurant ID, online rating, textual reviews, dining and review times, and corresponding weather information.

4.2. Variable measurement

4.2.1. Dependent variables

Xiaomishu uses a 5-point rating scale (1 = "very dissatisfied," 5 = "very satisfied"). In the first part of this study, the dependent variable *Rating* encompassed an overall rating (*Overall*) and three attribute ratings: taste of meal (*Taste*), restaurant environment (*Environ*), and service (*Service*). Other dependent variables were related to textual characteristics, including *Posemo*, *Negemo*, *Anx*, *Anger*, and *Sad*, respectively measured by the proportion of words expressing positive emotions, negative emotions, anxiety, anger, and sadness among the total number of words in a review (please refer to Appendix A for details). In the second part of the study, the dependent variable *TextLen* reflected the textual review length (Liu et al., 2019).

4.2.2. Independent variable

In line with prior studies (Tian et al., 2018), we coded the independent variable (*RevRainy*) as 1 if it was raining or snowing at the review hour and 0 otherwise. Similar operationalization methods (i.e.,

Table 2
Summary statistics.

Variable	Observations	Mean	Std. Dev	Min	Max	Skew.
Overall	149,388	4.110	0.845	1	5	-0.859
TextLen	149,388	40.687	66.279	1	2106	9.191
Posemo	149,355	6.741	11.940	0	100	4.164
Negemo	149,355	0.531	2.477	0	100	13.336
Anx	149,355	0.046	0.683	0	100	46.770
Anger	149,355	0.150	1.543	0	100	30.275
Sad	149,355	0.233	1.810	0	100	23.263
RevRainy	149,388	0.124	0.330	0	1	2.276
Experience_Overall	148,285	0.513	0.500	0	1	-0.052
RevTemp	149,388	17.950	9.306	-7	41	-0.014
RevWind	149,388	4.385	1.884	0	17	0.490
RevPress	149,388	1016.518	8.949	986	1042	0.009
DineRainy	149,388	0.116	0.320	0	1	2.400
DineTemp	149,388	18.389	9.233	-6	41	-0.100
DineWind	149,388	4.484	1.791	0	15	0.502
DinePress	149,388	1015.922	9.066	987	1041	0.068
RevNum	149,388	142.165	158.446	0	1096	3.076
AvgRating_Overall	148,285	4.078	0.306	1	5	-0.959
VarRating_Overall	148,285	0.840	0.204	0	2.828	-0.462
AvgText	148,285	51.528	29.394	1	1376	6.560
VarText	148,285	69.269	49.646	0	1108.743	2.963
AvgPrice	148,285	200.154	120.153	15.083	3036.662	2.955
Interval	149,388	124.596	313.978	0	3683	4.054
Weekend	149,388	0.259	0.438	0	1	1.100
RevTime	149,388	1.647	1.166	0	3	0.284

Table 3
Estimation results for impact of rainy weather on online review ratings.

DV	(1) *Overall*	(2) *Overall*	(3) *Overall*	(4) *Overall*
RevRainy	-0.0237***	-0.0250***	-0.0395***	-0.0547***
	(0.0147)	(0.0181)	(0.0216)	(0.0270)
RevRainy × Experience_Overall				0.0346**
				(0.0410)
Experience_Overall			8.1236***	8.1192***
			(0.2715)	(0.2719)
RevTemp		-0.0015*	-0.0042**	-0.0042**
		(0.0020)	(0.0024)	(0.0024)
RevWind		0.0028*	0.0058**	0.0058**
		(0.0033)	(0.0040)	(0.0040)
RevPress		-0.0015*	-0.0016*	-0.0016*
		(0.0017)	(0.0021)	(0.0021)
RevNum(log)		0.0539***	0.1253***	0.1253***
		(0.0104)	(0.0350)	(0.0350)
AvgRating_Overall		1.1332****	5.5110***	5.5111***
		(0.0560)	(0.1852)	(0.1852)
VarRating_Overall		-0.3008***	-0.2227	-0.2228
		(0.0905)	(0.2888)	(0.2888)
AvgPrice		0.0010***	0.0011***	0.0011***
		(0.0001)	(0.0002)	(0.0002)
Interval(log)		0.0373***	0.0336***	0.0336***
		(0.0039)	(0.0043)	(0.0043)
Weekend		-0.0072	-0.0006	-0.0006
		(0.0129)	(0.0170)	(0.0170)
Noon		0.0269*	0.0049	0.0050
		(0.0143)	(0.0174)	(0.0174)
Afternoon		-0.0654***	-0.0833***	-0.0832***
		(0.0182)	(0.0196)	(0.0196)
Evening and night		-0.1813***	-0.1372***	-0.1372***
		(0.0384)	(0.0476)	(0.0476)
DineRainy		0.0326***	0.0167**	0.0168**
		(0.0188)	(0.0229)	(0.0229)
DineTemp		0.0005	0.0005	0.0005
		(0.0015)	(0.0019)	(0.0019)
DineWind		-0.0012	-0.0024*	-0.0024*
		(0.0033)	(0.0038)	(0.0038)
DinePress		0.0014	0.0012	0.0011
		(0.0014)	(0.0018)	(0.0018)
Year FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Observations	149,388	148,285	148,285	148,285
Number of restaurants	1106	1106	1106	1106
Pseudo R^2	0.0194	0.0427	0.4571	0.4571
Wald chi2	9460.92	3165.31	4595.80	4600.41
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Log pseudolikelihood	-171,061.60	-129,803.57	-72,412.59	-72,412.25

Notes: Robust standard errors clustered by restaurants are reported in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. *Experience_Overall* was coded as 1 if the overall rating of a restaurant review was not lower than the average overall rating of prior reviews and 0 otherwise.

employing a dummy variable to denote whether precipitation occurred) are common in research (Bujisic et al., 2019; Li et al., 2017).

4.2.3. Moderating variables

The dummy variable for consumption experience (*Experience*) referred to a favorable experience if the overall/attribute rating of a restaurant review was not lower than the average overall/attribute rating of prior reviews and an unfavorable experience otherwise (Ho et al., 2017; Li et al., 2020). This variable included four sub-variables: *Experience_Overall* for overall rating, *Experience_Taste* for taste rating, *Experience_Environ* for environment rating, and *Experience_Service* for service rating.

