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The influence of patient-generated reviews and doctor-patient relationship on online consultations in China

Yajie Hu[1] · Huiwen Zhou[1] · Yuangao Chen[2] · Jianrong Yao[2] · Jiangwu Su[2]

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Abstract
Online reviews are increasingly being used and researched by people worldwide. Compared with previous studies on traditional products or services, research focused on online health communities (OHCs) is still insufficient. Thus, based on cue diagnosticity theory, this research concentrates on combining two mainstream studies by incorporating the patient-generated review with the unique characteristics of online medical services–the doctor-patient relationship–to study the information processing issues in choosing consultations. We clawed the dataset, including 2865 doctors related to 152,864 patient-generated reviews and information, from the GoodDoctor website. We then employed a negative binomial regression to test our hypotheses. Interestingly, we found that the effects of review length and review volume on doctors' consultations can be negatively moderated by the doctor-patient relationship. Our findings can serve patients, doctors, platform managers, and others to optimize the application of patients' information processing when choosing consultations.

Keywords Online health communities · Patient-generated review · Doctor-patient relationship · Cue diagnosticity theory

1 Introduction

Although "e-patients" can access online healthcare consultations in online health communities (OHCs) anywhere and anytime [1, 2], they are also disturbed by the severe information asymmetry that can hinder quality judgment [3]. To reduce the uncertainty and risk related to purchasing intention, consumers generally resort to voluminous information cues disclosing doctors' service quality, which helps in their judgment before they arrange consultations [4–6]. While several studies

✉ Huiwen Zhou
zhw_ZUFE@163.com

Extended author information available on the last page of the article

have contributed to the significance of novel information cues in OHCs, including patient-generated reviews and doctor-patient relationships [5, 7, 8], few studies have integrated and explored the effects of specific information cues: patient-generated reviews and doctor-patient relationships on doctor's online consultations in OHCs. This research, therefore, aims to serve patients, doctors, and platform managers in China by offering suggestions based on the exploration of the above novel effects in OHCs.

The cue diagnosticity theory indicates that various product cues empower individuals to make quality judgments simultaneously [9, 10]. Given the distinction of different cues' diagnosticity [9, 10], they can be classified into high- and low-scope cues [11, 12]. High-scope cues refer to those in which valence change requires considerable time and financial investment, and is perceived as more credible and diagnostic than low-scope cues [13]. In contrast, low-scope cues can be more easily manipulated, which are ambiguous in indicating quality [13]. Before the emergence of OHCs, previous studies explored the influence of patient-generated review cues, review length, and review volume on sales in various industries, including the book [14], entertainment [15], online retailer [16], and game industries [17]. In line with the perspective of cue diagnosticity, although the online review related cues are product-related attributes that indirectly assess product quality and can be altered[18], they are helpful in purchase decision-making by reducing uncertainties[19]. Extending these findings to the current research, review length and review volume are conceptualized as low-scope cues, as the above patient-generated review cues are relatively ambiguous and indirectly indicate the doctor's quality [20, 21]. Accordingly, both review length and review volume can serve as low-scope cues that indirectly indicate doctor-related quality attributes in OHCs; this can thereby contribute to consumers' quality judgments. With the rise of OHCs, the exploration of specific information characteristics has not remained limited to online review features; the significance of the doctor-patient relationship among various doctor-related information cues in OHCs has attracted growing scholarly attention [7, 22, 23]. On the one hand, some researchers indicated that the doctor-patient relationship, as a doctor's investment, can boost a doctor's reputation and economic returns in OHCs [7]. On the other hand, other researchers classified the seller's reputation as a high-scope cue, which significantly influences consumer product quality evaluation [21]. In addition, the doctor-patient relationship not only signals the recognition and confidence of patients [24] but also comprehensively represents the doctor's service quality [5], which plays a valuable role in patients' problem-solving, especially in China [24]. Accordingly, we classified the doctor-patient relationship into the high-scope cue, in which valence change requires considerable investment and is perceived as more credible and diagnostic than low-scope cues [11–13]. In sum, considering that consumers come in contact with and process various information cues simultaneously, not only the effects of social cues should be considered, but also the potential influence of other information should be included as well [20]. However, there is a dearth of doctors' online consultation-related studies that combine the perspective of doctor-patient relationships with patient-generated reviews in OHCs. To fill this gap, based on the

cue diagnosticity theory, this study clarifies the link between patient-generated reviews and doctors' online consultations by integrating the doctors' specific information attribute, the doctor-patient relationship in OHCs.

