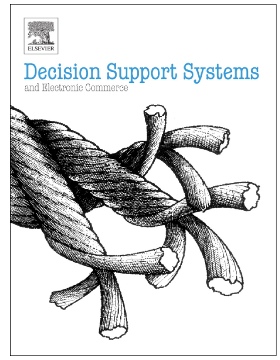

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Exploring Online Consumer Review-Management Response Dynamics: A Heuristic-Systematic Perspective

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Abstract

Although the effects of managerial responses (MRs) on subsequent customer reviews (CRs) has been explored, we lack a comprehensive theoretical framework to explain the interdependent relationships between previous and subsequent CRs—specifically the dynamic influences of MRs on future CRs. We draw on emotional contagion and regulation theories to develop a heuristic systematic model to explain CR-MR dynamics in online settings. We propose six systematic processing and three heuristic processing routes to delineate the determination and persuasion effects between previous and subsequent consumers' CRs. The systematic routes describe how current customers' compliments, complaints, and emotions influence their current rating scores. The heuristic processing routes describe how previous customers' rating scores and emotions influence current customers' rating scores and emotions. We suggest MR strategies to regulate these effects. The presence and length of MRs defines the numeric heuristic route while the positive-emotion heuristic route is conceptualized through expressions of thanks, sincerity, interaction, and complimenting customers. Expressions of apology, explanation, empathy, and remedy inform the negative-emotion heuristic route. We collect text from customers' reviews and managers' responses from the TripAdvisor website using text-mining techniques and analyze our hypotheses using Pooled Ordinary Least Squares (pooled OLS) and Generalized Method of Moment (GMM) modeling. Our findings not only enrich the theoretical underpinnings of the CR/MR literature, but also provide managerial guidance on how customers' emotional contagion and rating behaviors might be regulated.

Keywords: customer reviews, managerial responses, heuristic systematic model, emotion contagion, emotion regulation, GMM model

1 Introduction

User-generated content, and specifically online customer reviews (CRs), are integral to consumers' decision-making process (e.g., [1-8]). Typically, positive online reviews explain 87 percent of consumers' purchasing decisions while negative reviews countermanded 80 percent of them [9]. This indicates how online CRs significantly affect product sales and customer loyalty [1,10-12]. Consequently, offering online responses to consumer reviews is an intrinsic part of many firms' strategies for managing reputation and customer engagement.

By engaging in an online conversation, the firm changes the nature of the discourse. Entry into a conversation often takes the form of a management response (MR) or an open-ended passage of text from a company, which is permanently displayed beneath the review it addresses [13]. Online conversations send a credible signal to potential customers that the firm's management is listening and responding to both their feedback. This incentivizes customers to post future reviews [16,17] and, in the face of problems, provides a mechanism for restoring confidence [14,17]. Firms understanding the effect of MRs to online reviews and future reviewing behavior highlight positive comments (thus maintaining and increasing their customer base) and defuse criticism (thereby preventing customer churn and online firestorms).

Unfortunately, such enlightened firms are rare [17]. Use of MRs remains limited, with 72 percent of firms rating their preparedness for negative online word of mouth (WOM) as below average [18]. TripAdvisor, typifies this situation, as two-thirds of negative reviews receive no response from the reviewee [19].

Despite recognition in the marketing literature of the importance of MRs to online firm-customer interaction, the current perspective largely attends to the impact of MRs (mostly measured by their presence or absence, volume, speed, or length) on the volume/valence of subsequent CRs, business performance, or customer satisfaction (e.g., [13,16]). Consequently, studies do not yet adequately account for the complex effects of diverse MR practices (e.g., [17,22]). Specially, we lack a consensus about the mechanisms which relate future customer reviews to business performance (e.g., [13,16,18,20,21]).

The majority of studies use volume (number), valence (sentiment), and content length to measure online CRs and MRs [13,16,20,21]. Although researchers discuss various forms of relationship (e.g., causal, interrelated, interactive effects) between CRs and MRs (e.g., [13,16,18,20,21,23]), we currently lack a comprehensive framework to explain the interdependence between the distinct components of CRs and relating MR strategies. We argue this results in suboptimal MR strategizing as overlooks important metrics and their effects. This indicates the importance of identifying a more comprehensive set of metrics which can act as an overarching framework to explain the dynamics and effectiveness of MR strategies on specific CR components.

Our research design draws on a big data set of online customers' reviews (i.e., unstructured textual data from a platform facilitating management responses. Our analytic approach combines text mining, dictionary analysis, and dynamic modeling analyses, to answer our three research questions and, in the process, make three distinct contributions to the literature. First, we identify five critical CR and ten MR components serving different regulatory objectives in a significant departure from the current narrative around volume, valence, and length of CRs/MRs. We deepen understanding of CRs by accounting for compliments, complaints, and emotions, and the corresponding use of MR elements to regulate these CR components. Second, by using a heuristic-systematic lens [24] to illustrate CR-MR dynamics we model managerial strategies (i.e., the MR components we identify) regulating three heuristic processing routes. Our analysis of CR-MR dynamics from this perspective extends previous contributions [5,24] by moving beyond the dual process model.

Third, our results show the presence and length of MRs effectively regulate the numeric heuristic, while the MRs' expression of thankfulness, sincerity, compliments to clients, and good interactions with customers strengthen the positive emotion heuristic. The expressions of apology, explanation, empathy, and offering improvements/remedies mitigates the negative emotion heuristic.

We report a chronological framework explaining the effectiveness of MR strategies for managing online customers' heuristic processing routes. These theoretical contributions support managers designing decision support systems by enabling automatic categorization of reviews based on sentiment and then suggesting suitable response strategies. Such a capability enhances the decision-making process around MRs by enabling prompt and effective management of online customer interactions.

2 Theoretical Background and Research Framework

2.1 Identifying the Components of CRs

Customers gain various psychological benefits from reporting positive consumption experiences. Benefits include making sense of their experiences, reducing their cognitive dissonance, strengthening their social connections [25], communicating their identity [26], and creating a positive affect extending beyond the actual event itself [27,28]. Customers report that CRs also bring tangible benefits to the firm, as they enhance product diffusion, promote sales [29-31], generate positive word-of-mouth (WOM) [32], and boost other customers' moods [33].

