Not all words are beneficial: The impact of management response contents on customer engagement behavior

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43   **Not all words are beneficial: The impact of management response content on customer**

44   **engagement behavior**

45

46 **Abstract**

47 Online reviews play an important role in pushing hotels to enhance customer engagement

48 through appropriate management responses. However, the impact of management response on

49 customer engagement remains unclear. With data from hotel reviews and management

50 responses, this study demonstrates that customer engagement is significantly reduced when

51 causal explanations and certain words are included in management responses, as indicated by

52 the number of future reviews. We also observe that negative influence of causal explanations

53 can be alleviated when management responses contain uncertain words. Furthermore,

54 management responses which include positive-emotional words attenuate the negative impact

55 of causal explanations. However, no significant effect is found when negative-emotional words

56 are used in management responses. These findings can help managers develop effective

57 response strategies to influence customer engagement behavior.

58

59 **Keywords**

60 Management response content; Customer engagement; Causal explanations; Certain words;

61 Uncertain words; Emotional words

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70 **Highlights**

71 - Management response content plays an important role in motivating future customer

72   engagement.

73 - Causal and certain words in management responses reduce future customer engagement.

74 - Positive words in management responses enhance future customer engagement.

75 - Uncertain and positive words in management responses alleviate the negative influence

76   of causal words on future customer engagement.

77

1. Introduction

The importance of online reviews has increased tremendously over the past few years, particularly for products that customers cannot evaluate before consuming. These include hospitality-related products, such as hotels and restaurants (Ahani et al., 2019). Although online reviews significantly affect a hospitality firm's performance (De Pelsmacker et al., 2018), it is seen that customer engagement in writing reviews remains limited. This is because online reviews are similar to public goods; customers can make use of available reviews without having to contribute. Many hospitality firms now proactively seek ways to motivate more customers to write online reviews.

Customer engagement is likely to be increased when a hotel provides management responses. Thus, practitioners have started focusing on this. For example, some travel platforms, such as Tripadvisor.com, allow hotels to provide management responses to customer reviews. The impact of management responses on customer attitudes and the firm's performance has been identified in prior studies (Falk and Fischbacher, 2006; Chevalier et al., 2018). On the one hand, responses to negative reviews can turn an unsatisfied customer into a loyal one by addressing failures with descriptive solutions and assuring that the negative experience will not occur in the future (Pantelidis, 2010; Xie et al., 2014; Chevalier et al., 2018). On the other hand, responses to positive reviews can reinforce customer satisfaction by expressing appreciation and showing that managers are listening (Falk and Fischbacher, 2006; Xie et al., 2014). Recently, scholars have started paying attention to the influence of management responses on customer engagement (Wei et al., 2013). Li et al. (2017) reported that frequent and timely responses can encourage more reviews and greater review valence. However, there is a need to explore how the contents of a management response impact customer engagement.

Managers generally use responses to explain possible reasons for customer experience and/or

105 share their understanding and opinions on the experience or the review itself. To ensure

106 effective communication, managers may need to carefully craft the response content. Thus, the

107 research question in this study is: how the content of management response influences the

108 online engagement of future customers to the business? Word causality suggests a detailed

109 explanation and may influence customers' need for inquiry termination (Webster and

110 Kruglanski, 1994). Word certainty may indicate a level of ambiguity and activate or deactivate

111 customers' need for future communications, while word affectivity may broaden customer

112 attention to generate a new or additional need for future communications. Therefore, the prime

113 focus of this study is to understand the direct effect of word causality and the moderating effects

114 of word certainty and word affectivity in the management response.

115
116 This study makes important contributions to the current literature by constructing panel data

117 from two sources (Tripadvisor and the Texas Comptroller of Public Accounts) and analyzing

118 the data using Linguistic Inquiry and Word Count (LIWC), a computerized text analysis tool.

119 By treating management responses as a communication channel, we examine how response

120 content affects customer engagement. Although previous studies have investigated the impact

121 of management responses on customer attitude and firm performance (Gu and Ye, 2014; Xie et

122 al., 2017), only a few have focused on the influence of management responses on customer

123 engagement (Li et al., 2018; Chen et al., 2019). None of these studies considers the effect of

124 the word types included in management responses on customer engagement.

125
126 First, by investigating the effect of the contents of different responses on future reviews, this

127 study shows that using causal explanations in management responses reduces the number of

128 future reviews. This confirms the arguments in prior studies, which state that detailed

129 explanations satisfy customers' need for chasing an end, thus reducing future engagement

130 (Webster and Kruglanski, 1994). Second, the study finds that certain words have a negative

131 impact, while uncertain words have a positive moderating effect on future reviews. This

132 supports the idea that the inclusion of certain words in management responses provides more

133 information to customers (Disatnik and Steinhart, 2015) and satisfies their need for cognitive

134 closure. This makes it unnecessary for future customers with similar needs to post reviews.

135 Third, the inclusion of positive-emotional words in management responses can increase the

136 number of future reviews and attenuate the negative impact of causal explanations. Thus,

137 positive-emotional words may have a positive effect and broaden customer attention

138 (Fredrickson, 2001), thereby generating a need for cognitive closure and motivating customer

139 engagement behavior. These findings complement prior studies by suggesting that not all

140 response contents have the same impact on customer engagement and that managers should

141 consider this while developing a management response strategy.

142
143 **2. Theoretical background and hypotheses development**

144 *2.1. Customer engagement*

145 Customer engagement is among the top priorities for firms as it can improve customer

146 satisfaction and increase profits of firms (Ahn and Back, 2018; Zhang et al., 2017; Kim et al.,

147 2013; Brodie et al., 2015). For instance, in a virtual brand community, placing value on

148 engagement can increase customer satisfaction, emotional bonding, and loyalty towards a

149 brand (Brodie et al., 2015). However, neglecting customer engagement can result in customer

150 perceiving the brand as having low value and highlight the existing market disadvantages

151 (Kumar et al., 2010).

152
153 Customer engagement is perceived as a multidimensional concept with different definitions

154 (Rosado-Pinto & Loureiro, 2020). For example, social media literature mainly focuses on two

155 main streams of customer engagement conceptualization, namely, behavioral responses and

156 combinatorial responses (Yoshida et al., 2018; Zhang et al., 2017; Dolan et al., 2016; Lim et

al., 2015). The most commonly used concept of customer engagement is based on a behavioral model in which customer engagement refers to customers' behavioral manifestation towards a brand or firm beyond purchase behavior such as transactions (Van Doorn et al., 2010). Another conceptualization of customer engagement is based on a combination of cognitive, affective, and behavioral responses. In other words, customer engagement with a brand includes both the cognitive and affective commitments in an active relationship with the brand (Mollen and Wilson, 2010).

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In prior studies, scholars have identified various factors facilitating (online) customer engagement from different perspectives, including customer attitude (Itani et al., 2019), firm strategy (Pina et al., 2019), website design (Bilro et al., 2018) and customer motivations (Prentice and Loureiro, 2018; Bilro et al., 2019). For example, customers' attitudes toward a brand such as brand love can directly shape customer engagement (Prentice et al., 2019; Itani et al., 2019). In this study, we aim to understand how different kinds of words used in management responses influence customer engagement. From the two conceptualizations of customer engagement, we choose to consider behavior-based responses in this study. It is difficult to focus on the effect of different response words if we treat engagement as a multidimensional response with numeric indicators. There is an extensive body of literature that focuses on behavior-based customer engagement (Yoshida et al., 2018; Dolan et al., 2016). It includes but is not limited to referrals and recommendations, web posts and blog posts, participation in brand communities, and word-of-mouth activities (Van Doorn et al., 2010). Writing online reviews is a manifestation of word-of-mouth activities. It is motivated by several factors, such as concern for other customers, intentions of self-enhancement, and willingness to help the company (Hennig-Thurau et al., 2004; Yang, 2017).