4.2.4. Control variables

To eliminate potential confounds from other weather-related variables, we controlled for other weather conditions at the dining time and review time (Bujisic et al., 2019; Tian et al., 2018). To account for the restaurant heterogeneity effect, the overall/attribute average review rating prior to the review time (*AvgRating_Overall* and *AvgRating_Attri*) and the price of per capita consumption (*AvgPrice*) were controlled (Li et al., 2020; Zhang et al., 2016). Given the impact of existing review information on customers' evaluation behavior (Chen et al., 2018; Liu et al., 2019; Zhang et al., 2016), we controlled for prior review volume (*RevNum*), average prior review length (*AvgText*), variance in prior review ratings (*VarRating*, including *VarRating_Overall*, *VarRating_Taste*, *VarRating_Environ*, and *VarRating_Service*), as well as textual length (*VarText*) before the current review. We also controlled for certain characteristics of the review time, namely the interval between dining and review posting (*Interval*), whether a review was posted on a weekend (*Weekend*), and the time of day (*RevTime*), due to these aspects' potential effects on customers' emotions and online review behavior (Golder and Macy, 2011; Li et al., 2020; Liu et al., 2019).

Table 1 lists main variables used in this study, and Table 2 presents their descriptive statistics. Before testing the hypotheses, we conducted

Table 4
Extended conclusions on impact of rainy weather on attribute ratings.

DV	(1) *Taste*	(2) *Taste*	(3) *Environ*	(4) *Environ*	(5) *Service*	(6) *Service*
RevRainy	-0.0236**	-0.0625***	-0.0202**	-0.0429***	-0.0198**	-0.0268**
	(0.0231)	(0.0325)	(0.0226)	(0.0299)	(0.0207)	(0.0309)
RevRainy × *Experience_Attri*		0.0828**		0.0576**		0.0112
		(0.0404)		(0.0399)		(0.0383)
Experience_Attri	6.9180***	6.9078***	6.5894***	6.5823***	6.1162***	6.1149***
	(0.1064)	(0.1063)	(0.1038)	(0.1036)	(0.0834)	(0.0834)
AvgRating_Attri	4.4297***	4.4298***	4.2022***	4.2024***	3.2783***	3.2783***
	(0.1283)	(0.1283)	(0.0996)	(0.0996)	(0.0904)	(0.0904)
VarRating_Attri	0.7939***	0.7941***	0.5628***	0.5628***	0.4242***	0.4242***
	(0.1988)	(0.1987)	(0.1719)	(0.1720)	(0.1260)	(0.1260)
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES
Observations	148,285	148,285	148,285	148,285	148,285	148,285
Number of restaurants	1106	1106	1106	1106	1106	1106
Pseudo R^2	0.4448	0.4448	0.4816	0.4816	0.4163	0.4163
Wald chi2	6561.56	6575.08	6369.24	6382.25	8337.32	8340.64
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Log pseudolikelihood	-71,712.37	-71,710.37	-69,059.18	-69,058.25	-85,029.15	-85,029.11

Notes: Robust standard errors clustered by restaurants are reported in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *Experience_Attri* was coded as 1 if the attribute rating of a restaurant review was not lower than the average attribute rating of prior reviews and 0 otherwise. *Experience_Attri* refers to *Experience_Taste* in Models (1) and (2), *Experience_Environ* in Models (3) and (4), and *Experience_Service* in Models (5) and (6). *AvgRating_Attri* refers to *AvgRating_Taste*, *AvgRating_Environ*, and *AvgRating_Service* in different models. *VarRating_Attri* refers to *VarRating_Taste*, *VarRating_Environ*, and *VarRating_Service*, correspondingly. Controls refer to *RevTemp*, *RevWind*, *RevPress*, *RevNum(log)*, *AvgPrice*, *Interval(log)*, *Weekend*, *RevTime*, *DineRainy*, *DineTemp*, *DineWind*, and *DinePress*. Estimates of these variables are not presented for brevity.

Table 5
Estimation results for rainy effects on emotional expression in textual reviews.

DV	(1) *Posemo(log)*	(2) *Posemo(log)*	(3) *Negemo(log)*	(4) *Negemo(log)*	(5) *Anx(log)*	(6) *Anx(log)*	(7) *Anger(log)*	(8) *Anger(log)*	(9) *Sad(log)*	(10) *Sad(log)*
RevRainy	-0.0194	0.0078	0.0032	-0.0012	0.0043*	-0.0046*	0.0001	-0.0032	0.0050	-0.0026
	(0.0151)	(0.0196)	(0.0063)	(0.0094)	(0.0019)	(0.0027)	(0.0033)	(0.0052)	(0.0042)	(0.0064)
RevRainy × *Experience_Overall*		-0.0487*		0.0066		0.0006		0.0057		0.0036
		(0.0274)		(0.0112)		(0.0033)		(0.0058)		(0.0073)
Experience_Overall		0.3892***		-0.1218***		-0.0072***		-0.0445***		-0.0677***
		(0.0115)		(0.0047)		(0.0015)		(0.0026)		(0.0032)
Constant	1.9940	0.7154	-1.1316*	-0.7222	0.1203	0.1456	-0.1609	-0.0183	-0.9167**	-0.6885
	(1.5709)	(1.5630)	(0.6514)	(0.6479)	(0.1859)	(0.1857)	(0.3436)	(0.3430)	(0.4484)	(0.4473)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Customer FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	148,285	148,285	148,285	148,285	148,285	148,285	148,285	148,285	148,285	148,285
Number of restaurants	1106	1106	1106	1106	1106	1106	1106	1106	1106	1106
R^2	0.2774	0.2912	0.1953	0.2039	0.1457	0.1460	0.1844	0.1882	0.1864	0.1924
adj. R^2	0.1484	0.1647	0.0517	0.0618	0.0164	0.0168	0.0389	0.0433	0.0412	0.0482

Notes: Robust standard errors clustered by restaurants are reported in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *Experience_Overall* was coded as 1 if the overall rating of a restaurant review was not lower than the average overall rating of prior reviews and 0 otherwise. Controls refer to the same control variables in Table 3. Estimates of control variables are not presented for brevity.

Pearson's correlation analysis. The correlations among independent variables were relatively weak, reducing multicollinearity and enhancing the reliability and validity of our estimation results (please refer to Appendix B). Moreover, we reported the variance inflation factors (VIFs) and tolerance values of explanatory variables. All VIF values were less than 10 (range: 1.00–4.84), and all tolerance values exceeded 0.1; multicollinearity was therefore not a problem in our estimation models. We log-transformed skewed variables (i.e., *TextLen*, *RevNum*, *AvgText*, *Interval*, *Posemo*, *Negemo*, *Anx*, *Anger*, and *Sad*) to achieve normality.