Emotional contagion theory explains how receivers catch others' "positive or negative emotions" through social transmission [33,34]. The spread of online content is an emotionally contagious process driven by emotional words within social transmissions [34]. The extent to which a customer uses affective words in online CRs efficiently reveals their basic reactions and intentions. Pizam and Ellis [35] argue that positive emotional contagion arises from events with attributes that evoke satisfaction and so elicit customer compliments. Studies on this form of contagion provide managers with insights about how to drive customer satisfaction [36,37]. However, compliments and their association with positive emotions are not the only critical components of CRs. Negative CRs often have a viral quality and are more influential than positive CRs [38,39]. Customers share their negative consumption experiences through complaints [40] as a means of warning others and so coping with these events.

The valence of CRs are often made explicit through a scoring mechanism [1]. Consumers' individual assessments are generally aggregated into an average score. Potential customers infer that a service/product with a high score will result in a positive experience [41,42]. To summarize, CRs are characterized by: (1) positive emotions, (2) revealed compliments, (3) negative emotions, (4) expressed as complaints, and (5) a system of numeric rating scores.

2.2 Theoretical Components of MRs

Firms need to discern between emotional contagion and online CRs, as well as deciding how to respond effectively to customers' online reviews. Such strategies should minimize the effects of negative comments whilst maximizing the effects of positive reviews on the wider audience (e.g., potential customers). Emotional contagion theorists assert the importance of interpersonal relations, which enable the message recipients to evaluate others and devise appropriate responses [43]. This leads us, next, to relate emotion regulation perspectives with critical MR strategies.

2.2.1 Identifying the Components of MR Which Regulate Positive CRs

We adopt a social exchange perspective on how managers respond to online CR compliments. Which frames online communication between customers and managers as a two-sided, mutually dependent, and mutually rewarding process that is contingent on rewarding the reactions of others [44]. This positions MRs to online compliments (positive CRs) as a reciprocal response to feedback that is favorable and beneficial for the firm. The compliment responses literature [37] indicates that showing appreciation, expressing thankfulness, and generating firm-customer interactions are some MR components that regulate positive emotions. This follows assumptions in self-verification theory which argues people pursue a positive self-view [45-47] readily accepting and positively responding to statements that converge with their desired beliefs about themselves. When a firm publicly compliment a customer, they recognizing the merits of his/her contribution [15,17] and, such positive approval elevates his/her self-esteem. Drawing these perspectives together, we expect that the components of MRs regulating CR positive emotions include: (1) expressing thankfulness, (2) showing sincerity, (3) emphasizing customer-firm interaction, and (4) complimenting customers.

2.2.2 Identifying the MR Components to Regulate Negative CRs

Firms' aspiration to reduce the contagious effects of negative CR reflects theory on service recovery which indicates the importance of restoring relationship equity to complaining customers. This approach avoid contagion by diffusing the impact of negative CR . The viability of typical recovery approaches (e.g., offering an apology, giving compensation, responding empathically, or providing an explanation) are investigated mainly in the context of firm customer communications (e.g., [15,18,20]). There are two main approaches for regulating customers' negative emotions: displays of empathy and offering explanations. The empathic approach is spontaneous and affective; where the firm sympathizes (e.g., "we understand that you're unhappy") or directs the customer towards a more positive perspective (e.g., "we hope you'll have a better experience next time"). The explanatory approach involves substantial justifications in MRs. The decision outcome is more influenced by the number, rather than the substance, of the explanation [48]. In line with cognitive appraisal theory and the affect infusion model, Homburg et al. [49] propose that empathy is more effective in affect-intensive environments characterized by social interactions and spontaneous decisions. However, certain stimuli may be too emotionally intense for an empathic response to suffice since ustomers are seeking an explanation that enables them to reappraise the situation [50]. They may also have higher expectations of appropriate remedies [51]. Herhausen et al. [18] argue that firms' empathic responses divert the attention of consumers who are experiencing low-arousal negative emotions, but explanations are needed to mitigate the virality of high-arousal negative emotions. Nee [52] finds MRs explaining what went wrong positively influence customers' intentions to book a hotel room. Min et al. [53] study the impact of two MR ingredients on negative hotel reviews using empathy and explanatory statements. They report potential customers evaluate MRs containing empathy and explanation more positively than ones that contain neither.

Whatever MR strategy employed, online firms should create perceptions of similarity, approval, and trust (psychological synchrony) in the recipient [56]. Firms can build an empathic foundation and then trigger customers' cognitive appraisal processes by offering explanations or providing compensation to mitigate customers' negative emotions.

2.2.3 Identifying the MRs' Strategic Components to Regulate Numeric Rating Scores

The presence of MRs benefits firms in customer engagement contexts that are both positive and negative. When the intervention directs toward positive customer engagement, an MR in response to a positive online CR (on a platform such as TripAdvisor) has a positive effect on customers who read the interaction [57]. The presence (vs. absence) of MRs induces positive brand evaluation among customers who read reviews [17,58]. The CR length has both direct and indirect effects on readers' perception of communication quality. The length of an MR causes a heuristic association (i.e., writing long MRs requires more time and effort), which positively influences future reviewers' rating scores (e.g., [59]). We infer that the length of MRs cues potential reviewers about the future treatment from the firm [60]. These future reviewers, believing that the MR represents an authentic and sincere response, may leave higher rating scores for the firm.

2.3 Developing a Heuristic Systematic Model to Illustrate CR-MR Dynamics

The heuristic-systematic model (HSM) [61] proposes two co-existing modes of information processing: systematic and heuristic. Systematic processing involves individuals with the motivation and ability to deeply process information [61] (the sufficiency principle; [24]). This systematic processing involves customers' judgments reflecting the substance of the response over superficial cues [24]. By contrast, heuristic processing involves judgment shortcuts (i.e., simple schemas which reduce cognitive effort) to evaluate salient, easily processed cues in a way that is quick and relatively automatic. The heuristic view of persuasion holds that customers expend little effort by merely relying on the accessible portion of informational cues, such as previous CR rating scores [24].

Our HSM follows the rationale that it takes more cognitive effort for reviewers to devise their own forms of compliments and complaints about their specific experiences than if they simply reference previous customers' reviews and rating scores. Creating original content requires customers to process detailed information extracted from their memories (i.e., systematic processing). However, customer are likely to form quick judgement by simultaneously referring to numeric rating scores and the valence (positive or negative) of previous CRs (i.e., heuristic processing). In this study, we associate three of the five CR components (positive emotion, negative emotion, and rating score) with heuristic processing and the remaining two, compliments and complaints, with systematic processing. We thus hypothesize the following:

H1a: CR compliments positively influence customers' own positive emotions.

H1b: CR compliments positively influence customers' rating scores.

H1c: CR complaints negatively influence customers' rating scores.