2.2. Management responses

183 Management responses change unidirectional firm-customer communication into an

184 interactive process (Cowen and Montgomery, 2020; Gu and Ye, 2014). Several studies have

185 demonstrated that management responses have a positive impact on customer attitudes (Sparks

186 et al., 2016) and hotel performance (Xie et al., 2017). A management response can be defined

187 as an answer posted on behalf of a hospitality operator to address a specific review contributed

188 by a customer (Lui et al., 2018), and can be used to engage customers. For example, using

189 responses to address customer complaints in reviews motivates future reviews with high

190 valence (Wang and Chaudhry, 2018). A recent empirical study using data from Trip.com and

191 eLong.com focused on two types of management responses — detailed responses with specific

192 explanations and general responses expressing only appreciation or apologies — and found

193 that detailed responses can engage customers better to generate reviews (Chen et al., 2019).

194
195 *2.3 Causal explanations in management responses and customer engagement*

196 The need for closure is a concept related to an individual's motivation of information

197 processing and can be defined as the individual desire for forming an opinion or arriving at an

198 answer for a given topic (Webster and Kruglanski, 1994; Kruglanski et al., 1991). It has been

199 explored in several contexts, including the financial markets and political voting (Topa et al.,

200 2018; Okdie et al., 2016). For instance, a high need for closure is associated with a higher level

201 of financial management behavior (Topa et al., 2018) and attribute-based information searches

202 in the field of consumer choice (Choi et al., 2008).

203
204 In the context of e-commerce, management responses are used to address customer reviews.

205 By using causal explanations in responses, hotels may provide sufficient and convincing

206 answers to customer questions. In other words, hotels can solve problems and fulfill customers'

207 needs to achieve cognitive closure by responding to specific reviews (Chen et al., 2019). In

208 these situations, customers may not be motivated to ask further questions. Thus, the cause of

209   the suboptimal service experience becomes clear when causal explanations are used in

210   responses, and thus customers have no need to engage in future reviews. Therefore, we

211   hypothesize the following:

212
213   H1: Management responses with causal explanations result in low customer engagement.

214
215   *2.4. The effect of certain/uncertain words in management responses*

216   Certainty is viewed as a type of subjective information available in words (Rubin et al., 2006).

217   Its dictionary definition is "the quality or state of mind of being free from doubt, especially on

218   the basis of evidence" (Merriam-Webster Online Dictionary, 2004). Uncertainty is a

219   corresponding type of subjective information and refers to the difficulty of evaluating others'

220   perceptions or deciding one's own state (Kim and Krishnan, 2015). Several studies have

221   focused on the effect of certainty and uncertainty on customer sentiment and behavior. For

222   example, detecting seller uncertainty can reduce customer purchasing intentions (Bai et al.,

223   2015). However, the impact of including expressions of certainty or uncertainty in management

224   responses on customer perception is still unclear.

225
226   As discussed above, individuals have a need to arrive at an opinion or an answer to a given

227   topic. If an opinion or an answer contains ambiguity (i.e., a state of uncertainty), it may trigger

228   some affective discomfort and suggest an absence of finish for individuals (Webster and

229   Kruglanski, 1994). Individuals are then more likely to take action to reduce the ambiguity and

230   fulfil their need for closure (Disatnik and Steinhart, 2015). In our context, given that uncertain

231   words are used in management responses, customers may sense the ambiguity and engage in

232   future reviews to resolve the uncertainty. Furthermore, even though responses with causal

233   explanations can help customers arrive at inquiry termination, the existence of uncertain words

234   may disorganize it and trigger customers' uncertainty perception. This perception may

235   encourage customers to raise more questions (i.e., writing more reviews). With certain claims

236 in management responses, customers feel that the responder's mind has been made up, and

237 there is no need to seek more answers or clarifications, thus restraining their future review

238 posting behavior. If management responses contain both causal explanations and certain claims,

239 customers may feel more certain and less ambiguous, and their need for inquiry termination is

240 better fulfilled, thus leading to lower possibility for their future engagement in online review

241 activities. Therefore, we hypothesize as follows:

242

243 H2a: Certain words in management responses negatively affect customer engagement.

244 H2b: Uncertain words in management responses positively affect customer engagement.

245 H2c: Certain words in management responses aggravate the negative impact of causal

246 explanations on customer engagement.

247 H2d: Uncertain words in management responses alleviate the negative impact of causal

248 explanations on customer engagement.

249
250 *2.5. The effect of affective words in management responses*

251 Positive and negative affect are two fundamental dimensions of affective states (Watson et al.,

252 1988). Positive affect represents the extent of enthusiastic, active, and alert feelings, while

253 negative affect represents a general dimension of subjective distress containing a variety of

254 states such as anger and anxiety. Prior studies have found that positive affect increases product

255 or brand evaluation compared to negative affect (Bakamitsos, 2006). Additionally, it facilitates

256 strong customer loyalty (Chebat and Slusarczyk, 2005). Language plays a constitutive role in

257 affect perception (Lindquist and Gendron, 2013). In other words, a negative-emotional word

258 may have a general influence on negative affect, with a similar situation for a positive-

259 emotional word (Lindquist et al., 2006). Thus, affective words (positive- and negative-

260 emotional words) in a management response may impact customers' affective states,

261 perceptions of the management response, and future behavior.

262

263 The influence of positive affect on individuals' engagement toward future communications can

264 be discussed from two perspectives. On the one hand, based on the broaden-and-build theory,

265 positive affect leads to a broader scope of attention and thought-action repertoires (Fredrickson,

266 2001; Vermeulen, 2010). This broadened scope of attention and behavioral repertoires prompts

267 individuals to engage with their environment and display greater interest in more aspects of an

268 activity. To elaborate, customers who notice positive-emotional words in a management

269 response tend to form a positive affect and become interested in the communication activity

270 produced by the response. On the other hand, positive affect can motivate customer satisfaction

271 with increased interactions, which in turn boost customers' interest toward the communication

272 channel formed by management responses (Emmers-Sommer, 2004; Babin et al., 2005) and

273 customers' demand for hotel information conveyed by management responses (Van Kleef et

274 al., 2004). Consequently, customers pay more attention to the most recent responses and seek

275 further communications in the future.

276

277 Furthermore, in the presence of positive-emotional words, customers' fulfilled need for

278 cognitive closure is stimulated again with a response that contains causal explanations. This

279 results in future engagement. In general, the positive affect formed by these words can broaden

280 customers' attention scope and increase their interests in different aspects as well as their needs

281 for future communication. However, when negative-emotional words co-occur with causal

282 explanations in management responses, the negative affect induced may reduce customers'

283 attention and interest range, further promoting the arrival of inquiry termination and restraining

284 subsequent customer engagement. Therefore, we propose the following:

285
286 H3a: Positive-emotional words in management responses increase customer engagement.

287 H3b: Negative-emotional words in management responses reduce customer engagement.

288 H3c: Positive-emotional words in management responses alleviate the negative impact of

289   causal explanations on customer engagement.

290 H3d: Negative-emotional words in management responses aggravate the negative impact of

291   causal explanations on customer engagement.