4.3. Econometric specifications

We estimated the following equations to test our hypotheses:

$$Rating_{ij} = \beta_0 + \beta_1 RevRainy_{ij} + \beta_2 Experience_{ij} + \beta_3 RevRainy_{ij} \times Experience_{ij} + \sum \lambda_{ij} * Control_{ij} + Restaurant_j + Customer_i + Year_y + Month_m + \varepsilon_{ij} \quad (1)$$

Table 6
Estimation results for impact of rainy weather on review length.

Moderator	(1) *Experience_Overall*	(2) *Experience_Overall*	(3) *Experience_Taste*	(4) *Experience_Environ*	(5) *Experience_Service*
RevRainy	-0.0153**	-0.0283***	-0.0261***	-0.0174**	-0.0232***
	(0.0088)	(0.0112)	(0.0103)	(0.0102)	(0.0100)
RevRainy × *Experience*		0.0260**	0.0299**	0.0072	0.0270**
		(0.0138)	(0.0152)	(0.0144)	(0.0147)
Experience		0.0566***	0.0528***	0.0415***	0.0995***
		(0.0072)	(0.0064)	(0.0065)	(0.0070)
RevTemp	0.0008**	0.0008**	0.0007**	0.0007**	0.0007**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
RevWind	-0.0032**	-0.0032**	-0.0032**	-0.0033**	-0.0032**
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
RevPress	0.0004	0.0004	0.0004	0.0004	0.0004
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
RevNum(log)	-0.0474***	-0.0506***	-0.0496***	-0.0486***	-0.0499***
	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)
AvgText(log)	-0.4189***	-0.4152***	-0.4178***	-0.4199***	-0.4137***
	(0.0419)	(0.0419)	(0.0417)	(0.0419)	(0.0416)
VarText	0.0035***	0.0035***	0.0035***	0.0035***	0.0035***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
AvgPrice	-0.0002**	-0.0002***	-0.0002***	-0.0002**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Interval(log)	-0.0516***	-0.0513***	-0.0515***	-0.0516***	-0.0512***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Weekend	-0.0204***	-0.0206***	-0.0203***	-0.0204***	-0.0206***
	(0.0060)	(0.0060)	(0.0060)	(0.0060)	(0.0060)
Noon	-0.0406***	-0.0399***	-0.0400***	-0.0403***	-0.0400***
	(0.0077)	(0.0076)	(0.0076)	(0.0076)	(0.0076)
Afternoon	-0.0652***	-0.0668***	-0.0655***	-0.0651***	-0.0657***
	(0.0087)	(0.0086)	(0.0087)	(0.0087)	(0.0086)
Evening and night	-0.0838***	-0.0886***	-0.0855***	-0.0853***	-0.0864***
	(0.0167)	(0.0167)	(0.0167)	(0.0166)	(0.0167)
DineRainy	-0.0060	-0.0057	-0.0055	-0.0056	-0.0061
	(0.0070)	(0.0069)	(0.0069)	(0.0070)	(0.0069)
DineTemp	0.0025***	0.0025***	0.0026***	0.0026***	0.0025***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
DineWind	-0.0010	-0.0011	-0.0010	-0.0009	-0.0010
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
DinePress	0.0026***	0.0025***	0.0026***	0.0026***	0.0025***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Constant	3.0346***	3.0154***	2.9261***	2.9619***	3.0520***
	(0.8877)	(0.8844)	(0.8845)	(0.8867)	(0.8799)
Restaurant FE	YES	YES	YES	YES	YES
Customer FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
Observations	148,285	148,285	148,285	148,285	148,285
Number of restaurants	1106	1106	1106	1106	1106
R^2	0.6014	0.6020	0.6019	0.6017	0.6033
adj. R^2	0.5302	0.5309	0.5308	0.5306	0.5324

Notes: Robust standard errors clustered by restaurants are reported in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *Experience* was coded as 1 if the overall/attribute rating of a restaurant review was lower than the average overall/attribute rating of prior reviews and 0 otherwise. *Experience* refers to *Experience_Overall* in Models (1) and (2), *Experience_Taste* in Model (3), *Experience_Environ* in Model (4), and *Experience_Service* in Model (5).

$$EmotionalWords_{ij} = \beta_4 + \beta_5 RevRainy_{ij} + \beta_6 Experience_{ij} + \beta_7 RevRainy_{ij} \times Experience_{ij} + \sum \lambda_{ij} * Control_{ij} + Restaurant_j + Customer_i + Year_y + Month_m + \varepsilon_{ij} \tag{2}$$

$$TextLen_{ij} = \beta_8 + \beta_9 RevRainy_{ij} + \beta_{10} Experience_{ij} + \beta_{11} RevRainy_{ij} \times Experience_{ij} + \sum \lambda_{ij} * Control_{ij} + Restaurant_j + Customer_i + Year_y + Month_m + \varepsilon_{ij} \tag{3}$$

Table 7
Robustness check for rainy effects on online review ratings using OLS regression.

DV	(1) *Overall*	(2) *Overall*	(3) *Taste*	(4) *Taste*	(5) *Environ*	(6) *Environ*	(7) *Service*	(8) *Service*
RevRainy	-0.0271***	-0.0398***	-0.0108***	-0.0170***	-0.0137***	-0.0240***	-0.0095**	-0.0133**
	(0.0057)	(0.0076)	(0.0054)	(0.0082)	(0.0052)	(0.0078)	(0.0061)	(0.0095)
RevRainy × *Experience*		0.0263**		0.0153**		0.0168**		0.0102
		(0.0104)		(0.0100)		(0.0085)		(0.0100)
Experience	1.1010***	1.0977***	1.0825***	1.0813***	1.1079***	1.1058***	1.2729***	1.2732***
	(0.0040)	(0.0042)	(0.0038)	(0.0040)	(0.0036)	(0.0038)	(0.0042)	(0.0044)
Constant	0.5894	0.5900	0.7512	0.7516	1.1604**	1.1673**	0.8304	0.8298
	(0.5890)	(0.5889)	(0.5493)	(0.5493)	(0.5322)	(0.5322)	(0.6198)	(0.6198)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES	YES	YES	YES
Customer FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	148,285	148,285	148,285	148,285	148,285	148,285	148,285	148,285
R^2	0.7051	0.7051	0.7130	0.7130	0.7530	0.7531	0.7323	0.7323
adj. R^2	0.6560	0.6560	0.6652	0.6652	0.7119	0.7119	0.6877	0.6877

Notes: Standard errors are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Experience* was coded as 1 if the overall/attribute rating of a restaurant review was not lower than the overall/average attribute rating of prior reviews and 0 otherwise. *Experience* refers to *Experience_Overall* in Models (1) and (2), *Experience_Taste* in Models (3) and (4), *Experience_Environ* in Models (5) and (6), and *Experience_Service* in Models (7) and (8). Controls refer to the same control variables in Tables 3 and 4, correspondingly. Estimates of control variables are not presented for brevity. The estimation results using robust standard errors clustered by restaurants are highly consistent with the results using standard errors in this table.