Additionally, the joint effects of different cues in information processing should not be neglected when consumers are simultaneously exposed to various cues [20]. This viewpoint is supported by the cue diagnosticity theory, which highlights that cues do not work independently but act together on decision-making judgments [18]. For example, some researchers have studied the interactions of high-scope cues (i.e., brand reputation) and low-scope cues on consumer perceptions of quality [25]. Other researchers have investigated the effects of three-way interactions among different cues in consumers' hotel booking decision processes [26]. However, in the context of OHCs, the joint effects of patient-generated reviews and doctor-related information cues have not drawn adequate attention. Moreover, while both high -and low-scope cues are employed by practitioners and researchers, there still exists a conflicting conclusions regarding the interaction effects among different cues. Whereas the cue consistency theory insists on the synergetic effects of multiple consistent cues [20, 27], the cue diagnosticity theory indicates the attenuated effects of high-scope cues on low-scope cues [12, 13]. However, whether the interaction effect among novel information cues in OHCs is synergetic or attenuated remains under-researched. To this end, this study further investigates the joint effects of high- and low-scope cues by focusing on the moderating role of doctor-patient relationships in the effects of review length and review volume on doctors' consultations. Given the above research gaps, this research, therefore, aims to explore the following questions:

RQ1. *How do consumers possess information related to patient-generated reviews and the doctor-patient relationship in choosing doctors' consultations?*
RQ2. *Does the doctor-patient relationship moderate the effects of review length on doctors' consultations?*
RQ3. *Does the doctor-patient relationship moderate the effects of review volume on doctors' consultations?*

We constructed a research model based on the cue diagnosticity theory, exploring the effects of review volume, review length, and doctor-patient relationships on doctors' consultations. To verify the above hypotheses in the model, we collected data of 2865 doctors related to 152,864 patient-generated reviews and information, from the GoodDoctor website. Employing a negative binomial regression, we found that review length, review volume, and doctor-patient relationship positively affect doctors' consultations. More importantly, the doctor-patient relationship negatively moderates the effects of review length and review volume on doctors' consultations.

This study enriches the research on OHCs from two perspectives. First, following the current research hotspot, this study integrates and explores the effects of specific information attributes in OHCs: the doctor-patient relationship with review length and review volume on online consultations by extending the application of

cue diagnosticity theory in OHCs. Second, based on the cue diagnosticity theory, this study also contributes to the literature by investigating the moderating effects of the doctor-patient relationship on the influence of review length and review volume on doctors' online consultations in OHCs.

The remainder of this paper is organized as follows: In Sect. 2, we present the literature review; in Sect. 3, we focus on the research model and hypotheses; Sect. 4 is centered on the introduction of methods; Sect. 5 presents the results and robustness check of our study; and finally, we end the article with the discussion and conclusions.

2 Literature review

2.1 Patient-generated reviews

Patient-generated reviews refer to reviews generated by patients who have experienced online healthcare services [5, 28]. In practice, compared with online rating websites that have similar structures or forms of reviews, patient rating websites emphasize patient satisfaction and physicians' performance [29]. Additionally, previous studies on the characteristics of online reviews have provided a solid foundation for examining the effects of patient-generated reviews on doctors' online consultations in OHCs from various dimensions. Prior research has also laid the groundwork for exploring various review characteristics of OHCs. Studies have investigated the influence of review length on perceived review helpfulness from the perspective of information processing [30–32]. Many have explored the effects of review length on sales in various industries [33, 34]. Additionally, the influence of review volume on sales or purchase intentions has also been discussed in various industries [15, 16, 35]. In addition to review volume or review length, other review characteristics have also been explored by researchers from various perspectives. For example, some have used the automatic question answering method to enrich the questionnaire method, the result of which was an inspiration for the discovery of review sentiment [36]. Other studies focused on the deep mining of the four dimensions of review content details, user profiles, business neighborhoods, and business profiles, which enriched the relevant research on the usefulness of reviews [37]. There is also a cross-platform comparison of book reviews on e-commerce websites and social networking sites [38]. By conducting review content mining, research has confirmed the usefulness of perceived academic review [39]. Additionally, based on review information, research across China and the United States has pointed out differences in consumer behavior among different countries [40].