292
293 The hypotheses concerning the effect of management response content on customer

294 engagement are summarized in Figure 1.

295
296   Insert Figure 1 here

297
298 **3. Methodology**

299 *3.1. Data collection*

300 To study the effect of management response content on customer engagement, as behavior-

301 based engagement is commonly measured using the number of reviews (e.g., Wei et al., 2013;

302 Li et al., 2017), we combined information collected from two sources. One is Tripadvisor.com,

303 a leading hotel review website with more than 490 million monthly visitors and over 702

304 million reviews (Tripadvisor, 2018). The data for 1,158 hotels in the state of Texas, United

305 States of America (USA) is collected with numerical and textual content of online reviews and

306 textual content of hotel responses, and the data ranges from May 2002 to June 2015. We also

307 gathered revenue data from the Texas Comptroller of Public Accounts, an institution which

308 collects hotel property performance data, aggregates them, and reports the summary and

309 benchmarking data back to hotel properties. This source only contains revenue data for 732

310 hotels, so we correspondingly retained the data of these 732 hotels on Tripadvisor, including

311 198,128 reviews and 99,268 management responses from May 2002 to June 2015. These two

312 datasets were then merged to create an unbalanced panel dataset at the "Hotel × Month" level.

313 Our final sample for further analysis includes 37,403 observations for 732 hotels. Table 1 shows

314 the characteristics of hotel features included in our sample, including hotel star, hotel price, and

315   hotel room number.

316
317   Insert Table 1 here

318
319 *3.2. Variable Measurement*

320 **Dependent Variable**. $RevNum_{it}$ refers to the number of online customer reviews for hotel i in

321 month t. Prior studies have employed this to measure customer engagement (Chen et al., 2019).

322
323 **Explanatory Variables.** $RespCaus_{it-1}$ is measured by (#Causation-related words/#words in

324 responses)*100 for hotel i in month t-1.

325
326 $RespCert_{it-1}$ is measured by (#Certainty-related words/#words in responses)*100 for hotel i in

327 month t-1. $RespUncert_{it-1}$ is measured by (#Uncertainty-related words/#words in

328 responses)*100 for hotel i in month t-1.

329
330 $RespPos_{it-1}$ is measured by (#Positive-emotion related words/#words in responses)*100 for

331 hotel i in month t-1, while $RespNeg_{it-1}$ is measured by (#Negative-emotion related

332 words/#words in responses)*100 for hotel i in month t-1.

333
334 To calculate these explanatory variables, we used a text mining software, LIWC. This program

335 is designed to analyze individual or multiple language files quickly and efficiently by matching

336 them to a pre-defined dictionary (Pennebaker et al., 2015). The LIWC program has been

337 increasingly used in several areas such as information systems, and tourism and hospitality

338 studies (e.g., Hong et al., 2016; Li et al., 2019). As customers refer to previous information to

339 make current decisions, this study employs the lagged values of management response

340 characteristics to examine their influences on customer engagement. The recency effect

341 contends that there is an order of presentation effect. Thus, more recent information is better

342 remembered and receives a greater weight while forming a judgment, compared to information

343   presented earlier (Jones and Goethals, 1972). Therefore, the information presented on the most

344   recent page may have the strongest influence. On Tripadvisor, one review page presents five

345   reviews; in our data, the average number of reviews across hotels in one month is around five.

346   Therefore, it is reasonable to employ one month as the time lag to examine the effect of prior

347   management responses on current customer engagement. Additionally, the adoption of a one-

348   month time lag has been used in several studies focusing on the effect of management responses

349   (Li et al., 2017; Xie et al., 2014). Table 2 shows examples of causation related, certainty

350   (uncertainty) related, and positive-emotion (negative-emotion) related words that are used in

351   management responses.

352
353   Insert Table 2 here

354
355   We also listed management response examples that contain different types of words in

356   relatively high proportions. The examples are presented in Table 3.

357
358   Insert Table 3 here

359
360   **Control Variables.** To examine the impact of response contents, we controlled for other

361   factors at three levels: the outcome level, review level, and response level. First, we treat hotel

362   revenue as the control variable for the outcome level since prior literature has reported a

363   positive relationship between revenue and the number of future online reviews (e.g., Chen et

364   al., 2003). We use $TotalRev_{it}$ to represent the revenue for hotel i in month t. One month is

365   relatively enough time for customers to provide evaluations after purchase, so we choose the

366   hotel revenue in the current month as the control variable. In addition, we used the revenue for

367   hotel i in month t-1 ($TotalRev_{it-1}$) to replace the revenue for hotel i in month t ($TotalRev_{it}$) as

368   the control variable, and the results are shown in the last column of the following tables. This

369   allows us to include situations where customers posted comments relatively late (i.e., customers

370   wrote reviews more than one month after their check-in date). Second, the review level control

371   variables include the average and standard deviation of ratings, both of which can affect

372   product demand and future customer opinions (Sun, 2012). The average rating, *RatingAvg*$_{it-1}$,

373   is measured by the average of review ratings for hotel *i* in month *t*-1. The rating's standard

374   deviation, *RatingSD*$_{it-1}$, is measured by the standard deviation of ratings in reviews for hotel *i*

375   in month *t*-1. Third, the response level control variables, such as response speed and response

376   length, can also influence customer engagement, as indicated by the number of reviews (Li et

377   al., 2017). Thus, this study includes response length and speed as control variables.

378   *RespLength*$_{it-1}$, the average response length, is measured by #words for responses divided by

379   #responses for hotel *i* in month *t*-1. *RespSpeed*$_{it-1}$, response speed, is measured by the average

380   interval between response time and review time for hotel *i* in month *t*-1, as shown in Equation

381   (1) below:

382    $$\text{RespSpeed}_{it-1} = \frac{\sum(\text{response date} - \text{review date})}{\#\text{responses}} \qquad (1)$$

383   Table 4 displays the definitions of the main variables, while Table 5 presents a descriptive

384   analysis of the variables. Before the analysis, log transformations were used for several

385   variables such as *RevNum*$_{it}$, *TotalRev*$_{it}$, *RespLength*$_{it-1}$, and *RespSpeed*$_{it-1}$ to address the

386   normality problem.

387   Insert Table 4 here

388
389   Insert Table 5 here

390
391   **4. Data analysis and results**

392   *4.1 The effect of causal explanations in hotel responses*

393   We applied panel data analysis with hotel fixed effects to estimate the influence of the

394   explanatory variables. Panel data has commonly been employed in prior studies (e.g., Li et al.,

395   2017; Chen et al., 2019) since it can control for hotel-invariant variables and produce a reliable

396   estimation. To test the first hypothesis, we propose the model in Equation (2) as follows:

397

398    $$\text{RevNum}_{it} = \beta_{10} + \beta_{11}\text{RespCaus}_{i(t-1)} + \beta_{12}\text{TotalRev}_{it} + \beta_{13}\text{Controls}_{i(t-1)} + v_i + \varepsilon_{it} \quad (2)$$

399

400   where i represents the hotel ($i = 1, \dots, I$), t represents the month ($t = 1, \dots, T$); v_i represents a

401   vector of hotel fixed effects; ε_{it} indicates the standard error with a normal distribution. The

402   primary interest of our study is β_{11} to investigate the direct effect of causal explanations on the

403   number of future reviews.