Table 8
Robustness check for rainy effects on emotional expression in textual reviews using standard errors.

DV	(1) *Posemo(log)*	(2) *Posemo(log)*	(3) *Negemo(log)*	(4) *Negemo(log)*	(5) *Anx(log)*	(6) *Anx(log)*	(7) *Anger(log)*	(8) *Anger(log)*	(9) *Sad(log)*	(10) *Sad(log)*
RevRainy	-0.0194	0.0078	0.0032	-0.0012	0.0043*	-0.0046*	0.0001	-0.0032	0.0050	-0.0026
	(0.0142)	(0.0187)	(0.0061)	(0.0080)	(0.0019)	(0.0025)	(0.0032)	(0.0042)	(0.0041)	(0.0054)
RevRainy × *Experience_Overall*		-0.0487*		0.0066		0.0006		0.0057		0.0036
		(0.0253)		(0.0109)		(0.0034)		(0.0058)		(0.0073)
Experience_Overall		0.3892***		-0.1218***		-0.0072***		-0.0445***		-0.0677***
		(0.0103)		(0.0044)		(0.0014)		(0.0023)		(0.0030)
Constant	1.9940	0.7154	-1.1316*	-0.7222	0.1203	0.1456	-0.1609	-0.0183	-0.9167**	-0.6885*
	(1.4527)	(1.4395)	(0.6200)	(0.6169)	(0.1959)	(0.1959)	(0.3273)	(0.3266)	(0.4151)	(0.4138)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Customer FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	148,285	148,285	148,285	148,285	148,285	148,285	148,285	148,285	148,285	148,285
R^2	0.2774	0.2912	0.1953	0.2039	0.1457	0.1460	0.1844	0.1882	0.1864	0.1924
adj. R^2	0.1484	0.1647	0.0517	0.0618	0.0164	0.0168	0.0389	0.0434	0.0412	0.0483

Notes: Standard errors are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Experience_Overall* was coded as 1 if the overall rating of a restaurant review was not lower than the average overall rating of prior reviews and 0 otherwise. Controls refer to the same control variables in Table 3. Estimates of control variables are not presented for brevity.

In our econometric model, $EmotionalWords_{ij}$ refers to variables relevant to emotion-related words in the review of restaurant j posted by customer$i$, namely $Posemo_{ij}$, $Negemo_{ij}$, Anx_{ij}, $Anger_{ij}$, and Sad_{ij}. Furthermore, to control for restaurant-related heterogeneity due to factors such as the restaurant category and systematic differences in ratings across restaurants, we included restaurant fixed effects ($Restaurant_j$) in our models. We also considered customer fixed effects ($Customer_i$) to control for individual specific effects of evaluation behavior. Year and month fixed effects ($Year_y$ and $Month_m$) were included as well to account for temporal heterogeneity (e.g., temporal trends and seasonality).

Online review ratings are typically ordinal. As such, we adopted an ordered logit model involving ratings (i.e., overall ratings and attribute ratings) in line with previous literature (Godes and Silva, 2012; Zhang et al., 2016). However, estimating an ordered logit model with a large number of restaurant and customer fixed effects was infeasible. We therefore excluded restaurant and customer fixed effects from our main estimation. We then conducted robustness checks by treating rating as a continuous cardinal measure with restaurant and customer fixed effects. We used an ordinary least squares regression model to test our hypotheses involving emotional expression in textual reviews and review length. Considering the presence of heteroscedasticity, we estimated all models with clustered robust standard errors.

5. Results

5.1. Impact of rainy weather on emotional expression

Table 3 displays the estimation results of the ordered logit model. We used different model specifications in Models (1) to (4) and obtained

Table 9
Robustness check for rainy effects on review length using standard errors.

Moderator	(1) *Experience_Overall*	(2) *Experience_Overall*	(3) *Experience_Taste*	(4) *Experience_Environ*	(5) *Experience_Service*
RevRainy	-0.0153**	-0.0283***	-0.0261***	-0.0174**	-0.0232***
	(0.0072)	(0.0098)	(0.0087)	(0.0088)	(0.0086)
RevRainy × *Experience*		0.0260**	0.0299**	0.0072	0.0270**
		(0.0129)	(0.0134)	(0.0132)	(0.0135)
Experience		0.0566***	0.0528***	0.0415***	0.0995***
		(0.0054)	(0.0054)	(0.0053)	(0.0053)
Constant	3.0346***	3.0154***	2.9261***	2.9619***	3.0520***
	(0.7397)	(0.7392)	(0.7393)	(0.7394)	(0.7380)
Controls	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES
Customer FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
Observations	148,285	148,285	148,285	148,285	148,285
R^2	0.6014	0.6020	0.6019	0.6017	0.6033
adj. R^2	0.5302	0.5310	0.5308	0.5306	0.5324

Notes: Standard errors are reported in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. *Experience* was coded as 1 if the overall/attribute rating of a restaurant review was lower than the average overall/attribute rating of prior reviews and 0 otherwise. *Experience* refers to *Experience_Overall* in Models (1) and (2), *Experience_Taste* in Model (3), *Experience_Environ* in Model (4), and *Experience_Service* in Model (5). Controls refer to the same control variables in Table 6. Estimates of control variables are not presented for brevity.

consistent results. Model (1) includes only the independent variable, while Model (2) adds control variables. In Models (3) and (4), the moderating variable and interaction term are added gradually. As shown in Model (4), the coefficient of *RevRainy* was significantly negative, suggesting that rainy weather at the comment time tended to decrease customers' ratings. The significant positive coefficient of *RevRainy* × *Experience_Overall* indicates that favorable consumption experiences moderated the effect of rainy weather during the review process on customers' ratings. In other words, given a favorable consumption experience, the negative influence of rainy weather at the comment time on a customer's rating was weak. The coefficients of control variables reveal that a restaurant's higher number of previous reviews, higher prior average review rating, and higher consumption price positively influenced customers' online review ratings. Additionally, customers posting ratings within a longer temporal interval after dining were more likely to rate their experiences positively.