H1d: CR complaints positively influence customers' negative emotions.

H1e: Customers' positive emotions positively influence their rating scores.

H1f: Customers' negative emotions negatively influence their rating scores.

We also posit that prior customers' positive or negative emotions and rating scores influence current customers' emotions and rating scores through three potential heuristic processing routes. First, a numeric-heuristic path, relates previous CRs' numeric rating scores to current customers' CR ratings. Second, an emotional-heuristic path, associates previous CRs' negative or positive emotions with current customers' CR emotions. Third is the influence of the presence and length of MRs on the customer's numeric heuristic route. Our prior arguments indicate firms should regulate customers' positive-emotions though positive emotion regulation strategies (i.e., (1) expressing thanks, (2) showing sincerity, (3) emphasizing customer-firm interaction, and (4) complimenting customers). To regulate customers' negative-emotions, firms should use negative emotion regulation strategies (i.e., (1) making apologies, (2) showing empathy, (3) providing explanations, and (4) offering compensation or remedies). This leads us to:

H2a: CR scores positively influence subsequent CR scores via the numeric-heuristic route.

H2b: Customers' numeric-heuristic route is influenced by the numeric regulation strategies of the (1) presence and (2) length of MRs in a way that strengthens the positive relationship between previous and subsequent CR rating scores.

H3a: Positive emotions in CRs positively influence the positive emotion of later CRs via the positive-emotion heuristic route.

H3b: Customers' positive-emotion heuristics are influenced through positive-emotion regulation strategies in a way that strengthens the positive relationship between the positive emotions in CRs' and the positive emotions expressed in later CRs.

H4a: Negative emotion in CRs positively influences the negative emotion of subsequent CRs via the negative-emotion heuristic route.

H4b: Customers' negative-emotion heuristics are influenced through the negative-emotion regulation strategies in MRs in a way that weakens the positive relationship between the negative emotions in CRs and the expression of negative emotion in later CRs.

Fig. 1 presents our conceptual framework, which integrates the HSM with the emotional regulation model to illustrate the three heuristic processing routes from CRs to subsequent CRs, and the systematic routes among focal customers' CR components. This framework also accounts for MRs' emotion regulation components, which might exert different effects on the heuristic processing route.

3 Method

3.1 Data

We collect longitudinal, unstructured, textual data using scraping techniques from the well-known travel website TripAdvisor. This site allows customers to provide online reviews for, inter alia, hotel stays, and allows hotel managers to respond to these CRs. The voluminous verbatim reviews on TripAdvisor demand a sampling strategy. In such circumstances, researchers typically adopt random sampling without repetition [62-64]. We elected to focus on properties listed on TripAdvisor in the Los Angeles (LA) city (USA). We chose this city because it is one of the top ten largest US cities and is a vibrant destination for international tourists. To mitigate the risk of selection bias, our research employs a simple random sampling approach [65] which ensures each hotel listed on TripAdvisor in LA has an equal and independent chance of being selected [66]. Our sampling process started by identifying all hotels in LA listed-on TripAdvisor[i]. This involved using web scraping techniques based on Python algorithms, which parsed the HTML code of the website to extract the relevant information. Next, we scraped the TripAdvisor website and randomly selected 10 percent of our results i.e., a total of 88 hotels. We then used our scraping procedure to extract guests' online reviews, rating scores, and the hotels' managerial responses (if any) from our sample of hotels. The process resulted in a total of 44,650 customer comments and rating scores, and 32,257 hotel management responses in the year period between July 1st, 2018, to August 31st, 2019 (i.e., predating the Covid-19 pandemic).

Next, following Humphreys and Wang [67], we used text mining to measure the compositional elements of CRs and MRs. We employed a dictionary-based method to measure our constructs given the clarity of our concepts. This involves counting the presence or absence of particular words that represent a construct. In our study, we operationalize 15 focal variables pertaining to the components of CRs and MRs. The sentiment aspects of CRs, categorized as positive and negative emotion, are operationalized utilizing the established LIWC dictionary [68-70], while rating scores are directly observable on TripAdvisor. Compliments and complaints in CRs are deduced using a custom dictionary, comprising of words or phrases indicative of praise and dissatisfaction. Turning to MRs, we ascertain their presence and evaluate their length directly through observations on TripAdvisor. Subsequent components, including thankfulness, sincerity, interactions, complementing the guest, apology, empathy, explanation, and remedy, are operationalized by employing custom dictionaries featuring pertinent words or phrases. Table A.1 in the web appendix shows the operationalization of focal variables. By adapting Rocklage et al. [71], Singh et al. [72], Balducci and Marinova [73], Humphreys and Wang [67], Marinova et al. [74], we created a six-step process to develop and validate the custom dictionary (Table 1).

Table 1. Steps to Develop our Custom Dictionary

Steps	Actions	Outputs or Results
1. Entity extraction	We extracted and identified the most frequent words and phrases in our dataset. We then cleaned the results using spell-checking and removed stop words (Facilitated with WordStat 9 software).	An initial list of 1,442 words or phrases from CR and 1,090 words or phrases from MRs.
2. Develop a construct coding scheme.	We integrated academic definitions of focal constructs with 300 randomly-selected comments from the dataset to develop the coding scheme and to select seed words/phrases related to the 2 CR and 8 MR components.	A coding scheme with seed words or phrases
3. Custom dictionary development	Two linguistic experts classified the words and phrases into the coding scheme for an interrater reliability of .92 after three iterations. Remaining inconsistencies were resolved by two of this paper's authors. ▪ Two research assistants conducted a further interrater analysis of the final coding scheme and associated words or phrases. Agreement of .90 was reached for each construct.	A final custom dictionary.
4. Assigning positive and negative emotions to CRs	▪ Emotions were identified based on the LIWC dictionary.	Emotional valence of the categories assigned
5. Transform the unstructured text dataset into a structured numeric dataset	▪ The standardized LIWC dictionary acted as a measure of the two CR constructs. The custom dictionary measured ten constructs. The three remaining components (rating scores, presence of MR, and length of MR) were directly extracted from the website.	Production of the final 15 (i.e., including (rating scores, presence of MR and length of MR) numeric variables for further analysis

6. Evaluate the validity of the nine focal constructs	▪ Conducted internal discriminate validity evaluation through correlation matrix among all variables.
	▪ Conducted external validation by:
	  ▪ Comparing the descriptive statistical values between two sub-datasets to check the robustness of using the LIWC and custom dictionaries to measure focal constructs
	  ▪ Evaluating the predictive performance of 14 focal constructs on rating scores
		Achieve internal and external validities

In our first step, we created an initial list of customers' and managers' verbatim words and phrases with the support of WordStat 9, a text-mining natural language processing (NLP) software. The second step involved developing a coding scheme based on the theoretical rationale of the CR and MR components. We randomly selected 300 reviews from our text-based dataset and invited two research assistants to independently identify the seed words and phrases related to two CR components (compliments and complaints) and eight MR components (thankfulness, sincerity, interaction, complimenting guests, apology, explanation, empathy, remedy). The two assistants (A and B) discussed discrepancies in how they had allocated the data until their views coalesced at 88% agreement. We used this final list of seed words or phrases (see Table 1 for examples) to develop the coding scheme.