404

405   We report the results of this model in Table 6. Model 1.1 includes only the independent

406   variables of interest, and Model 1.2 includes both the control and independent variables. The

407   estimation results show that including causal explanations in management responses has a

408   significantly negative influence on the number of future reviews (coefficient = −0.0228, $p <$

409   0.01), suggesting that management responses with causal explanations tend to reduce the

410   number of a hotel's future reviews. Therefore, Hypothesis 1 is supported.

411

412   Among the control variables, the negative impact of response length is noteworthy. Scholars

413   who have studied the impact of response length have found a non-significant effect on customer

414   engagement (Li et al., 2017). It is possible that longer responses cause information overload

415   and lower customers' intention to read the response (Liang et al., 2006), leading to a decrease

416   in future customer engagement (i.e., a lower number of reviews).

417

418   Insert Table 6 here

419

420   *4.2 The effect of certain words in hotel responses*

421   In terms of the impact of certain/uncertain words in responses on customer engagement, we

422   propose a second model. We focus on using β_{22}, β_{23}, β_{24}, and β_{25} to examine the direct and

423   moderating effects of certain and uncertain words on the number of reviews. The model is

424   presented in Equation (3) as follows:

425

426   $RevNum_{it} = \beta_{20} + \beta_{21}RespCaus_{i(t-1)} + \beta_{22}RespCert_{i(t-1)} + \beta_{23}RespUncert_{i(t-1)} +$

427   $\beta_{24}RespCaus_{i(t-1)} * RespCert_{i(t-1)} + \beta_{25}RespCaus_{i(t-1)} *$

428   $RespUncert_{i(t-1)} + \beta_{26}TotalRev_{it} + \beta_{27}Controls_{i(t-1)} + v_i + \varepsilon_{it}$ (3)

429

430   The results are shown in Table 7. In Model 2.1, certain words have a significantly negative

431   effect (coefficient = -0.0144, $p < 0.01$), while the influence of uncertain words is not significant

432   (coefficient = 0.0020, $p > 0.1$). In other words, including certain words in hotel responses tends

433   to reduce the number of online reviews, but the usage of uncertain words has no significant

434   effect on the number of future reviews. Thus, Hypothesis 2a is supported, and Hypothesis 2b

435   is rejected. The results of Models 2.2 - 2.4 demonstrate that uncertain words have a significant

436   moderating effect, while the moderating influence of certain words is insignificant. These

437   results indicate that the inclusion of uncertain words is likely to curb the reduction in the

438   number of reviews caused by including causal words in response. However, the inclusion of

439   certain words with causal words in response has no significant impact on the number of reviews.

440   Therefore, Hypothesis 2c is not supported, and Hypothesis 2d is supported. Figure 2 further

441   illustrates the moderating effect of uncertain words on customer engagement.

442

443   Insert Table 7 here

444

445   Insert Figure 2 here

446

447   *4.3 The effect of affective words in hotel responses*

448   To investigate the role of affective words (positive-emotional and negative-emotional words)

449   on customer engagement, we propose the model shown below in Equation (4). As with the

450   previous model, we focus on β_{32}, β_{33}, β_{34}, and β_{35}.

451

452 $\text{RevNum}_{it} = \beta_{30} + \beta_{31}\text{RespCaus}_{i(t-1)} + \beta_{32}\text{RespPos}_{i(t-1)} + \beta_{33}\text{RespNeg}_{i(t-1)} +$

453 $\beta_{34}\text{RespCaus}_{i(t-1)} * \text{RespPos}_{i(t-1)} + \beta_{35}\text{RespCaus}_{i(t-1)} * \text{RespNeg}_{i(t-1)} +$

454 $\beta_{36}\text{TotalRev}_{it} + \beta_{37}\text{Controls}_{i(t-1)} + v_i + \varepsilon_{it}$ (4)

455

456 Table 8 shows the regression results for Equation (4). The results of Model 3.1 indicate that

457 positive-emotional words have a significant effect (coefficient = 0.0130, $p < 0.01$), while the

458 effect of negative-emotional words is insignificant (coefficient = 0.0123, $p > 0.1$), suggesting

459 that using positive-emotional words in hotel responses can enhance the number of future

460 reviews. Thus, Hypothesis 3a is supported, and Hypothesis 3b is rejected. In addition to this,

461 the estimation results of Models 3.2 and 3.4 demonstrate that positive-emotional words in

462 management responses have a significantly negative moderating role. However, Models 3.3

463 and 3.4 show that the moderating impact of negative-emotional words is insignificant. In other

464 words, including positive-emotional words tends to increase the number of hotel reviews,

465 which decreased because of causal words, while there is no significant interaction effect on the

466 number of future reviews of combining negative-emotional words and causal explanations in

467 management responses. Therefore, Hypothesis 3c is supported. Figure 3 further demonstrates

468 how positive-emotional words moderate the effect of causal explanations on customer

469 engagement.

470
471 Insert Table 8 here

472
473 Insert Figure 3 here

474
475 *4.4 The influence of hotel category*

476 To examine the conditions under which response contents have different effects, we separate

477 data by hotel category (i.e., hotel class) and then conduct regression on the data across premium

478 hotels as well as low-end hotels, respectively. The results are presented in Tables 9 and 10,

479 showing that the effect of response content on customer engagements remains constant for

480 premium hotels (3-star and above). Unlike their counterparts in premium hotels, managers in

481 low-end hotels usually leave simple and uniformed responses due to limited resources for

482 online response management. For customers, simple and uniformed responses seem random

483 and suggest hotels pay less attention to customer opinions (Zhang et al., 2020). This type of

484 response is not efficient enough to trigger customers' further engagement, thus posing less

485 influence on future online interaction between customers and hotels. In addition, as customers

486 of low-end hotels pay less for the stay and have a low expectation, they focus less on the quality

487 of management response as diagnostic cues.

488
489   Insert Table 9 here

490
491   Insert Table 10 here

492
493 **5. Discussion and Implications**

494 **5.1 Discussion**

495 Online review platforms have become an important source of information for customer

496 purchase decisions. Thus businesses proactively engage in strategies to communicate with

497 customers through online reviews. Management responses are an effective strategy. Gathering

498 review and response data from Tripadvsior.com and hotel revenue data from the Texas

499 Comptroller of Public Accounts, this study focuses on the effect of management response

500 content on customer engagement. In particular, this study empirically examined the direct

501 influence of causal explanations and the direct and moderating effects of certain and uncertain

502 words and positive- and negative-emotional words.

503
504 The primary conclusions are as follows. First, management responses with causal explanations

505 tend to reduce potential customer engagement (i.e., there are fewer future reviews). Causal

explanations involve detailed answers to customer questions and provide sufficient information about what happened. Responses with such explanations can fulfil customers' need for cognitive closure and reduce their intention to seek further information, thus lowering subsequent customer engagement.

Second, the existence of certain words in hotel responses can reduce customer engagement. That is, employing responses that include certain words reduces a hotel's number of future reviews. However, the results show that using uncertain words in management responses does not increase the number of reviews as expected. While individuals' understanding of certainty may be similar, their feelings about uncertainty may be very different. Thus, the direct effect of certain words is confirmed and that of uncertain words is diminished. Our results also show that including uncertain words in management responses can stop the reduction in the number of reviews due to causal explanations, but certain words have no significant moderating role. When certain words are included in management responses, customers' ambiguity perception does not change because the management responses with causal explanations already leave little room for customers to guess. In other words, when hotels provide management responses with causal explanations, including certain words in responses may not be helpful to influence customers' tendency for future communications. Thus, certain words do not aggravate the negative effect of causal explanations on customer engagement.