By reviewing previous research (see Table 1), we found that the information attributes of patient-generated reviews are not the only significant predictor of doctors' online consultations. We discovered that other important doctors' attributes, such as the doctor-patient relationship, may also affect doctors' consultations. The doctor-patient relationship refers to the relationship that is primarily constructed by the elements of knowledge, trust, loyalty, and respect which reciprocally relate doctors and patients [41, 42]. However, few studies have explored the predictors

of doctors' online consultations by bridging doctors' information attributes among patient-generated reviews with doctor-patient relationships. Moreover, although previous research has deepened our understanding of the influence of review length, review volume, and doctor-patient relationship, they may have overlooked the interaction of review characteristics and doctor-patient relationships on doctors' online consultations. Do the effects of review length or review volume on doctors' online consultations, vary with different contexts of the doctor-patient relationship? To answer this question, this research further explored the joint effects of the doctor-patient relationship and patient-generated reviews on doctors' online consultations.

2.2 Cue diagnosticity theory

The cue diagnosticity theory indicates that consumers rely on the diagnosticity of cues in assisting them in making quality judgments [9, 10], which helps in the understanding of the effects of cues on quality judgments and purchase decisions [10, 45]. Diagnosticity refers to the reliability and accuracy of the classification of quality judgments [13, 26]. Quality assessment can be understood as the categorization process by which consumers classify an item into a specific category based on available cues [2, 13]. The more clearly the quality can be classified, the more diagnostic the cue will be [13]. In the context of the present research, consumers may rely on processing various specific information cues, such as patient-generated reviews, related indicators of the doctor-patient relationship, and so on, to assist their decision-making before online consultations in OHCs. Furthermore, cue diagnosticity theory also indicates that cues can be classified into high- or low-scope cues based on diagnosticity [11, 12]. Compared with low-scope cues, high-scope cues are more reliable and diagnostic, requiring more time and financial investment; however, it is also less likely to be altered by other cues [13]. In contrast, the diagnosticity of low-scope cues is relatively weaker, unstable, and is susceptible to high-scope cues [26]. Extending this information to the current research, the doctor-patient relationship plays an important role in high-scope cues of information processing in OHCs, which not only signals the recognition and confidence of patients [24] but also comprehensively represents the doctor's service quality [5]. Moreover, compared with other information cues, such as review volume or review length, the doctor-patient relationship not only requires more time and financial investment, but it also more directly reflects the intrinsic characteristics of doctors.

Furthermore, cue diagnosticity theory holds that information cues are not independent in actual judgments, but jointly influence the decision-making process [18]. For instance, Khare et al. [40] found interactions among various cues, including the need for uniqueness, WOM volume, and WOM valence interaction. Wen et al. [26] indicated that online reviews could moderate brand familiarity with booking intentions. Moreover, high-scope cues have the characteristics of dominance and prominence [26], implying that the influence of high-scope cues on decision-making includes both direct and indirect effects [12], although it enhances or weakens the diagnosticity of low-scope cues [13]. The current research investigates such potential

Table 1 Summary of studies in OHCs

Studies	Data source	Independent Variables	Dependent Variables	Main Findings
[22]	Haodf.com	Status capital; Decisional capital	Social Returns; Economic Returns	Both social and economic returns are positively and significantly derived from doctors' status capital and decisional capital
[23]	Haodf.com	Written consultation service; Telephone consultation service; Doctor gifts; Doctor title	Online Booking Service in Hospitals	Written consultation positively influences the online booking service in hospitals. Telephone consultation has a negative effect on online booking services in hospitals. The mitigating role of doctor's reputation played in the link between consultation services on online booking services in hospitals
[7]	Haodf.com	Doctor–patient relationship strength	Economic returns; Social returns	Both the weak ties and strong ties between doctors and patients do increase both the social and economic returns of doctors. The significant mediating role of strong ties on weak ties in doctor-patient communication
[43]	Questionnaire	Doctor-patient relationship; Reliability of online health information; Health information seeking scores; Health care profession; Reasonability of data exchange; Age; Education; Gender	Using the Internet as a source of health information	Most respondents (79%) rely on the Internet to seek health information, which is regarded as the most commonly used source for health information. The usage of the Internet as a source for health-related information across digital age groups
[24]	Haodf.com	Online interpersonal unfairness; Online informational unfairness; Professional seniority; Disease severity	Patient–doctor relationship quality	Online interpersonal unfairness has negative effects on patient-doctor relationship quality. Online informational unfairness positively influences patient-doctor relationship quality. Both the doctor's professional seniority and disease severity strengthen the link between unfairness perceptions and doctor-patient relationship quality