We then conducted additional analyses taking various attribute ratings, rather than overall ratings, as the dependent variable. As listed in Table 4, these results were significant and consistent with our expectations except for the coefficient of *RevRainy* × *Experience_Attri* in Model (6), generally supporting H1 and H3. Essentially, customers appeared more likely to assign taste and environment lower ratings in rainy weather, and this negative effect was weakened if customers were satisfied with their experiences. The insignificant moderating effect of customers' service experiences on the relationship between rainy weather and service ratings may have been due to the heterogeneous effects of attribute ratings. Taste, environment, and service represent three types of clues that reflect a dining experience (i.e., functional clues, mechanic clues, and humanic clues; Berry et al., 2002). Consistent with previous research, the taste of food plays a primary role; the physical environment is also pivotal in one's restaurant experience (Zhang et al., 2014). However, employee service is associated with the humanic factor and is more subjective. It is therefore difficult for customers to form consistent expectations from peer reviews.

We were also interested in the possible existence of rainy weather effects on emotional expression in textual reviews. Thus, we extracted emotion-related words and analyzed whether the effect of rainy weather was significant on the proportion of these words in textual reviews. Specifically, the coefficients of *RevRainy* in Table 5 were not significant. We added moderating variables into the models and observed that the moderating effect of consumption experience was generally not significant. H2 and H4 were therefore not supported.

5.2. Impact of rainy weather on review length

Based on data from the first part of the study, we included review length as the dependent variable in our research models to test H5 and H6. Model (1) in Table 6 presents the results of the baseline model. We noted a negative coefficient of *RevRainy* in that customers devoted less effort when posting textual reviews during rainy weather, lending support to H5. In Model (2), the coefficient of *RevRainy* × *Experience* was significantly positive, suggesting that an unfavorable consumption experience moderated the effect of rainy weather during the review process on review length. In detail, for reviews with below-average ratings, the negative influences of rainy weather while writing a review on customers' review length was weak. Thus, H6 was supported. Similarly, we investigated the influence of unfavorable experiences related to different restaurant attributes (i.e., taste, environment, and service) as moderators. The findings in Models (3) to (5) were nearly consistent. One exception is that the moderating effect of an unfavorable experience due to a restaurant's environment was non-significant. In addition, the coefficients of control variables suggest that the number of previous reviews, prior average review length, and average consumption price each negatively influenced online review length, while variation in previous review length had a positive impact. Customers posting reviews within a longer temporal interval after dining, on weekends, and after 12 pm were more likely to post briefer reviews.

5.3. Robustness check

We first conducted robustness checks to substantiate the identified rain-related effects on online review ratings. To test the robustness of our results and verify their sensitivity, we re-estimated our empirical models by using ordinary least squares regression with restaurant and customer fixed effects. The newly estimated results in Table 7 were quantitatively similar to those in Tables 3 and 4.

Furthermore, we re-estimated the models involving emotional expression in textual reviews and review length in Tables 5 and 6 using standard errors. The estimation results presented in Tables 8 and 9 were highly consistent with those reported in Tables 5 and 6.

6. Conclusion and discussion

Based on combined restaurant online review and weather data, the present study examined how rainy weather when writing online reviews influenced customers' evaluation behavior in a restaurant context. Our empirical results can be summarized as follows. First, customers tended to assign lower overall ratings and attribute ratings when it was raining as they wrote their reviews. This study also expounds on rainy weather effects on online review ratings at the comment stage by considering the consumption stage at the same time. In addition, customers' favorable consumption experiences seemed to lessen the negative effects of rainy weather on their ratings for general dining, taste, and environment. The taste of food and the quality of the environment are non-human elements influencing customers' restaurant experiences as well as their expectations (Wall and Berry, 2007). Yet compared with other attributes, the quality of restaurant service tends to differ depending on the quality of staff (Zhang et al., 2014). Different customers may have unique demands for service and hold disparate expectations based on past reviews. Therefore, the moderating effect of service-related experiences on the relationship between rainy weather and service ratings was not supported in this study.

Second, rain-related factors were not identified as antecedents of customers' emotional expression in textual reviews. The impact of rainy weather on patrons' emotional expression through ratings and textual reviews can differ, potentially due to varied means of information processing. The processing of review ratings is more imaginative (i.e., involving nonverbal and sensory information recall), whereas the processing of textual reviews is more analytical (i.e., semantic and rational) (Childers et al., 1985; Oliver et al., 1993). The interpretation of review ratings involves a holistic process and may be more susceptible to weather-related factors; by contrast, text interpretation relies on language retrieval and coding and is less relevant to internal sensory experiences (Macinnis and Price, 1987). Customers are especially more likely to attribute negative emotions to unsatisfactory consumption when assigning general ratings without much thought (Buchheim and Kolaska, 2016; Schwarz and Clore, 1983). Furthermore, they may make different attributions after careful editing and consideration while writing textual reviews, leading to less emotional stimulation based solely on rainy weather. Their textual reviews and corresponding emotional intensity could therefore contain less bias. This finding suggests an active way for potential customers to use online textual reviews to obtain less biased information compared to simply glancing at a rating score.

Third, our findings revealed that customers tend to exhibit less engagement when composing textual reviews during rainy weather. Considering the impact of rain on people's physiology and psychology, such weather conditions may cause customers to be indolent and increase the cost associated with writing a review. We further examined the moderating effects of consumption experiences on the relationship between rainy weather and review length. Specifically, customers who had unfavorable experiences in terms of overall dining, cuisine taste, and service quality were motivated to write longer reviews and less likely to be influenced by rainy weather.

6.1. Theoretical implications

Although research has focused on the importance and determinants of improving online ratings (Bakhshi et al., 2014; He et al., 2020), it remains unclear how weather-related factors, which are external environmental factors, affect customers' online evaluation behavior. This study makes several theoretical contributions to the literature. First, this study is among the first to empirically investigate the prominent role of weather in online evaluation generation in the hospitality industry. Unlike Bujisic et al.'s (2019) work, which focused on the impacts of rainy weather at the consumption stage on customer reviews and WOM, this study considered rainy weather during the comment stage and controlled for other weather conditions at the time of consumption and reviewing based on hourly weather data.

Second, our results unveiled whether and how rainy weather affects customers' numerical review ratings compared with textual review content. Prior studies only examined basic numerical indicators such as overall rating valence (Bakhshi et al., 2014; He et al., 2020). The current study considered various attribute ratings, extending the literature on weather-related effects and customers' online rating behavior in a hospitality setting. By leveraging a text mining technique, we investigated the impact of rainy weather on specific emotion-related words. This study complements the literature on emotional expression in user-generated content and online review biases by considering weather effects. Furthermore, our findings delineate several weather-related influences on customer engagement in review length.