Third, including positive-emotional words in management responses can increase customer engagement and attenuate the negative impact of causal explanations. In other words, when responses contain positive-emotional words, the number of future reviews may increase, and the diminished number of future reviews caused by causal explanations can be restored to some extent. However, the results of both the direct and moderating effects of negative-emotional words are non-significant. Although negative-emotional words may activate negative affect

532 and decrease the range of customer attention, the situation may be different in the context of

533 management responses because hotels may use negative-emotional words to express their

534 remorse or regret and then give some plans for further improvements, which may reduce

535 customers' certainty perception and the formation of inquiry termination caused by causal

536 explanations. As a result, the effect of negative-emotional words is attenuated and becomes

537 non-significant.

538
539 **5.2 Theoretical implications**

540 The present study makes several contributions to consumer engagement and management

541 response literature. Although previous studies focused on the importance and determinants of

542 customer engagement (Winterich et al., 2009; Kim et al., 2013), it is still unclear how

543 management responses impact customer engagement (Li et al., 2017). This study is among the

544 first attempts to empirically investigate the prominent role of management responses in

545 customer engagement. Unlike Li et al.'s (2017) study, which focused on the impact of numeric

546 indicators such as the frequency and speed of responses, this study examines how management

547 response content influences customer engagement. In existing studies that investigated the

548 response content (Li et al., 2018; Chen et al., 2019), only a simple classification of management

549 responses (e.g., general responses versus. specific responses) was carried out without a detailed

550 exploration of response content. Taking advantage of text mining technology, we focus on the

551 effect of specific types of words in responses to subsequent customer reviews and thus, extend

552 the existing literature in management response and customer engagement motivation.

553
554 Furthermore, this study contributes to the management response and customer engagement

555 literature by introducing a new theoretical framework—the need for cognitive closure.

556 Specifically, this study explores how causal explanations in a response influence the number

557 of future reviews from this theoretical perspective. Since a response with causal explanations

558   provides sufficient answers and fulfills customers' need for inquiry termination, it may

559   constrain their desire to involve in future communications (Webster and Kruglanski, 1994).

560   This study also investigates how the existence of certain and uncertain words affects future

561   customer engagements. When certain (uncertain) words are used in a response, customers may

562   perceive a strong opinion (an ambiguous opinion) from the responder, and then their need to

563   seek more answers is further fulfilled (is open again), thus restraining (promoting) their future

564   engagements. This study also examines the effect of affective words on future customer

565   engagements. In other words, it identifies that positive words in response can help customers

566   form a positive affect, thereby broadening their attention range and reducing the possibility that

567   customers achieve a state of inquiry termination while increasing future engagements

568   (Vermeulen, 2010).

569
570   **5.3 Practical implications**

571   An increasing number of firms employ management responses as tools to communicate with

572   customers on social media. However, only a few firms know how to take advantage of these

573   responses and effectively interact with customers. Our results show that adjusting and

574   combining different types of response contents could be an effective way to motivate more

575   future reviews, with several implications for firms. First, this study demonstrates an existing

576   and diverse influence on customer engagement activities in response to varying response

577   content. In other words, although management responses could work as an effective tool for

578   influencing future reviews, simply adopting this strategy without proper skills is not sufficient

579   to enhance subsequent customer engagement. Instead, firms should adjust their response

580   content to suit the situation as different content has distinct impacts on customer perception

581   and behavior.

582

583   Second, a causal explanation (suggested by causal words such as "because" and "hence") may

584   be perceived as a detailed explanation for an event and leave less room for customers to think,

585   thereby reducing customers' intention to engage in more communications. This will decrease

586   the influence of management responses on customer engagement. Therefore, we suggest that

587   hotels avoid causal explanations in responses and focus on other kinds of explanations that will

588   not restrain customers' desire to further questions. For example, hotels could use concrete

589   narration to explain what happened in some issues expressed in online reviews.

590
591   Third, our results also show that certain words such as "always" and "never" have a negative

592   impact on the number of future reviews, while uncertain words such as "maybe" and "guess"

593   can attenuate the reduction in the number of future reviews due to causal explanations in

594   management responses. Uncertain words indicate that a big room for customers to engage in

595   systematic thinking and then motivate customers to involve in future communications; on the

596   contrary, certain words suggest a state of affirmation and leave little space for customers to ask

597   further questions. Thus, we suggest that managers employ uncertain words in their responses

598   while avoiding certain words. For example, hotels may use "maybe" or "perhaps" to explain

599   the reasons for issues proposed by customers and steer clear of certain words (e.g., always)

600   when communicating with customers in management responses.

601
602   Finally, including positive words (i.e., "nice" and "sweet") in hotel responses can increase the

603   number of future reviews and alleviate the negative influence of causal explanations on the

604   number of reviews. Positive-emotional words can trigger a positive effect, which can broaden

605   the range of customer attention and motivate customers to engage in related activities (i.e.,

606   writing more reviews). We thus suggest that hotels include more positive-emotional words,

607   such as "appreciation" and "love", in their management responses to communicate with

608   customers better and prompt more reviews.

5.4 Limitations and future directions

This study has several limitations which are worth exploration in future research. First, it focuses on a limited form of customer engagement, i.e., the number of future online reviews. While the number of reviews is one of the most common behavioral manifestations of customer engagement on online platforms, other types of engagement, including affective engagement (i.e., review valence) are also important for service management (Li et al., 2017). Future research could focus on gathering more data to assess the influence of management response content on other indicators of customer engagement.

Second, although this study investigates several aspects of response content, it does not consider varied situations. For example, for a hotel with higher valence, causal explanations in their responses may not be perceived by customers as a denial of responsibility, but as a reasonable interpretation. However, for a hotel with lower valence, responses, which include causal explanations, may indicate that the hotel is shirking its responsibility. Additionally, a premium or luxury hotel may devote more resources to management responses, influencing the customer's perceptions of the hotel or its communication with customers. In the case of a low-end hotel, the response to customers may be arbitrary and have little impact on their cognition and behavior. Future studies can take review valence or hotel class into account to examine whether the response content differs based on different review valences or hotels. This will expand the understanding of the effect of management responses on customer engagement.

Third, this study gathers data from Tripadvisor.com. Although large volumes of secondary data can provide relatively objective results, they may not identify underlying mechanisms; for example, in this study, we assume that positive-emotional words in a management response can broaden customer attention and keep customers away from a state of inquiry termination. We suggest that checking this assumption may be a potential direction for future research. Thus,

636   conducting qualitative research using case studies may enhance our understanding of the

637   underlying mechanism of the effect of response content on customer engagement.

638
639   Fourth, the use of secondary data only enables us to explore the effect of causal explanations

640   identified by the software in a generic manner and cannot help us identify the underlying

641   mechanism behind the effect. We recognize the need for a more in-depth classification of

642   causal explanations in management responses based on theory. For example, according to

643   causal attribution theory (Folkes, 1984; Weiner, 1985), customers' attribution may be

644   determined by several factors including locus of control (i.e., who is responsible for the failure)

645   and failure stability (i.e., whether a failure is temporary or permanent). Thus, different causal

646   explanations in responses or different responders may influence customers' perceptions on a

647   problem's attribution and persistence differently, both of which in turn play important roles in

648   future customer behavior. As it is difficult to conduct a more detailed classification of causal

649   words using secondary data, we believe that future studies can test the influence of different

650   causal explanations using experimental design methods. In addition, the theory in this study

651   cannot be verified due to the use of secondary data. More methods, such as experimental design,

652   can be conducted in future research to explore the need for cognitive closure behind the effect

653   of different words in management responses.