Table 1 (continued)

Studies	Data source	Independent Variables	Dependent Variables	Main Findings
[5]	Haodf.com	Patient generated information; System generated information	The number of patients who visited a physician's homepage; The number of patients who consulted a physician online	Both the positive patient-generated and system-generated information can positively influence patients' reactions
[8]	Questionnaire	Review valence; Disease risk; Trust	Patient choice	Review valence has positive effects on physician selection, and negative reviews have greater influence than positive reviews
[44]	Questionnaire	Review style; Number of reviews	Attitude toward the reviewed physician	Information attributes, such as review style and review number have effects on the patient's attitude toward the rated doctor

indirect effects by focusing on the moderating role of doctor-patient relationships in the effects of review length and review volume on doctors' online consultations.

3 Research model and hypotheses

Based on cue diagnosticity theory, we constructed a research model to investigate the effects of patient-generated reviews and doctor-patient relationships on doctors' consultations. As shown in Fig. 1, we hypothesized that the review volume, review length, and doctor-patient relationship positively affect doctors' consultations. However, the doctor-patient relationship can weaken the effects of review volume and review length on doctors' consultations.

3.1 The effects of review characteristics on doctors' consultations

While higher uncertainty tied to information asymmetry results in lower sales, online reviews are helpful in purchase decision-making as they reduce uncertainties [19]. Given that the review content contains valuable information about products and services, consumers tend to read related online reviews before making a decision [46]. As a reflection of review content details, review length refers to the total number of words in a review [47], which plays an important role in indicating review quality [19]. Lengthy reviews are beneficial for clearing information uncertainty and mitigating information asymmetry, which positively influences sales in various industries [33, 34]. In other words, review length captures the clearance of information uncertainty, thereby affecting consumers' purchase decisions.

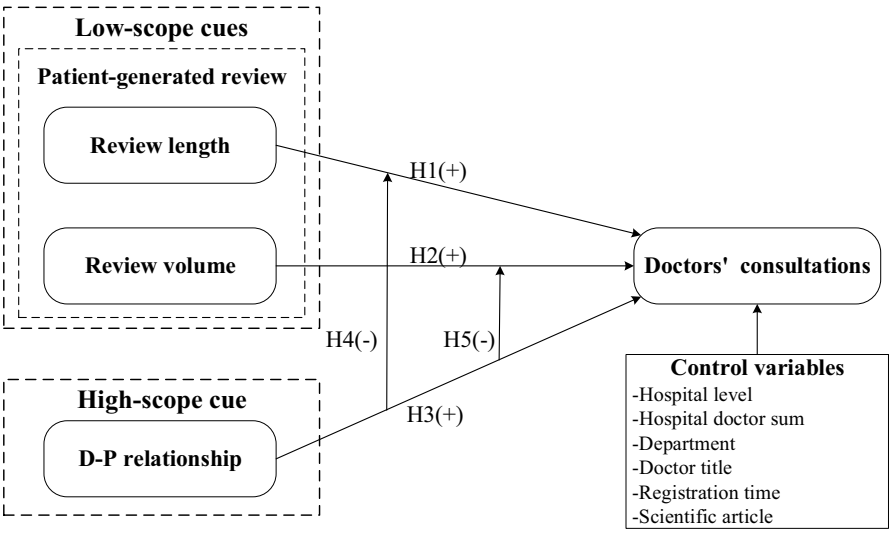

Fig. 1 Research model

In the context of OHCs, previous studies have shown that the majority of ratings and reviews posted on physician-rating websites of OHCs are positive [48–52]. Combined with the cue diagnosticity theory, review length may also work as a diagnostic cue in OHCs, indicating the reduction of information uncertainty, and thereby boosting doctors' consultations. Whereas a longer review can benefit doctors' online consultations by providing more details and mitigating information uncertainty [53], the richness of information in shorter reviews might be limited to a certain extent, thus discounting the potential effects of mitigating information asymmetry. Thus, we infer that longer reviews may have a positive influence on doctors' consultations. Accordingly, we posit the following hypothesis:

H1 Review length has a positive effect on doctors' consultations.