Third, this study sheds light on the role of customers' consumption experiences, which serves as an underlying moderator for weather effects on online review behavior. We uncovered a possible mechanism behind reducing the impact of rain on reviewers' emotional expression and review length for the first time. Scholars have focused on the direct effects of consumption experiences on customer satisfaction and online ratings (Ho et al., 2017; Tang and Yu, 2021). We have added to this body of work by demonstrating the moderating effects of favorable and unfavorable consumption experiences on the relationship between weather and online evaluation behavior.

6.2. Managerial implications

The present study provides several important managerial implications for service businesses and online platform management. Our findings suggest that special attention should be given to rainy weather. We especially recommend that managers, waiters, and other practitioners realize the potential for bias in customers' restaurant evaluations due to poor weather. We further recognize that customers who had favorable consumption experiences are less likely to be influenced by rainy weather when writing online evaluations. Restaurant service plays a crucial role in meeting customers' expectations and later influences patrons' rating scores and review length (i.e., active engagement) during rainy weather. Acknowledging these relationships is vital when analyzing customer reviews and managing employees' shifts. Management and service employees should also be aware that customers may be more sensitive, or irritated, as a consequence of weather. Weather can thus shape customers' moods and affective experiences.

From a service provider standpoint, given that rainy weather at the time of writing a review is likely to lower customers' online ratings, service providers should strive to offer patrons a pleasant experience during consumption to promote guests' satisfaction and weaken their recall of disappointing memories when rating the establishment later. We therefore suggest that managers implement creative strategies to meet customers' expectations. For example, providing high-quality food and beverages is necessary. A warm and comfortable environment with pleasant music or scents and even unexpected gifts could also serve as effective experience-enhancing strategies. Managers should encourage service staff to maintain high service standards and attend more deliberately to customers' demands on rainy days.

With respect to online evaluation platforms, the accuracy of online reviews and customers' engagement are each critical to these platforms' reputation and long-term development. A few strategies could be applied to mitigate review biases and to incentivize users to write reviews. First, platforms could develop a system interface that includes a weather widget to monitor weather conditions in real time. When weather conditions become unpleasant, the rating system could offer customers helpful tips to consider when assigning ratings (e.g., encouraging quotes and/or warm greetings) and provide more contribution credits for textual reviews. When weather conditions are pleasant, platforms could alert users via mobile messages, encouraging them to post an evaluation. Second, the rating system could adjust a business's overall rating by employing an algorithm that considers the impact of weather at review time on ratings. For example, platform settings could adapt ratings based on whether reviews were posted on rainy or sunny days. Lastly, platforms could post a symbol (e.g., sunny, rainy, cloudy, windy) beside each online review reflecting the weather conditions at the time the review was written to help potential customers make more accurate judgments by taking weather-related effects into account.

6.3. Limitations and future studies

Several limitations exist in the present study. First, due to data availability, we could not test the effect of rainfall. It would be interesting to test various specifications of rainy weather (e.g., light, medium, or heavy rain; rain as measured in millimeters) or a combination of weather factors (e.g., temperature and wind) as data become available. Second, as the temporal interval between consumption and review posting increases, customers' recall of an experience and associated extreme emotions can wane. This fading may influence the impact of rainy weather on online evaluation behavior (Li et al., 2020). Future studies could analyze the interaction between the time interval and weather effects. Third, considering that customers from different regions with diverse climatic conditions likely possess unique cultural characteristics and consumption patterns, our results do not necessarily apply to the service industry at large. Therefore, subsequent research can extend our sample to other regions to examine differences across heterogeneous social and cultural segments. Fourth, we observed a significant influence of rainy weather at the comment stage on customers' evaluation behavior based on secondary online review data. We thus assumed customers were aware of the weather conditions even if they dined indoors. To address this limitation, future studies can employ an experimental design to further verify our findings by manipulating customers' awareness of weather conditions.

Acknowledgments

The authors acknowledge the support of research funds from the National Natural Science Foundation of China (72131005, 72171062, 71772053 and 71671049), the Fundamental Research Funds for the Central Universities (HIT.HSS.202103), and the National Key Research and Development Program of China (2017YFC1601903).

Appendix A. Text analysis

We used text mining techniques to extract additional insight from textual information. Text analysis is a word count–based linguistic analytics approach used to quantify psychological characteristics of textual reviews. Linguistic inquiry and word count (LIWC) dictionaries offer a reliable and robust function for content ratings to calculate the proportion of words that match predefined dictionaries (Ludwig et al., 2013; Tausczik and Pennebaker, 2010). To acquire scores on psychological characteristics, customers' review texts were operationalized in steps using the LIWC program with the Simplified Chinese LIWC2007 Dictionary, obtained from the LIWC website after software purchase (Pennebaker et al., 2015).[1]

The first step involved data pre-processing. The space character is a normal approximation of a word divider (i.e., word delimiter) in many languages that use the Latin alphabet, such as English. However, the Chinese language has no equivalent to this character. We therefore used an open-source Chinese natural language processing platform, the Language Technology Platform,[2] to segment review text into words. We chose this platform given its high accuracy in word segmentation (Che et al., 2010).

The second step included measuring the degree to which each review contained several types of emotion-related words, namely those indicative of positive emotion, negative emotion, anxiety, anger, and sadness (examples of word categories are shown in Table A1). In the dictionary, these five emotion-related words are coded as a number from 126 to 130. Each word can be classified as more than one type of emotion-related word. The percentage of each of the five emotional expression categories (in total number of words) was calculated automatically for each review. For example, if "开心" ("happy" in English) appeared in a review, the count of positive emotion-related words was 1. If the word "棒" ("great") appeared in the same review, the total score for positive emotion-related words became 2. If this review text contained no other positive emotions, and the total word count was 100, its percentage of positive emotion-related words was 2%. We used the following equation to derive the proportions of different emotional expressions in a given textual review (positive emotions are used in this example):

Table A1
Examples of word categories.

Category	Chinese example	English example
Positive emotion	喜欢, 好, 甜蜜	love, nice, sweet
Negative emotion	伤心, 丑, 可恶	hurt, ugly, nasty
Anxiety	担心, 害怕, 不安	worried, fearful, uneasy
Anger	讨厌, 伤害, 烦	hate, kill, annoyed
Sadness	哭泣, 忧伤, 难过	crying, grief, sad

$$Posemo = \frac{PE}{TextWC} \times 100 \tag{A1}$$

where *Posemo* denotes the percentage score for positive emotions, *PE* denotes the number of positive emotion-related words in the review text, and *TextWC* denotes the review text's total number of words.