654
655   Last, this study uses a time lag of one month in the panel data. In other words, we investigate

656   the effect of management responses at month *t* based on the number of subsequent customer

657   reviews at month *t+1*. Although the usage of one month as a base unit is supported by the

658   recency effect and other prior literature, it is possible that potential long-term effects exist,

659   warranting further attention. Thus, we suggest that future studies focus on time lags beyond

660   one month (i.e., one quarter) to understand the effect of management responses on customer

661   engagement more effectively.

662
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839
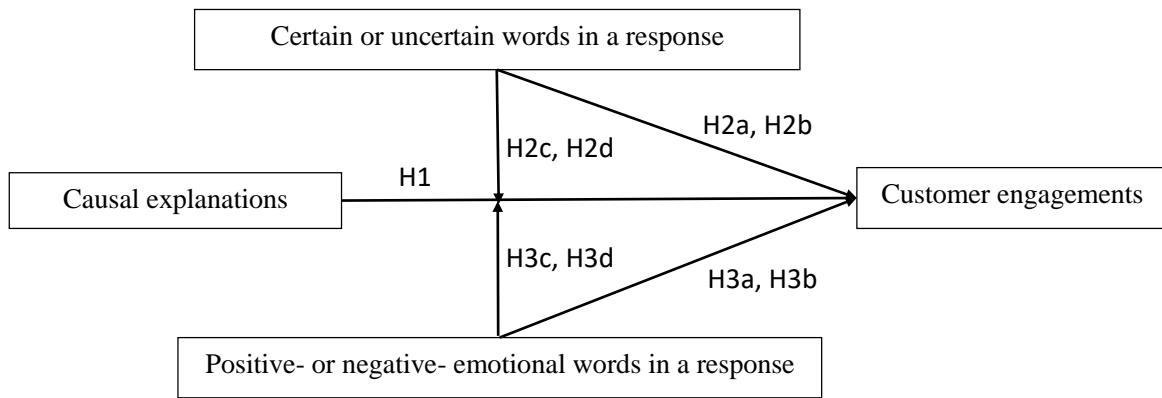
Figure 1. The effect of response content on customer engagements
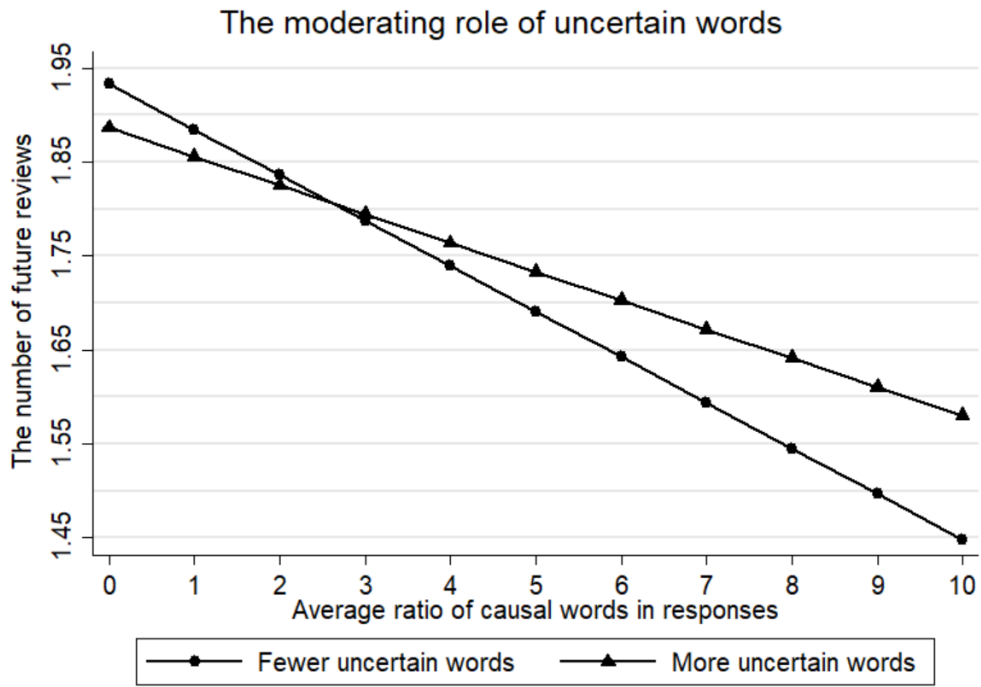
Figure 2. The moderating effect of uncertain words on customer engagements
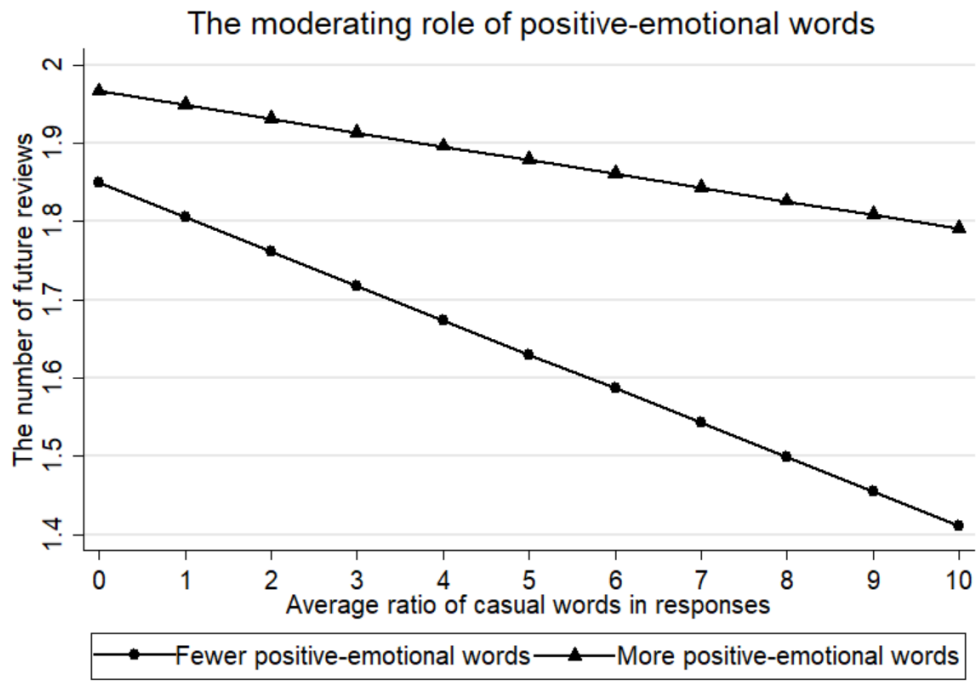
Figure 3. The moderating effect of positive-emotional words on customer engagements

Table 1. Frequency analysis on hotel characteristics

Hotel rating	%	Room number	%	Hotel price	%
1-star	0.56	<75 rooms	24.24	<500 RMB	11.77
2-star	40.87	75-149 rooms	45.15	500-799 RMB	32.13
3-star	46.91	150-299 rooms	19.25	800-1099 RMB	25.21
4-star	10.81	300-500 rooms	8.31	1100-1400 RMB	13.30
5-star	0.84	>500 rooms	3.05	>1400 RMB	17.59

Table 2. Examples of different types of words in management responses

Causation-related words	because, cause, therefore, due to, as a result
Certainty-related words	always, definitely, certainly, assure, confirm
Uncertainty-related words	perhaps, wonder, expect, alternatively, hopefully
Positive emotion-related words	appreciation, grateful, delightful, enjoy, pleasant
Negative emotion-related words	concerned, unpleasant, regrettable, disappointment, disturbed