In contrast to content detail indicators, such as review length, review volume is a reflection of social consensus, referring to the total number of posted reviews [54]. The influence of review volume on sales has aroused general discussion in various industries, including the book [14], entertainment [15], online retailer [16], and game industries [17]. Review volume not only captures the awareness of purchase but also represents the product's popularity [35, 55], which serves as an important predictor of sales. The review volume does play an informative role in increasing the frequency of communication, which can enhance the probability of other users to notice and purchase products [16]. That is, increasing exposure to online reviews leads to a higher possibility of consumer awareness and purchase [16]. Similarly, a flood of reviews generally indicates the popularity of products and drives an increase in product sales [14, 35]. Given the uncertainty-reduction benefit and informativeness, a larger volume of WOM is considered more diagnostic and influential in information quality [56]. Extrapolating these findings to the current research, a larger review volume may also be associated with an increase in doctors' consultations, with the dominance of positive reviews in OHCs. Thus, an increase in review volume may drive the promotion of doctors' consultations. Accordingly, we propose the following:

H2 Review volume has a positive effect on doctors' consultations.

3.1.1 The effects of doctor-patient relationship on doctors' consultations

In addition to the effects of indirect signals of extrinsic cues, such as review length or review volume, on consumers' online decision-making, the direct roles of intrinsic cues should also not be neglected [12]. In the context of OHCs, the doctor-patient relationship is intrinsic to the doctor's attribute and refers to the relationship primarily built by the elements of knowledge, trust, loyalty, and regard, which reciprocally relate doctors and patients [41, 42]. On the one hand, some researchers indicated that the doctor-patient relationship, as a doctor's investment, can boost a doctor's reputation and economic returns in OHCs [7]. On the other hand, other researchers classified the seller's reputation as a high-scope cue, which significantly influences consumer product quality evaluation [21]. Given the serious information asymmetry,

the doctor-patient relationship captures the intrinsic and diagnostic attributes of doctors, which may work as an important factor driving the increase in doctors' consultations. As per cue diagnosticity theory, the doctor-patient relationship not only signals the recognition and confidence of doctors [24] but also comprehensively represents the doctor's medical skills and service attitude, which effectively helps customers tackle information asymmetry in purchase decision-making [45]. In sum, we infer that the doctor-patient relationship may positively influence the doctor's consultations. Thus, we hypothesize:

H3 The doctor-patient relationship has a positive effect on doctors' consultations.

In view of consumers being exposed to and processing various information simultaneously in OHCs, the influence of information cues on doctors' online consultations needs to be further examined by considering the joint effects of various cues [20]. When multiple cues are supplied by OHCs, cue diagnosticity theory sheds light on the mechanism of the joint effects mentioned above. The theory indicates that there exist attenuating effects between high- and low-scope cues; high-scope cues with more diagnosticity weaken the diagnosticity of other cues [18, 26]. In other words, the diagnosticity of low-scope cues can be altered by high-scope cues [56]. The theory also suggests that customers are more inclined to use high-scope cues, rather than low-scope ones, as key diagnostic cues for judgments [12]. We can infer that there may exist a competition between review length and the doctor-patient relationship in mitigating information asymmetry. Accordingly, we assume that the doctor-patient relationship may negatively moderate the effect of review length on doctors' consultations.

In line with cue diagnosticity theory, intrinsic cues generally dominate extrinsic cues [18, 20]. Specifically, the former are inherent to the product itself, distinct from the latter, which are indirectly associated with product-related attributes [18]. Extending this information to the present research, in contrast to review length as an extrinsic patient-generated information attribute of the doctor, the doctor-patient relationship directly draws on doctors' intrinsic attributes, which can be classified as high-scope cues with elevated diagnosticity. That is, the doctor-patient relationship is more directly indicative of intrinsic attributes by representing the patients' satisfaction and gratitude to doctors' medical level and service attitude [24]; this could be more diagnostic in helping potential consumers make quality judgments, compared to low-scope cues such as review length [13]. Thus, there may exist an attenuating effect of the doctor-patient relationship on the review length. Given the above discussion, we infer that the doctor-patient relationship may weaken the effects of review length on doctors' consultations.

H4 The positive effect of review length on doctors' consultations is negatively moderated by the doctor-patient relationship.