In our third step, we categorize the words or phrases into the coding structure. We sought two expert assistants (C and D) with a background in linguistics. We then followed Berger et al.'s [75] internal dictionary validation approach (inter-rater consistency) which reached 92% after three iterations. Two authors of this paper resolved the remaining inconsistencies. Then, two research assistants (E and F) performed an interrater analysis of the final dictionary. We calculated the level of overall agreement between these two assistants across ten categories (i.e., the two CR, and eight MR components) and each category exceeded the 90% threshold [76]. This finalized our custom dictionary, which captured 10 of our 15 components. The remaining five were captured as follows: positive and negative CR emotion were extracted from the LIWC standardized dictionary [77], while the rating score and presence and length of MR were directly extracted from the website.

In the fifth step we transformed the unstructured text data into structured numeric data for further analysis with the LIWC 2022 software. The LIWC 2022 software used a combination of (a) text processing, (b) dictionary matching (i.e., matches each word in the input text against our predefined dictionaries, including standardized and custom), (c) numerical transformation (i.e., assigning a numerical value to represent the degree to which the word belongs to a particular category in the dictionaries) and (d) aggregation (i.e., aggregating the numerical values of all words in each category to obtain a single numeric category score). For each hotel reviewer there are five output variables (rating score, positive emotion, negative emotion, compliments, and complaints) and ten MR variables (presence, length, thankfulness, sincerity, interaction, complimenting the guest, apology, explanation, empathy, and remedy). Next, we used the following procedure to clean the numeric datapoints for each hotel. We focused on daily reviews to average scores for those hotels with multiple reviews and recorded missing values for those hotels that received no reviews. We then aggregated individual-level data (an individual guest's comment/individual manager's response) into weekly-level data to build up the CR-MR dynamics from a firm's perspective. The result was panel datasets for each hotel at average weekly levels.

In our sixth, and final step, we evaluated the discriminant validity of our focal constructs. Table A.2 in Web Appendix shows the results of our correlation matrix for the 15 variables and these support discriminant validity [75]. We also examined the external validity of our custom dictionary using a descriptive statistical analysis [67]. This generated congruent results, supporting the external validity of our custom dictionary. Finally, we followed Berger et al.'s [75] approach for predicting performance measures [78]. We included 14 numeric variables, derived from our datasets, in the regression model, and ran analysis to predict the key outcome, i.e., the reviewers' rating score. We find that the text-based constructs (CR/MR components) associate with this key performance measure, supporting the model's predictive validity.

Table A.2 in Web Appendix presents the descriptive statistics and correlation coefficient matrices, including Spearman rank correlations and Pearson correlation coefficients, presenting in the upper and lower triangular matrices, respectively. We observe that the Spearman rank and Pearson correlations express similar values and patterns. This suggests that the relationships between focal variables are consistent. Please reference Web Appendix A.3-A.4 for more discussion, exploration, and testing of linear/non-linear relationships among the focal variables and the evidence of model fit.

3.2 Estimation Methods

To analyze H1a-H1f, we used Pooled Ordinary Least Squares (pooled OLS). Our analysis investigates the overall relationship between independent variables (focal customers' current emotions, compliments, and complaints) and the dependent variable (current rating score), rather than examining differences in these relationships across hotels. Our dependent variable is focal customers' rating scores ($Score_{it}$), and our explanatory variables are focal customers' compliments ($Compliment_{it}$), positive emotions ($P\_Emotion_{it}$), complaints ($Complaint_{it}$), and negative emotions ($N\_Emotion_{it}$). Pooled OLS is suitable for estimating such overall relationships in a pooled dataset. The is particularly salient, as our study does not involve the investigation of longitudinal effects which would anticipate the use of random or fixed-effects models. To address potential concerns about unobserved heterogeneity or omitted variable bias , we added control variables in the pooled OLS model. Our control variables are hotels' star rankings, their list-price, and their ownership. We account for seasonal differences across months by including dummy variables for all but the first sampled month (i.e., our reference category). Controlling for the monthly fixed effects picks up market-wide effects that impact all hotels.

To test H2-H4, we employed the generalized method of moments model (GMM) to capture the dynamic relationships between previous CR components, previous MR components, and current

CR components. The GMM refers to a class of estimators constructed by exploiting the sample moment counterparts of population moment conditions of the data generating model. Estimators under GMM have large sample properties that facilitate comparison [79] and they can be constructed without specifying the full data-generating process [80,81]. We exploit this characteristic by using, potentially mis-specified, dynamic models designed to match target moments [82].

The GMM estimation technique allows for lags in the dependent variables and provides consistent results in the presence of unobserved, simultaneous, and dynamic endogeneity [83]. The use of GMM addresses dynamic endogeneity bias in panel data and so is particularly suitable for this study. We operationalize a two-step GMM method to conduct the internal transformation process [84-86]. This approach uses forward orthogonal deviations, which avoids unnecessary data loss and provides consistent estimates of the coefficients [84,87,88]. The GMM models are specified as equations (1) - (3), in which μ_{it} is hotel-specific effects (official ranking stars, hotel chains, listed prices) and ε_{it} represents the error term.