Table 3. Management response examples

Word types	Management response examples	Explanation of examples
causal words	When you were with us, we were less than a week old. **You may imagine** that a new hotel would face some hurdles…….	In this example, the hotel was giving details or reasons about the issues and leaving less room for further conversations.
certain words	We assure you that what you experienced was **certainly** a rare exception and was **definitively** not a rule in our hotel…….	In this example, the hotel made a certain statement that the customer experience is an exception and the hotel quite understood the customer feeling. This kind of certainty reduces customers' intention for in-depth questions.
uncertain words	I'm **not sure** why you were given a room with two twin beds and will follow up with this issue……	In this example, with the existence of uncertain expressions, customers formed a sense of ambiguity and intended to engage in further questions.
Positive-emotional words	I'm **pleased** to see your comfortable stay. It is our **pleasure** to make each and every one of our guests happy with their stay! ……	In this example, the response may bring a positive mood to customers and broaden their range of attention, thus influencing their future behavior.
negative-emotional words	I am **disappointed** to hear that your stay was not great. It **upsets** me more to know that you received **horrible** service from the employee in the front desk……	In this example, the response with negative words may convey a negative mood to customers and narrow their range of attention, thus affecting their future behavior.
Causal and certain words	I **definitely** understand your frustrations about the unkept grass area. I **assure** you that **it is not a usual thing** for the grass to not be mowed or in perfect landscaping condition…..	In this example, the response provides explanations for the "unkept grass area" problem by assuring this problem is not a usual thing.

Causal and uncertain words	I am **uncertain** to what you meant about your lost item. After spoking to our Guest Service Manager, I knew she had returned your lost item. We deal with many lost and found items daily and **is not unusual** to take several days to deal with any one case……	In this example, the responder first expresses that he/she talks with the manager who's in charge because he/she is uncertain about what happened. Then the responder points out that it's not common to find an item for so long time.
Causal and positive words	You mentioned that our TV channel selection left a bit to be **desired** so we know you are going **like us even more** on your next visit **because** our TV channel is getting "revamped"……	In this example, the response with positive words gives the reason about why TV channel selection is not very efficient now.
Causal and negative words	I'm not sure if you were truly **unsatisfied** with the room. You claimed that you wanted to cancel your reservation because the room was **dirty**. **After** we offered you another room, **you still wanted** to cancel the room as you thought the hotel wasn't safe……	In this example, the hotel uses several negative words and is trying to explain the negative experience to the guest.

Table 4. Variable Definition

Variable	Description
Dependent variable	
$RevNum_{it}$	Number of online reviews for hotel i in month t
Explanatory variables	
$RespCaus_{it-1}$	Percentage of causal words in response words for hotel i in month t-1
$RespCert_{it-1}$	Percentage of certain words in responses for hotel i in month t-1
$RespUncert_{it-1}$	Percentage o of uncertain words in responses for hotel i in month t-1
$RespPos_{it-1}$	Percentage of positive-emotional words in responses for hotel i in month t-1
$RespNeg_{it-1}$	Percentage of negative-emotional words in responses for hotel i in month t-1
Control Variables	
$TotalRev_{it}$	Revenue for hotel i in month t
$RatingAvg_{it-1}$	Average rating of reviews for hotel i in month t-1
$RatingSD_{it-1}$	Standard deviation of rating of reviews for hotel i in month t-1
$RespLength_{it-1}$	Average of response length for hotel i in month t-1
$RespSpeed_{it-1}$	Average of response speed for hotel i in month t-1

Table 5. Descriptive Analysis

	N	Mean	S.D.	Min	Max
$RevNum_{it}$	37403	5.276502	9.38179	1	195
$RespCaus_{it-1}$	15744	0.7673385	0.8711024	0	9.09
$RespCert_{it-1}$	15744	1.549932	1.228899	0	10.71
$RespUncert_{it-1}$	15744	1.80491	1.350714	0	12.9
$RespPos_{it-1}$	15744	10.03938	3.258477	0	28.04333
$RespNeg_{it-1}$	15744	0.6015292	0.8387322	0	8
$TotalRev_{it}$	37403	525903.5	702004.3	340	21900000
$RatingAvg_{it-1}$	37403	3.715246	1.076346	1	5
$RatingSD_{it-1}$	23943	0.9170264	0.5817921	0	2.828427
$RespLength_{it-1}$	15744	438.4274	228.9084	86	2397
$RespSpeed_{it-1}$	15744	24.2848	46.33419	0	367

Table 6. Results for main effect

	Model 1.1	Model 1.2	Model 1.3[#]
RespCaus$_{it-1}$	-0.0409***	-0.0228***	-0.0232***
	(0.0066)	(0.0075)	(0.0076)
TotalRev$_{it}$		0.6312***	0.5367***
		(0.0207)	(0.0212)
RatingAvg$_{it-1}$		0.1324***	0.1452***
		(0.0101)	(0.0102)
RatingSD$_{it-1}$		0.0789***	0.0821***
		(0.0121)	(0.0123)
RespLength$_{it-1}$		-0.0895***	-0.0920***
		(0.0149)	(0.0151)
RespSpeed$_{it-1}$		-0.1176***	-0.1192***
		(0.0061)	(0.0062)
Constant	1.9130***	-5.9578***	-4.7646***
	(0.0070)	(0.2946)	(0.3032)
Hotel fixed effects	Yes	Yes	Yes
R-squared	0.0030	0.1427	0.1210
F	38.05***	296.73***	245.37***
Observations	13216	11,273	11,273
Number of hotel clusters	569	569	569

Notes: Standard errors are shown in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$; In Model 1.3[#], the control variable—TotalRev$_{it}$ is replaced by TotalRev$_{it-1}$.

Table 7. Results for moderating effect of certain/uncertain words

	Model 2.1	Model 2.2	Model 2.3	Model 2.4	Model 2.5#
$RespCaus_{it-1}$	-0.0203***	-0.0157	-0.0425***	-0.0385***	-0.0378**
	(0.0076)	(0.0113)	(0.0116)	(0.0145)	(0.0147)
$RespCert_{it-1}$	-0.0144***	-0.0121*	-0.0139***	-0.0121*	-0.0114*
	(0.0053)	(0.0067)	(0.0053)	(0.0067)	(0.0068)
$RespUncert_{it-1}$	0.0020	0.0020	-0.0071	-0.0071	-0.0069
	(0.0048)	(0.0048)	(0.0060)	(0.0060)	(0.0061)
$RespCaus_{it-1}$* $RespCert_{it-1}$		-0.0027		-0.0022	-0.0024
		(0.0048)		(0.0048)	(0.0049)
$RespCaus_{it-1}$* $RespUncert_{it-1}$			0.0123**	0.0122**	0.0118**
			(0.0049)	(0.0049)	(0.0049)
$TotalRev_{it}$	0.6295***	0.6294***	0.6299***	0.6298***	0.5347***
	(0.0207)	(0.0207)	(0.0207)	(0.0207)	(0.0212)
$RatingAvg_{it-1}$	0.1331***	0.1331***	0.1327***	0.1327***	0.1454***
	(0.0101)	(0.0101)	(0.0101)	(0.0101)	(0.0103)
$RatingSD_{it-1}$	0.0792***	0.0790***	0.0790***	0.0789***	0.0821***
	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0123)
$RespLength_{it-1}$	-0.0843***	-0.0848***	-0.0859***	-0.0863***	-0.0890***
	(0.0151)	(0.0151)	(0.0151)	(0.0151)	(0.0153)
$RespSpeed_{it-1}$	-0.1177***	-0.1177***	-0.1177***	-0.1177***	-0.1192***
	(0.0061)	(0.0061)	(0.0061)	(0.0061)	(0.0062)
Constant	-5.9530***	-5.9520***	-5.9308***	-5.9302***	-4.7289***
	(0.2946)	(0.295)	(0.2947)	(0.2947)	(0.3033)
Hotel fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.1433	0.1433	0.1438	0.1438	0.1220
F	223.62***	198.80***	199.58***	179.63***	148.65***
Observations	11,273	11,273	11,273	11,273	11,273
Number of hotel clusters	569	569	569	569	569

Notes: Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. In Model 2.5#, the control variable—$TotalRev_{it}$ is replaced by $TotalRev_{it-1}$.