Appendix B

See Table B1.

[1] http://liwc.wpengine.com/interpreting-liwc-output/.
[2] https://github.com/HIT-SCIR/ltp.

Table B1
Correlation analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) RevRainy	1.000																	
(2) Experience_Overall	-0.002	1.000																
(3) RevTemp	-0.104	-0.003	1.000															
(4) RevWind	0.048	-0.001	0.028	1.000														
(5) RevPress	-0.056	-0.002	-0.845	-0.040	1.000													
(6) DineRainy	0.079	0.007	-0.033	0.000	-0.014	1.000												
(7) DineTemp	-0.027	-0.003	0.604	0.030	-0.505	-0.100	1.000											
(8) DineWind	0.009	-0.006	0.028	0.123	-0.039	0.023	0.022	1.000										
(9) DinePress	-0.000	-0.004	-0.556	-0.039	0.566	-0.064	-0.853	-0.039	1.000									
(10) RevNum	-0.000	-0.048	0.005	-0.000	-0.013	0.000	0.006	0.014	-0.005	1.000								
(11) AvgRating_Overall	-0.006	-0.177	0.002	0.013	0.003	-0.002	0.012	0.024	-0.008	0.086	1.000							
(12) VarRating_Overall	0.005	0.000	-0.016	-0.004	0.019	0.003	-0.005	-0.012	0.003	0.051	-0.262	1.000						
(13) AvgText	-0.001	0.065	0.005	-0.017	-0.005	0.007	-0.001	-0.036	-0.005	-0.098	-0.207	0.105	1.000					
(14) VarText	-0.002	0.032	0.001	-0.003	-0.004	0.004	-0.001	-0.022	-0.007	0.036	-0.079	0.150	0.482	1.000				
(15) AvgPrice	0.005	-0.024	-0.004	0.008	0.005	0.003	-0.007	-0.002	0.005	-0.055	0.335	-0.138	-0.072	0.031	1.000			
(16) Interval	0.006	0.006	-0.020	-0.000	0.025	0.001	0.003	-0.020	-0.007	0.107	0.007	0.031	-0.045	-0.011	0.006	1.000		
(17) Weekend	0.011	-0.005	-0.004	-0.017	0.000	0.008	-0.008	-0.003	0.008	-0.000	-0.001	-0.002	-0.007	-0.002	0.006	-0.010	1.000	
(18) RevTime	0.000	-0.012	-0.087	-0.089	-0.015	0.001	-0.007	-0.006	0.005	0.024	-0.004	0.002	-0.003	0.001	-0.008	-0.006	0.030	1.000

References

Ahn, D., Park, H., Yoo, B., 2017. Which group do you want to travel with? A study of rating differences among groups in online travel reviews. Electron. Commer. Res. Appl. 25, 105–114.

Bai, X., Marsden, J.R., Ross Jr., W.T., Wang, G., 2020. A note on the impact of daily deals on local retailers' online reputation: mediation effects of the consumer experience. Inf. Syst. Res. 31 (4), 1132–1143.

Bakhshi, S., Kanuparthy, P., Gilbert, E., 2014. Demographics, weather and online reviews: a study of restaurant recommendations. In: Proceedings of the 23rd International Conference on World Wide Web. Association for Computing Machinery, pp. 443–454.

Baylis, P., Obradovich, N., Kryvasheyeu, Y., Chen, H., Coviello, L., Moro, E., Cebrian, M., Fowler, J.H., 2018. Weather impacts expressed sentiment. PLOS ONE 13 (4), e0195750.

Berry, L.L., Carbone, L.P., Haeckel, S.H., 2002. Managing the total customer experience. MIT Sloan Manag. Rev. 43 (3), 85–89.

Buchheim, L., Kolaska, T., 2016. Weather and the psychology of purchasing outdoor movie tickets. Manag. Sci. 63 (11), 3531–3997.

Bujisic, M., Bogicevic, V., Parsa, H.G., Jovanovic, V., Sukhu, A., 2019. It's raining complaints! How weather factors drive consumer reviews and word-of-mouth. J. Hosp. Tour. Res. 43 (5), 656–681.

Busse, M.R., Pope, D.G., Pope, J.C., Silva-Risso, J., 2015. The psychological effect of weather on car purchases. Q. J. Econ. 130 (1), 371–414.

Chaves, M.S., Gomes, R., Pedron, C., 2012. Analysing reviews in the Web 2.0: small and medium hotels in Portugal. Tour. Manag. 33 (5), 1286–1287.

Che, W., Li, Z., Liu, T., 2010. Ltp: a Chinese language technology platform. In: Proceedings of the 23rd International Conference on Computational Linguistics: Demonstrations. Association for Computational Linguistics, pp. 13–16.

Chen, P., Hong, Y., Liu, Y., 2018. The value of multidimensional rating systems: evidence from a natural experiment and randomized experiments. Manag. Sci. 64 (10), 4629–4647.

Childers, T.L., Houston, M.J., Heckler, S.E., 1985. Measurement of individual differences in visual versus verbal information processing. J. Consum. Res. 12 (2), 125–134.

Connolly, M., 2013. Some like it mild and not too wet: the influence of weather on subjective well-being. J. Happiness Stud. 14 (2), 457–473.

Deckert, M., Schmoeger, M., Auff, E., Willinger, U., 2020. Subjective emotional arousal: an explorative study on the role of gender, age, intensity, emotion regulation difficulties, depression and anxiety symptoms, and meta-emotion. Psychol. Res. 84 (7), 1857–1876.

Dehaan, E., Madsen, J., Piotroski, J.D., 2017. Do weather-induced moods affect the processing of earnings news? J. Account. Res. 55 (3), 509–550.

Dellarocas, C., Narayan, R., 2006. A statistical measure of a population's propensity to engage in post-purchase online word-of-mouth. Stat. Sci. 21 (2), 277–285.

Forgas, J.P., Goldenberg, L., Unkelbach, C., 2009. Can bad weather improve your memory? An unobtrusive field study of natural mood effects on real-life memory. J. Exp. Soc. Psychol. 45 (1), 254–257.

Godes, D., Silva, J.C., 2012. Sequential and temporal dynamics of online opinion. Mark. Sci. 31 (3), 448–473.

Golder, S.A., Macy, M.W., 2011. Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. Science 333 (6051), 1878–1881.