Although the review volume focuses on a more holistic level of review characteristics rather than review length, which reflects the content details of online review

[35], both can indirectly reflect the information related to consulted doctors. Similarly, based on the attenuating effect of a high-scope cue on low-scope cues in cue diagnosticity theory [18], we infer that the doctor-patient relationship may weaken the effect of review volume on doctors' consultations. Specifically, when a good doctor-patient relationship is exhibited, OHC users may prefer to use such high diagnostic cues, thus weakening the role of review volume in doctor quality judgment [54]. In contrast, when information cues, such as the doctor-patient relationship are missing or are unhelpful, users tend to invest more cognitive effort in extrinsic cues to assess the doctor's quality [18]. Accordingly, the doctor-patient relationship may not only work as a high-scope cue assisting medical consultation judgments but may also attenuate the effects of review volume on doctors' consultations. Besides, previous research on high-scope cues in other fields also gives support for our conjecture. Some previous studies classified reputation or brand names as high-scope cues in their studies [13, 26], while others found that reputation has a moderating effect on sales [12, 23]. Similarly, the doctor-patient relationship is an important doctor's social capital investment, which not only helps in predicting the doctor's reputation but also benefits the doctor's economic returns in OHCs [7]. Based on the above discussion, we infer that the doctor-patient relationship may weaken the effects of review volume on doctors' consultations. Thus, we hypothesize:

H5 The positive effect of review volume on doctors' consultations is negatively moderated by the doctor-patient relationship.

4 Methods

4.1 Data collection

To test the above hypotheses, we randomly collected data from the GoodDoctor website (www.haodf.com), one of the earliest and largest patient-generated review platforms in China [57]. Currently, more than 10,000 hospitals and more than 600,000 doctors are featured on the website. We chose this site for several reasons. First, it is large in scale, and previous research on this platform has laid the foundation for our research. Second, given the platform public abundant patient-generated review, which could support us with sufficient data for research. Third, the platform has a review process to identify the authenticity of the reviewer identity information and medical information, which resolves our concerns about false reviews or invalid comments to a certain extent. Figure 2 shows an example of a doctor's homepage. Figure 3 shows an example of a hospital's homepage.

We then used a Python-developed crawler program to collect all the required data for the first round, from December 5, 2019, to December 11, 2019. At the hospital level, we collected the primary data from each hospital. At the department level, following the guidance of the previous study [58], we chose six departments for our research: traditional Chinese medicine, pediatrics, cardiovascular medicine, obstetrics and gynecology, blood internal medicine, and thoracic surgery. At the doctor's

Fig. 2 An example of a doctor's homepage

level, we primarily collected all reviews of each doctor and information about doctors posted on the platform. Furthermore, following the previous strategy, we matched the URL and the name of each level to integrate this dataset [59]. After deleting abnormal or missing data, we finally obtained a dataset of 2,865 doctors and related 152,864 reviews for the first round. To solve the potential impact of reversed causality, we collected the dependent variable data again on March 7, 2020.

Fig. 3 An example of hospital's homepage

4.2 Variables and measurements

The dependent variable was doctors' consultations, and it was measured by calculating the number of online consulted patients for each doctor [5]. The independent variables included review volume, review length, and the doctor-patient relationship. Review volume is measured by referring to the doctor's total number of patient-generated reviews [54]; and review length was measured by calculating the average length of each doctor's patient-generated review.

As for the moderating variable, under the guidance of previous research, the doctor-patient relationship was measured by the number of virtual gifts [24]. The measurement of doctor-patient relationships can be interpreted from the following aspects. First, the doctor-patient relationship, a form of social capital, helps doctors obtain market and non-market benefits [7, 60]. Virtual gifts can help doctors increase their income and improve their social reputation by exhibiting such gifts on the doctor's personal homepage [5, 23, 61]. Therefore, as social capital is constituted by the relationship, the number of gifts might concisely reflect the quality of the relationship. Second, as for the patients, the virtual gift stands for the patients' appreciation, trust, and confidence in their doctors [23, 24]. A previous study indicated

that gift-giving behavior plays a significant role in strengthening this relationship [62]. In contrast to the official payment channel, giving gifts represents an informal payment, that indicates the patient's confidence in the doctor's performance [63]. Patients are willing to pay additional costs to purchase virtual gifts to express their confidence in and gratitude to the doctor, representing a high-quality relationship [24, 64]. Third, the designed website also notes and encourages patients to give virtual gifts as a channel to express a good relationship. Thus, it is reasonable to apply the number of virtual gifts as a proxy for the doctor-patient relationship.