Table 8. Results for moderating effect of affective words

	Model 3.1	Model 3.2	Model 3.3	Model 3.4	Model 3.5[#]
RespCaus$_{it-1}$	-0.0214***	-0.0921***	-0.0188**	-0.103***	-0.0787***
	(0.0075)	(0.0214)	(0.0090)	(0.0250)	(0.0254)
RespPos$_{it-1}$	0.0130***	0.0079***	0.0130***	0.00749***	0.0087***
	(0.0024)	(0.0028)	(0.0024)	(0.00286)	(0.0029)
RespNeg$_{it-1}$	0.0123	0.0137	0.0157	0.00838	0.0146
	(0.0084)	(0.0084)	(0.0106)	(0.0108)	(0.0109)
RespCaus$_{it-1}$* RespPos$_{it-1}$		0.0072***		0.00785***	0.0057**
		(0.0020)		(0.00219)	(0.0022)
RespCaus$_{it-1}$* RespNeg$_{it-1}$			-0.0037	0.00594	0.0013
			(0.0070)	(0.00746)	(0.0076)
TotalRev$_{it}$	0.6280***	0.6289***	0.6278***	0.629***	0.5314***
	(0.0207)	(0.0207)	(0.0207)	(0.0207)	(0.0212)
RatingAvg$_{it-1}$	0.1268***	0.1273***	0.1269***	0.127***	0.1408***
	(0.0104)	(0.0104)	(0.0104)	(0.0104)	(0.0106)
RatingSD$_{it-1}$	0.0787***	0.0788***	0.0787***	0.0789***	0.0818***
	(0.0121)	(0.0121)	(0.0121)	(0.0121)	(0.0123)
RespLength$_{it-1}$	-0.0487***	-0.0482***	-0.0490***	-0.0477***	-0.0527***
	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0171)
RespSpeed$_{it-1}$	-0.1165***	-0.1158***	-0.1164***	-0.116***	-0.1177***
	(0.0061)	(0.0061)	(0.0061)	(0.00613)	(0.0062)
Constant	-6.2805***	-6.2468***	-6.2790***	-6.246***	-5.0121***
	(0.3004)	(0.3004)	(0.3004)	(0.300)	(0.3088)
Hotel fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.1450	0.1460	0.1451	0.146	0.1238
F	226.80***	203.21***	201.62***	182.94***	151.13***
Observations	11,273	11,273	11,273	11,273	11,273
Number of hotel clusters	569	569	569	569	569

Notes: Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. In Model 3.5[#], the control

variable—TotalRev$_{it}$ is replaced by TotalRev$_{it-1}$.

Table 9. The influence of different words in management responses for premium hotels

	Premium hotel (hotel star=3, 4, 5)		
	Model 4.1	Model 4.2	Model 4.3
RespCaus$_{it-1}$	-0.0282***	-0.0454***	-0.115***
	(0.0086)	(0.0169)	(0.0282)
RespCert$_{it-1}$		-0.0127*	
		(0.0076)	
RespUncert$_{it-1}$		-0.0104	
		(0.0068)	
RespCaus$_{it-1}$* **RespCert**$_{it-1}$		-0.00180	
		(0.0058)	
RespCaus$_{it-1}$* **RespUncert**$_{it-1}$		0.0129**	
		(0.0056)	
RespPos$_{it-1}$			0.0092***
			(0.0032)
RespNeg$_{it-1}$			0.0189
			(0.0124)
RespCaus$_{it-1}$* **RespPos**$_{it-1}$			0.0093***
			(0.0025)
RespCaus$_{it-1}$* **RespNeg**$_{it-1}$			-0.0018
			(0.0084)
TotalRev$_{it}$	0.677***	0.674***	0.676***
	(0.0239)	(0.0239)	(0.0238)
RatingAvg$_{it-1}$	0.176***	0.175***	0.168***
	(0.0123)	(0.0123)	(0.0127)
RatingSD$_{it-1}$	0.117***	0.118***	0.117***
	(0.0146)	(0.0146)	(0.0146)
RespLength$_{it-1}$	-0.103***	-0.0987***	-0.0557***
	(0.0167)	(0.0169)	(0.0188)
RespSpeed$_{it-1}$	-0.124***	-0.124***	-0.122***
	(0.0010)	(0.0070)	(0.0010)
Constant	-6.751***	-6.708***	-7.104***
	(0.344)	(0.344)	(0.350)
Hotel fixed effects	Yes	Yes	Yes

R-squared	0.157	0.158	0.162
F	276.21	167.01	171.61
Observations	9,294	9,294	9,294
Number of hotel clusters	395	395	395

Notes: Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 10. The influence of different words in management responses for low-end hotels

	Low-end hotel (hotel star=1, 2)		
	Model 5.1	Model 5.2	Model 5.3
RespCaus$_{it-1}$	-0.00373	-0.00921	-0.0334
	(0.0142)	(0.0270)	(0.0517)
RespCert$_{it-1}$		-0.00712	
		(0.0130)	
RespUncert$_{it-1}$		0.000202	
		(0.0120)	
RespCaus$_{it-1}$* RespCert$_{it-1}$		-0.00250	
		(0.00808)	
RespCaus$_{it-1}$* RespUncert$_{it-1}$		0.00620	
		(0.00927)	
RespPos$_{it-1}$			0.00229
			(0.00599)
RespNeg$_{it-1}$			-0.0292
			(0.0202)
RespCaus$_{it-1}$* RespPos$_{it-1}$			0.000226
			(0.00443)
RespCaus$_{it-1}$* RespNeg$_{it-1}$			0.0372**
			(0.0152)
TotalRev$_{it}$	0.434***	0.436***	0.438***
	(0.0387)	(0.0388)	(0.0389)
RatingAvg$_{it-1}$	0.0345**	0.0360**	0.0337**
	(0.0161)	(0.0163)	(0.0168)
RatingSD$_{it-1}$	0.00226	0.00178	0.00226
	(0.0199)	(0.0199)	(0.0200)
RespLength$_{it-1}$	0.0125	0.0126	0.0256
	(0.0314)	(0.0320)	(0.0366)
RespSpeed$_{it-1}$	-0.0910***	-0.0917***	-0.0915***
	(0.0119)	(0.0120)	(0.0119)
Constant	-3.500***	-3.513***	-3.626***
	(0.515)	(0.517)	(0.532)
Hotel fixed effects	Yes	Yes	Yes

R-squared	0.102	0.103	0.106
F	34.15	20.64	21.22
Observations	1,979	1,979	1,979
Number of hotel clusters	174	174	174

Notes: Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.