He, D., Yao, Z., Zhao, F., Feng, J., 2020. How do weather factors drive online reviews? The mediating role of online reviewers' affect. Ind. Manag. Data Syst. 120 (11), 2133–2149.

Hennig-Thurau, T., Gwinner, K.P., Walsh, G., Gremler, D.D., 2004. Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the Internet? J. Interact. Mark. 18 (1), 38–52.

Ho, Y.C., Wu, J., Tan, Y., 2017. Disconfirmation effect on online rating behavior: a structural model. Inf. Syst. Res. 28 (3), 626–642.

Hsiang, S.M., Burke, M., Miguel, E., 2013. Quantifying the influence of climate on human conflict. Science 341, 1235367.

Isen, A.M., 2001. An influence of positive affect on decision making in complex situations: theoretical issues with practical implications. J. Consum. Psychol. 11 (2), 75–85.

Keller, M.C., Fredrickson, B.L., Ybarra, O., Côté, S., Johnson, K., Mikels, J., Conway, A., Wager, T., 2005. A warm heart and a clear head the contingent effects of weather on mood and cognition. Psychol. Sci. 16 (9), 724–731.

Lambert, G.W., Reid, C., Kaye, D., Jennings, G.L., Esler, M.D., 2002. Effect of sunlight and season on serotonin turnover in the brain. Lancet 360 (9348), 1840–1842.

Li, C.X., Luo, X.M., Zhang, C., Wang, X.Y., 2017. Sunny, rainy, and cloudy with a chance of mobile promotion effectiveness. Mark. Sci. 36 (5), 762–779.

Li, H., Xie, K.L., Zhang, Z., 2020. The effects of consumer experience and disconfirmation on the timing of online review: field evidence from the restaurant business. Int. J. Hosp. Manag. 84, 102344.

Lin, X., Lachlan, K.A., Spence, P.R., 2016. Exploring extreme events on social media: a comparison of user reposting/retweeting behaviors on Twitter and Weibo. Comput. Hum. Behav. 65, 576–581.

Liu, X., Zhang, Z., Law, R., Zhang, Z., 2019. Posting reviews on OTAs: motives, rewards and effort. Tour. Manag. 70, 230–237.

Lu, J., Chou, R.K., 2012. Does the weather have impacts on returns and trading activities in order-driven stock markets? Evidence from China. J. Empir. Financ. 19 (1), 79–93.

Lucas, R.E., Lawless, N.M., 2013. Does life seem better on a sunny day? Examining the association between daily weather conditions and life satisfaction judgments. J. Personal. Soc. Psychol. 104 (5), 872–884.

Ludwig, S., De Ruyter, K., Friedman, M., Brüggen, E.C., Wetzels, M., Pfann, G., 2013. More than words: the influence of affective content and linguistic style matches in online reviews on conversion rates. J. Mark. 77 (1), 87–103.

Macinnis, D.J., Price, L.L., 1987. The role of imagery in information processing: review and extensions. J. Consum. Res. 13 (4), 473–491.

Mano, H., Oliver, R.L., 1993. Assessing the dimensionality and structure of the consumption experience: evaluation, feeling, and satisfaction. J. Consum. Res. 20 (3), 451–466.

Mehrabian, A., Russel, J.A., 1974. An Approach to Environment Psychology. MIT Press, Cambridge, MA.

Murray, K.B., Muro, F.D., Finn, A., Leszczyc, P.T., 2010. The effect of weather on consumer spending. J. Retail. Consum. Serv. 17 (6), 512–520.

Oliver, R.L., Robertson, T.S., Mitchell, D.J., 1993. Imaging and analyzing in response to new product advertising. J. Advert. 22 (4), 35–50.

Pennebaker, J.W., Booth, R.J., Boyd, R.L., Francis, M.E., 2015. Linguistic Inquiry and Word Count: LIWC2015. Pennebaker Conglomerates, Austin, TX. ⟨www.LIWC.net⟩.

Pham, M.T., Lee, L., Stephen, A.T., 2012. Feeling the future: the emotional oracle effect. J. Consum. Res. 39 (3), 461–477.

Phillips, D.M., Baumgartner, H., 2002. The role of consumption emotions in the satisfaction response. J. Consum. Psychol. 12 (3), 243–252.

Reser, J.P., Swim, J.K., 2011. Adapting to and coping with the threat and impacts of climate change. Am. Psychol. 66 (4), 277–289.

Schlager, T., De Bellis, E., Hoegg, J., 2020. How and when weather boosts consumer product valuation. J. Acad. Mark. Sci. 48 (4), 695–711.

Schwarz, N., Clore, G.L., 1983. Mood, misattribution, and judgments of well-being: informative and directive functions of affective states. J. Personal. Soc. Psychol. 45 (3), 513–523.

Suddath, C., 2014. The weather channel's secret: less weather, more clickbait. Bloom. Bus. ⟨https://www.bloomberg.com/news/articles/2014-10-09/weather-channels-web-mobile-growth-leads-to-advertising-insights⟩.

Tang, Z., Yu, L., 2021. The configurational influence mechanism of film consumption experience on customer satisfaction. J. Consum. Behav. 20 (1), 132–147.

Tausczik, Y.R., Pennebaker, J.W., 2010. The psychological meaning of words: LIWC and computerized text analysis methods. J. Lang. Soc. Psychol. 29, 24–54.

Tian, J., Zhang, Y., Zhang, C., 2018. Predicting consumer variety-seeking through weather data analytics. Electron. Commer. Res. Appl. 28, 194–207.

Tversky, A., Kahneman, D., 1973. Availability: a heuristic for judging frequency and probability. Cogn. Psychol. 5 (2), 207–232.

Wall, E.A., Berry, L.L., 2007. The combined effects of the physical environment and employee behavior on customer perception of restaurant service quality. Cornell Hotel Restaur. Adm. Q. 48 (1), 59–69.

Wang, Z., Wang, H., Wang, S., Lu, S., Saporta, G., 2020. Linear mixed-effects model for longitudinal complex data with diversified characteristics. J. Manag. Sci. Eng. 5 (2), 105–124.

Wei, W., Miao, L., Huang, Z., 2013. Consumer engagement behaviors and hotel responses. Int. J. Hosp. Manag. 33, 316–330.

Zhang, Z., Zhang, Z., Law, R., 2014. Relative importance and combined effects of attributes on customer satisfaction. Serv. Ind. J. 34 (6), 550–566.

Zhang, Z., Zhang, Z., Yang, Y., 2016. The power of expert identity: how website-recognized expert reviews influence travelers' online rating behavior. Tour. Manag. 55, 15–24.