To test H2a and H2b:

$$Scores_{i,t} = Score_{i,t\text{-}1} + (MR\_Presence_{i,t\text{-}1} * Score_{i,t\text{-}1}) + (MR\_Length_{i,t\text{-}1} * Score_{i,t\text{-}1}) + \mu_{i,t} + \varepsilon_{i.t} \quad (1)$$

To test H3a and H3b:

$$\begin{aligned} Positive\_Emotion_{i,t} = {} & Positive\_Emotion_{i,t\text{-}1} + (MR\_Thankfulness_{i,t\text{-}1} * Positive\_Emotion_{i,t\text{-}1}) + (MR\_Sincerity_{i,t\text{-}1} * Positive\_Emotion_{i,t\text{-}1}) \\ & + (MR\_Compliment_{i,t\text{-}1} * Positive\_Emotion_{i,t\text{-}1}) + (MR\_Interaction_{i,t\text{-}1} * Positive\_Emotion_{i,t\text{-}1}) + \mu_{i,t} + \varepsilon_{i.t} \end{aligned} \quad (2)$$

To test H4a and H4b:

$$Negative\_Emotion_{i,t} = Negative\_Emotion_{i,t-1} + (MR\_Apology_{i,t-1} * Negative\_Emotion_{i,t-1}) + (MR\_Explanation_{i,t-1} * Negative\_Emotion_{i,t-1}) + (MR\_Empathy_{i,t-1} * Negative\_Emotion_{i,t-1}) + (MR\_Remedy_{i,t-1} * Negative\_Emotion_{i,t-1}) + \mu_{i,t} + \varepsilon_{i,t} \quad (3)$$

To arrive at this stage, we used a Python algorithm to scrape a random sample of textual data from the TripAdvisor website. We then employed the software packages WordStat and LIWC 2022 alongside manual coding to conduct a dictionary analysis process. This transformed our qualitative (text) into quantitative (numeric) data which facilitated our correlation analysis. We now turn to our pooled OLS and GMM analysis (run with use EViews software) relating to H1-H4 and mediation analysis corresponding to H1 (run under the PROCESS macro tool).

4 Empirical Results

4.1 Systematic Processing Routes

Table 2 shows the current CR's positive emotions, compliments, negative emotions, and complaints result in the current CR rating scores. Specifically, current positive emotions are determined by current CR's compliments, and current CR's negative emotions are a result of current CR's complaints. Thus, we find support for H1a - H1f. Web Appendix A.3-A.4 provides further justification for assuming linear rather than non-linear relationships between the dependent and independent variables.

In Table 2, the coefficients of the relationship between the independent, (current compliments, current positive emotions) and the dependent variables (current rating scores) show significant positive effects (.185 and .293, respectively; $p < 0.001$). Current negative emotions and current compliments have significant and negative effects (-.252 and -.185, respectively; $p < 0.001$) on current rating scores. Moreover, current compliments exert significant and positive effects on current positive emotions (.781, $p < 0.001$), and current complaints exert significant and negative effects on current positive emotions (.352, $p < 0.001$). This supports the assertions in H1a - H1f, regarding consumers' systematic processing routes.

Table 2. The Estimation of Pooled OLS for H1a-H1f

	Unstandardized Coefficient β	**S.D**	**Standardized Coefficient β**	**T**	**Significance**	**VIF**
DV= Rating Scores ($R^2 = 0.461$; Adjusted $R^2 = 0.457$)						
Constant	3.434	0.093		37.101	0.000	
CR_Compliment	0.054	0.014	0.185	3.829	0.000	2.628
CR_Complaints	-0.202	0.036	-0.185	-5.683	0.000	1.192
CR_Positive Emotion	0.100	0.017	0.293	6.024	0.000	2.655
CR_Negative Emotion	-0.289	0.038	-0.252	-7.595	0.000	1.236
DV: CR_Positive Emotion ($R^2 = .610$; Adjusted $R^2 = 0.609$)						
Constant	1.878	0.160		11.752	0.000	
CR_Compliment	0.669	0.022	0.781	30.819	0.000	1.000
DV: CR_Negative Emotion ($R^2 = 0.124$; Adjusted $R^2 = 0.122$)						
Constant	0.527	0.039		13.650	0.000	
CR_Complaints	0.335	0.036	0.352	9.252	0.000	1.000

We then conducted conditional path analysis using the PROCESS macro tool to test the mediation effect of positive emotions and negative emotions. By default, PROCESS generates bias-corrected confidence intervals for indirect effects. Table 3 shows that the mediating effects of current CR's positive emotions are significant between current compliments and current rating scores (the

LLCI and ULCI of the indirect effect of positive emotion does not include zero). Moreover, the mediating effects of current CR's negative emotions are significant between current CRs' complaints and current CR's rating scores (the LLCI and ULCI of the indirect effect of negative emotion does not include zero). This supports the assertion of the mediating effects of positive and negative emotions on current rating scores.

Table 3. The Mediating Effects of Positive and Negative Emotions

Mediating Effect of Positive Emotion between Compliments and Rating Scores				
	Indirect Effects	**Boot SE**	**Boot LLCI**	**Boot ULCI**
Positive Emotion	0.087	0.014	0.060	0.113
Mediating Effect of Negative Emotion between Complaints and Rating Scores				
Negative Emotion	-0.144	0.036	-0.223	-0.082

4.2 Heuristic Processing Routes

We used GMM to analyze the heuristic processing routes. In addition to the dependent (at time t) and independent variables (at time t-1) presented in our model, we also included other time lags of dependent and independent variables (e.g., CR_Rating Score $_{t-2}$, CR_Rating Score $_{t-3}$, CR_Rating Score $_{t-2}$ * MR_ Presence $_{t-2}$) as instrumental variables to estimate the results. Table 5 shows results relating to H2 - H4. In H2a and H2b, we argue that previous CR rating scores influence subsequent CR rating scores, and that the presence and length of MRs operate as a numeric regulating strategy. The results show that previous rating scores exert significant and positive effects on subsequent rating scores (.143, $p < 0.05$). Moreover, the presence of MR positively moderates (strengthens) the positive relationship between previous rating scores and later rating scores (.003, $p = 0.051$) while the length of MR negatively moderates (weakens) the positive relationship between previous rating scores and subsequent rating scores (-.009, $p = 0.050$). In H3a and H3b, we posit that the positive emotions of previous customers influence those of later customers. Additionally, we propose four MR strategic components with the potential to regulate later customers' positive emotions (i.e., expressing thankfulness, sincerity, good interaction, complimenting clients). The results show that previous positive emotions exert significant and positive effects on later positive emotions (3.260, $p < 0.001$). Moreover, our proposed MR strategic components positively moderate (strengthen) the positive-emotion heuristic route (.226, .399, .046, .076; p values < 0.001). Our H4a and H4b argue that previous negative emotions influence subsequent negative emotions. We propose four MR components with the potential to regulate later customers' negative emotions (i.e., expressing apology, explanation, empathy, and providing remedies). The results show that previous negative emotions exert positive effects on subsequent negative emotions (5.706, $p < 0.001$). Moreover, our proposed MR strategic components do, indeed, negatively moderate (weaken) the negative-emotion heuristic route (-.321, -.340, -.583, -.319, respectively; all p values < 0.001). The results support H2a, H2b, H3a, H3b, H4a, and H4b. Fig. 2 summarizes the empirical results relating to all our hypotheses.