The control variables of doctors include: (1) the total number of published academic articles by a doctor; (2) their registration time; (3) the total number of doctors in their hospital; (4) department; (5) hospital level; and (6) title. From the hospital's perspective, in line with a previous study, we employed a scale from one to six to indicate the different levels of the hospital [65]. Additionally, we considered the total number of doctors in each hospital. From the department's perspective, a dummy variable was applied to measure the doctors' department (1 represents the specified department variable, and 0 otherwise). In line with previous research, we categorized doctors' titles according to the professional grade standards of Chinese doctors, rather than the education title [65]. Doctors' medical titles included resident doctors, attending doctors, associate chief physicians, and chief physicians; we used the numbers 1, 2, 3, and 4, respectively, to assign values. We operationalized the number of days from registration until December 11, 2019, as the doctors' registration time. We considered the scientific article as the number of doctors' scientific articles shared on the website [66].

4.3 Model specification

For the dependent variable, doctors' consultations belong to a non-negative count variable. It is more suitable to use a negative binomial regression or Poisson regression rather than a standard multiple regression [53]. It is also worth noting that the dependent variable's mean is not equal to the variance, which might indicate an over-dispersion problem. Unlike the negative binomial regression, the Poisson regression requires the variable's mean to be equal to the variance; otherwise, an over-dispersion problem might still exist, and the estimated standard error might be biased downward. Therefore, as the negative binomial regression does not have the limitation of equidispersion, it is more suitable and efficient to select a negative binomial regression [53]. Moreover, because robust standard errors can avoid the effects of heterogeneity problems, robust standard errors are also considered.

We established a subsequent model to verify the proposed hypotheses. In this model,α_0 stands for the constant term, controls represent the control variables, and ε represents the idiosyncratic error.

$$\begin{aligned} Doctor's\ consultations = \alpha_0 + \beta_1 \text{Review length} + \beta_2 \text{Review Volume} + \beta_3 DP \text{ Relationship} \\ + \beta_4 (\text{Review length} \times DP \text{ Relationship}) \\ + \beta_5 (\text{Review Volume} \times DP \text{ Relationship}) \\ + \beta_6 \text{Controls} + \varepsilon \end{aligned}$$

5 Empirical results

5.1 Results

Tables 2 and 3 present the descriptive statistics and correlations of our data. The minimum number of consultations of 2865 doctors was 0, and the maximum was 31,236. Regarding reviews, the review volume ranged from one to 2263. The log value of the review length is between 6.58 and 0.41. Based on previous research, we also performed a logarithmic treatment if the variable had high skewness (skewness > 1) [66]. This included review length, number of doctors' scientific articles, and the hospital's doctor sum. In addition, variance inflation factors (VIFS) of variables ranged from 3.14 to 1.05, and were 1.98 on average, indicating that multicollinearity is unlikely to affect our results [67].

Table 4 presents the estimates of negative binomial regression. The base model included only the control variables. The second model was enlarged by adding independent variables. Finally, we gradually imported moderating variables into the third and fourth models. Considering multicollinearity, we mean-centered all the variables [68]. To deal with the problems of heteroscedasticity, we used robust standard errors [69, 70].

Table 2 Table of descriptive statistics

Variable	Minimum	Mean	Maximum	Standard deviation
1.Doctor's consultation	0	1038.12	31,236.00	2231.17
2.Doctor-patient relationship	0	91.19	6769.00	292.83
3.Review length(log)	0.41	2.94	6.58	0.94
4.Review volume	1	53.36	2263.00	109.77
5. Scientific article (log)	0	1.24	8.86	1.44
6. Registration time	12	2201.91	4299.00	1182.94
7.Hospital doctor sum (log)	0.69	6.53	7.61	0.77
8.Department 1	0	0.08	1	0.27
9.Department 2	0	0.19	1	0.39
10.Department 3	0	0.24	1	0.43
11.Department 4	0	0.14	1	0.35
12.Department 5	0	0.22	1	0.41
13.Department 6	0	0.13	1	0.34
14.Hospital level	0	5.96	6	0.32
15.Doctor title	1	3.44	4	0.71