Table 4. The Estimation Results of GMM to Test H2-H4

	Coefficient	Std. Error	t-Statistic	Prob.
Results of H2a and H2b				
Dependent Variable: CR_Rating Score$_t$				
Independent Variables:				
CR_Rating Score $_{t-1}$	0.143	0.045	3.168	0.002
CR_Rating Score $_{t-1}$ * MR_ Presence $_{t-1}$	0.003	0.000	1.956	0.051
CR_Rating Score $_{t-1}$ *MR_ Length $_{t-1}$	0.009	0.003	1.962	0.050
Results of H3a and H3b	Coefficient	Std. Error	t-Statistic	Prob.
Dependent Variable: CR_ Positive Emotion $_t$				
Independent Variables:				
CR_ Positive Emotion$_{t-1}$	3.260	0.026	126.245	0.000
CR_ Positive Emotion$_{t-1}$*MR_Thankfulness $_{t-1}$	0.226	0.007	33.932	0.000
CR_ Positive Emotion$_{t-1}$ *MR_Interaction$_{t-1}$	0.046	0.001	42.293	0.000
CR_ Positive Emotion$_{t-1}$*MR_Compliment Guests $_{t-1}$	0.17[illegible]	0.002	73.453	0.000
CR_ Positive Emotion $_{t-1}$* MR_ Sincerity $_{t-1}$	0.399	0.004	113.855	0.000
	Coefficient	Std. Error	t-Statistic	Prob.
Results of H4a and H4b				
Dependent Variable: CR_ Negative Emotion $_t$				
Independent Variables:				
CR_ Negative Emotion $_{t-1}$	5.706	0.231	24.658	0.000
CR_ Negative Emotion $_{t-1}$*MR_Apology$_{t-1}$	-0.321	0.034	-9.416	0.000
CR_ Negative Emotion $_{t-1}$*MR_ Explanation $_{t-1}$	-0.340	0.046	-7.404	0.000
CR_ Negative Emotion $_{t-1}$*MR_ Empathy$_{t-1}$	-0.583	0.024	-23.869	0.000
CR_ Negative Emotion $_{t-1}$*MR_ Remedy$_{t-1}$	-0.319	0.018	-18.176	0.000

5 Discussion and Conclusion

We begin our general discussion by summarizing the results in relation to our hypotheses. Anchored in our HSM perspective, our first six hypotheses explore the systematic processing routes for current CR components. Our results support the assertion that customers' current rating scores are positively influenced by their current compliments and current positive emotions while negatively influenced by their current complaints and current negative emotions (H1a to H1f). Moreover, current positive emotions act as an effective mediator between customers' current compliments and rating scores, while current negative emotions similarly mediate between customers' current complaints and rating scores. Our remaining six hypotheses (H2a, H2b, H3a, H3b, H4a, and H4b) integrate HSM and the emotion regulation perspectives with the CR/MR literature to specify three heuristic processing routes: numeric (between the rating scores of previous and current customers), positive emotions (between the positive emotions of previous and subsequent customers), and negative emotions (between the negative emotions of previous and subsequent customers). The systematic routes are determined by customers' own compliments, complaints, and emotions. However, we show that customers are heuristically influenced by other reviewers' emotions and rating behaviors. Drawing on the emotion regulation and MR literature, we propose strategies for regulating these three heuristic processing routes through MR components.

We develop a GMM model to investigate the dynamics of previous and future CR with MR regulation. This approach uses standard analysis procedures to account for dynamic endogeneity bias and to provide consistent estimations for our dynamic panel dataset. The GMM results provide evidence that shows customers' use of the three heuristic processing routes adds to the effectiveness of the MR regulating strategies. We find that the previous rating scores significantly influence future customers' rating scores and that subsequent customers experience emotional contagion effects. We also find evidence to support the importance of the presence and length of MRs. Regarding the components of MRs, we find that four of these (expressions of thankfulness, sincerity, interaction, and complimenting guests) have a significant effect on the regulation of positive emotions—with expressions of sincerity and thankfulness being the two most important. We find that the other four components (expression of apology, explanation, empathy, and remedy) significantly regulate negative emotions by weakening the negative emotional contagion between previous and subsequent customers. The expression of empathy is the most important component. These findings form the basis of our contributions to the literature, which we now detail.

5.1 Theoretical Contribution

Our research results present significant theoretical contributions, expanding the domain of decision support and decision-making processes through the context of online customer reviews (CRs) and associated management responses (MRs).

First, we offer an innovative extension to the HSM [24] by introducing six systematic processing routes and three heuristic processing routes. This enriched HSM model proposes ten strategic MR components specifically designed to govern these heuristic processing routes. By incorporating the theoretical domains of HSM, emotion contagion, and emotion regulation, we delve deeper into the realm of consumer decision-making. This advancement augments our understanding of the interactions between prior and subsequent CRs, as well as the dynamics among firms' managers and customers, elucidating their impact on future customer decision processes.

Second, our study highlights how decision support can be enhanced by understanding the crucial dynamics between prior and future customers' rating behaviors and emotions [17]. By identifying key strategic MR components, that guide the numeric and emotional heuristic routes, we demonstrate how firms can effectively manage customer emotions and rating scores. This enhances the decision-making process, in response to customer reviews [89], while also supporting the development of more robust decision support systems [17]. As a noteworthy extension of previous research [17], our theoretical framework explicates the strategic role of distinct MR components in either amplifying or mitigating the transmission of positive and negative emotions in online environments. In this way, our findings provide crucial insights to better inform strategic planning by enabling a more data-driven and customer-centric approach in responding to customer feedback.

Third, our research addresses existing inconsistencies within the literature regarding the impact of MRs on the quantity and sentiment of subsequent CRs, resulting in an enriched perspective for decision support and advanced decision-making [13,16,21,60]. We reconcile these disparities through our identified MR strategies that concurrently regulate both positive and negative emotions within CRs. Our work provides a comprehensive understanding of how MRs can shape future customer reviews, thereby furnishing organizations with improved strategies for their decision-making process. Specifically, our research bridges a gap in the CR/MR literature by extending the work of Chen et al. [21], who examine the external effects of MR and establish that MRs significantly increase the volume of subsequent CRs. However, the effect on the sentiment of subsequent CRs remains unclear in their work. Our findings reconcile these observations with those of earlier contributors such as Ma et al. [60], who suggest that a firm's service intervention could inadvertently incite negative customer feedback. We confirm that MR strategies are indeed effective tools in mitigating negative CRs. Similarly, our findings help to resolve conflicting perspectives from Proserpio and Zervas [13], who propose that MRs lead to a decrease in negative reviews due to the anticipated scrutiny from reviewers, and Chevalier et al. [16], who contend that MRs might trigger negative CRs as potential reviewers perceive these as more impactful. We reconcile these contradictions by presenting MR strategies as nuanced tools that empower firms to manage the emotional balance of CRs effectively. This approach simultaneously amplifies positive, while diffusing negative emotions. This enhanced understanding of MR strategies delivers crucial insights into the decision-making process for online customer interactions and paves the way for developing improved decision support systems similar contexts.

Fourth, the majority of the extant literature captures CR and MR through volume and/or valence (e.g., [49,87]). We add granularity to this approach by processing longitudinal unstructured online textual data from a unique dataset of customer reviews and management responses taken from the TripAdvisor website. This methodological contribution, inspired by Liu et al. [17], Biswas et al. [90], and Siering et al. [11], advances the analytical frontier by integrating text mining-related techniques and econometric modeling analysis. We use a computational linguistic technique to develop a custom dictionary, following traditional dictionary development standards [67]. Our dictionary-analysis approach uses top-down text-mining to transform an unstructured, textual dataset into structured, numeric data. We next systematically analyze the data using econometric methods. Researchers who wish to examine written or transcribed management responses in firm-customer exchanges may use these dictionaries as a starting point for their own investigations into response strategies.

5.2 Managerial Implications and Limitations

The research findings suggest four managerial implications for regulating customers' emotions, rating behaviors and firms' reputations in online environments. First, our study confirms that firms can strategically utilize an array of MR tools to concurrently manage both positive and negative consumer emotions and rating scores. This provides companies with a more sophisticated approach to customer relationship management and decision-making in online dialogues, paving the way for the development of more robust decision support systems tailored to this purpose.

Second, we advise firms to communicate sincerity and offer compliments to their customers in MRs to intensify positive emotional contagion. On the other hand, expressing empathy and proposing remedies in MRs are effective tactics to mitigate the spread of negative emotions among customers. These strategic recommendations improve firms' decision-making capabilities by providing actionable approaches that positively shape customer emotions, enhancing online reputation management.

Third, our study reveals that the presence and length of MRs are valuable in controlling consumer rating behaviors. This finding serves as a practical decision-making tool for firms—guiding formulation and implementation of effective customer review response strategies.

Fourth, we furnish firms with a comprehensive reputation management step-by-step guide for collecting, monitoring, and influencing customer social conversations. This significant practical contribution enhances decision-making processes related to reputation management in digital spaces, thereby offering firms an informed approach to navigating the intricate landscape of online customer relations.

Our analysis, naturally, has limitations. First, this study quantitively investigated online manifestations of a single industry. Future research might assess whether our results hold true for other industries. Second, we focus on specific online textual data to represent online CR/MR components. Other online channels used by customers and firms to express their opinions are not captured here. Third, since online CR/MR textual data may suffer from selection bias, a fully randomized experiment might help to validate the findings. Fourth, and most importantly, it would be valuable to extend this study and connect the online CR/MR data with the transactional data of the focal firms, such as sales, sales growth, booking rates, and stock prices, on a longitudinal scale, to assess whether the moderating effects of MRs do, in fact, impact a firms' actual business performance.

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Figures

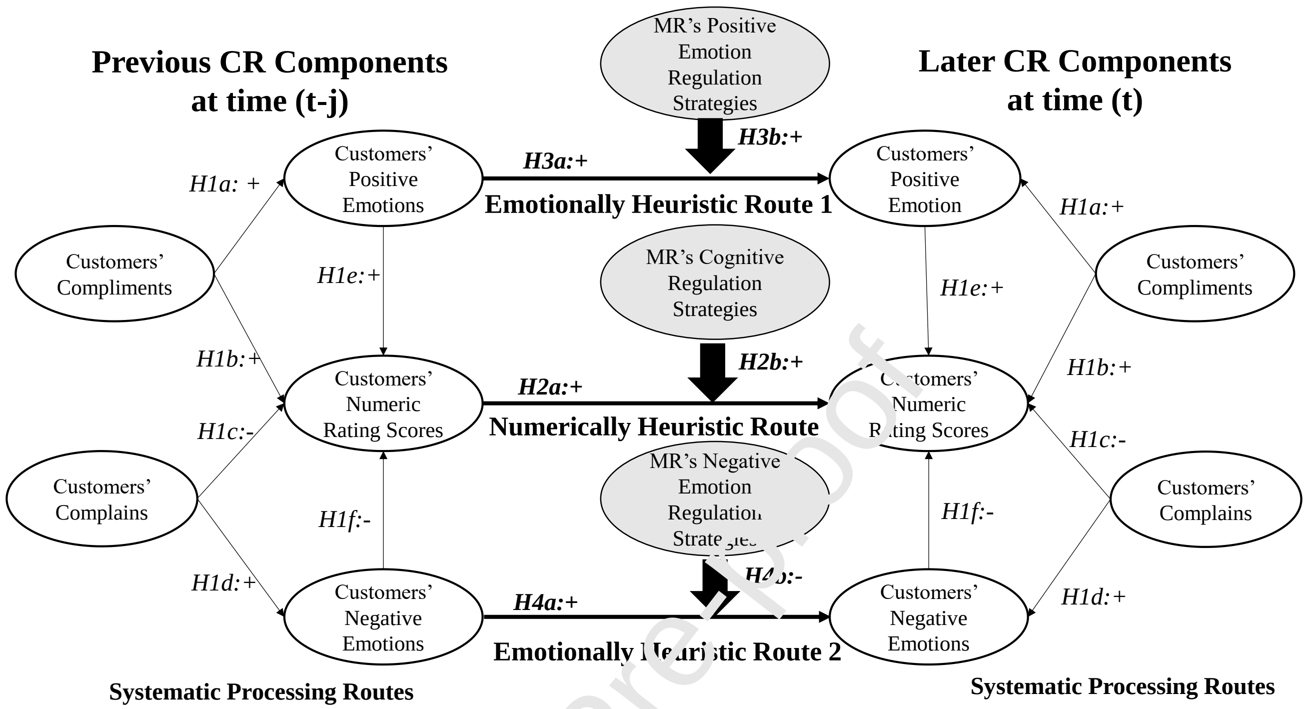

Fig. 1 The Conceptual Framework to Depict CR-MR Dynamic

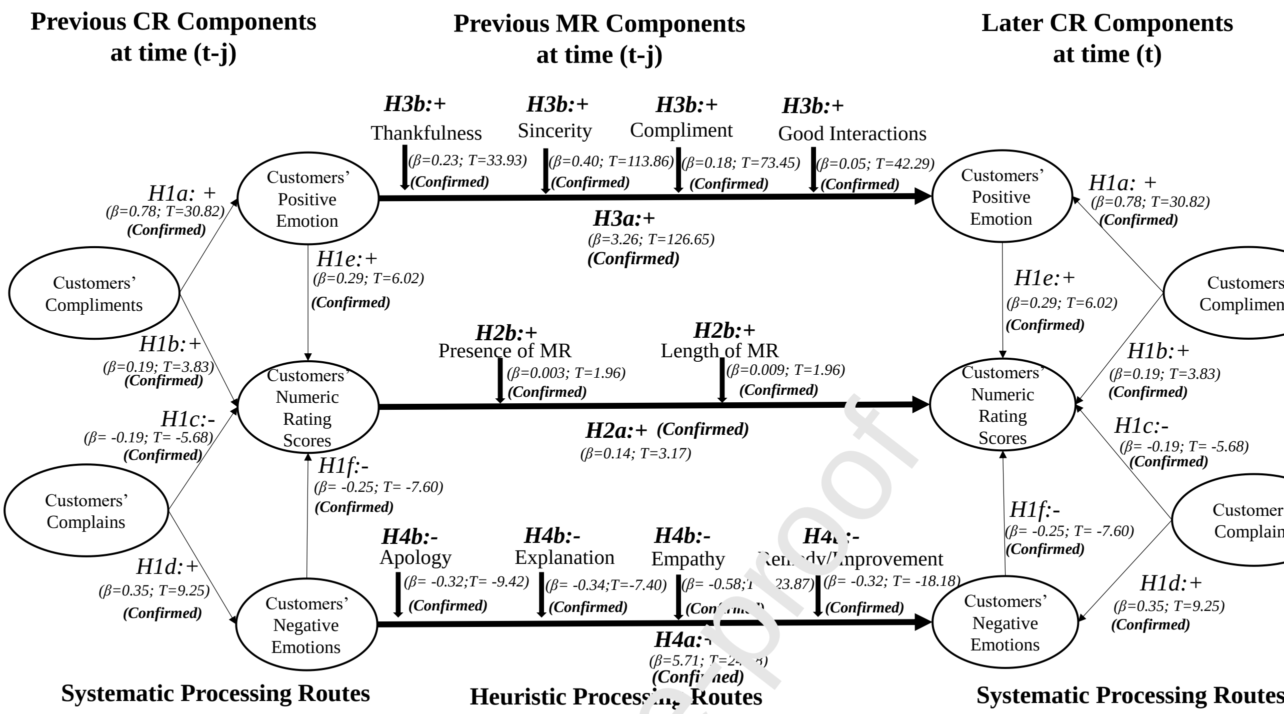

Fig. 2 The Summary of Empirical Results of H1-H4

Author Biography

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Hsiu- Yu is an assistant professor of marketing at National Taiwan Normal University. Her research interests include customer experience, customer journey, dynamic relationship management, the marketing strategic application of big data and text analysis.

2. Yansong Hu

Yansong is an Associate Professor of Marketing at Warwick Business School. His research focuses on new product development and diffusion, and social networks, and has won several international awards, including the Best Paper in Marketing and Technology Track in American Marketing Association Winter Marketing Educators' Conference (Austin), the M.Wayne DeLozier Best Conference Paper Award at the Academy of Marketing Science Conference (Florida), and an Honorable Mention Award in American Marketing Association TechSIG Best Dissertation Competition (Washington D.C.). His co-authored research output has appeared in marketing and management journals, including Marketing Science, and Journal of Product Innovation Management. He has taught both undergraduates and postgraduates, as well as business executives, and has received Excellent Teaching Award from Warwick Business School.

3. Nick Lee

Professor Lee leads the core Marketing module on the WBS Distance Learning MBA, which is currently the top-ranked distance learning MBA in the world (FT Rankings 2018, 2019, 2020, 2021, 2022). He also teaches quantitative research methods on the WBS DBA, and Philosophy of Science and Quantitative Methods on the WBS PhD. He is the Research Environment Lead for the Marketing Group at WBS. In 2009, Nick was one of the youngest-ever scholars in marketing to be appointed to a Full Professorship, a year in which he was also featured in The Times as 'one of the 15 scientists whose work will shape the future'. Nick's work has appeared in world-leading journals across multiple fields of business research and behavioral / psychological science, including The Journal of Marketing Research, The Journal of the Academy of Marketing Science, Organization Science, Journal of Management, Journal of Business Ethics, Human Relations, Organizational Research Methods, Frontiers in Human Neuroscience, the American Journal of Bioethics, and PLOS One. These papers have been cited over 9500 times (1 July 2022) since his first publication in 2005.

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Hsien-Tung is a Professor of Marketing at Business Administration Department of National Taipei University. His research focuses on online community behavior, brand community, customer relationship management and service innovation. Professor Tsai's work has appeared in world-leading journals including MIS Quarterly, Decision Support Systems, Journal of the Association for Information Systems, Information & Management, International Journal of Human-Computer Studies, European Journal of Marketing, Psychology and Marketing.

Credit Author Statement

Hsiu-Yu Hung: Conceptualization, Methodology, Data curation, Writing- Original draft preparation.

Yansong Hu: Dictionary development and validation, Investigation, Methodology Consultant.

Nick Lee: Supervision, Writing- Reviewing and Editing.

Hsien-Tung Tsai: Writing- Reviewing and Editing, Project and Revision Consultant.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Highlights

- Integrates HSM, emotion contagion, and regulation theories for a comprehensive CR/MR model.
- Identifies ten strategic MR components for regulating heuristic processing routes.
- Employs text mining and econometric modeling for analyzing longitudinal online data.
- Provides practical guidance to firms for effectively managing online customers' emotions.
- Connects online CR/MR data with transactional data for potential impact on business performance.

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[i] Footnote: you can find the github link https://github.com/NashXU/Tripadvisor_LA_Scraper for using python programming algorithm to conduct simple random sampling (without repetition) and the following data collection procedueres here.