Table 3 Table of variable correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.D-P relationship	1.00													
2.Review length(log)	0.08	1.00												
3.Review volume	0.74	0.14	1.00											
4. Scientific article (log)	0.29	0.13	0.37	1.00										
5. Registration time	0.15	−0.02	0.11	0.25	1.00									
6.Hospital doctor sum (log)	0.04	0.03	0.03	−0.10	0.09	1.00								
7.Department 1	−0.02	−0.04	−0.05	0.04	0.03	−0.11	1.00							
8.Department 2	0.07	−0.06	0.05	0.03	−0.10	−0.07	−0.14	1.00						
9.Department 3	0.07	0.03	0.07	−0.04	−0.04	0.01	−0.16	−0.27	1.00					
10.Department 4	−0.02	0.00	0.01	−0.06	0.06	0.11	−0.12	−0.20	−0.23	1.00				
11.Department 5	−0.09	0.07	−0.04	0.02	0.08	−0.02	−0.15	−0.26	−0.30	−0.22	1.00			
12.Department 6	−0.04	−0.01	−0.07	0.01	−0.02	0.06	−0.11	−0.19	−0.22	−0.16	−0.20	1.00		
13.Hospital level	−0.01	0.00	−0.02	−0.06	−0.01	0.39	−0.06	−0.03	−0.01	0.03	0.03	0.03	1.00	
14.Doctor title	0.05	−0.10	0.00	0.02	0.32	−0.08	0.00	0.05	0.02	0.11	−0.15	−0.02	−0.02	1.00

Table 4 Results of negative binomial regression analyses

Variables	Model 1	Model 2	Model 3	Model 4
Scientific article(log)	0.5979***	0.3794***	0.3680***	0.3552***
	(0.0250)	(0.0213)	(0.0202)	(0.0202)
Registration time	0.0002***	0.0002***	0.0002***	0.0002***
	(3.51e−05)	(2.99e−05)	(2.88e−05)	(2.92e−05)
Hospital doctor sum (log)	−0.0043	−0.1148*	−0.1147**	−0.1260**
	(0.0525)	(0.0456)	(0.0441)	(0.0454)
Department	Included	Included	Included	Included
Hospital level	−0.0476	0.0023	0.0014	0.0139
	(0.0916)	(0.0671)	(0.0645)	(0.0636)
Doctor title	−0.0211	0.0169	0.0187	0.0235
	(0.0546)	(0.0419)	(0.0415)	(0.0422)
Doctor-patient relationship		0.0010**	0.0020***	0.0019***
		(0.0003)	(0.0003)	(0.0003)
Review length(log)		0.2906***	0.2254***	0.2277***
		(0.0415)	(0.0413)	(0.0404)
Review volume		0.0070***	0.0061***	0.0078***
		(0.0006)	(0.0006)	(0.0006)
Relationship × Review length			−0.0017***	−0.0011***
			(0.0003)	(0.0003)
Relationship × Review volume				−2.03e-06***
				(1.76e-07)
Constant	6.1910***	6.1021***	6.1609***	6.1897***
	(0.1574)	(0.1372)	(0.1379)	(0.1392)
Log pseudolikelihood	−20,524.238	−20,094.959	−20,065.995	−20,016.237
Wald chi2	1118.69	1633.24	1714.75	1832.25
P-value chi2	0.0000	0.0000	0.0000	0.0000
Observations	2865	2865	2865	2865

*$p<0.05$, **$p<0.01$, *** $p<0.001$, +$p<0.1$

First, Hypothesis 1 predicts that longer reviews can positively influence doctors' online consultations. Based on the results of Model 2, we found that review length had a positive effect on doctors' consultations ($\beta=0.2906$, $p<0.001$). Therefore, Hypothesis 1 was supported. Second, Hypothesis 2 indicates that a larger review volume has a positive effect on doctors' online consultations. Drawing on the regression results, review volume was positively associated with doctors' consultations ($\beta=0.0070$, $p<0.001$). Thus, Hypothesis 2 was supported. Third, Hypothesis 3 posits that a good doctor-patient relationship can boost doctors' consultations. Considering the positive and significant results, the doctor-patient relationship had a positive influence on doctors' consultations ($\beta=0.0010$, $p<0.01$). Thus, Hypothesis 3 is supported.

Hypothesis 4 suggests that the doctor-patient relationship could weaken the effects of review length on doctors' consultations. We found that Hypothesis 4 was supported, as displayed by the negative coefficient, which is significant at the 0.1% level ($\beta = -0.0011$, $p < 0.001$). Hypothesis 5 assumes that the doctor-patient relationship negatively moderates the influence between review volume and doctors' consultations. The results also support hypothesis 5, as the positive relationship was weakened by the doctor-patient relationship at a 0.1% significance level ($\beta = -2.03e\text{-}06$, $p < 0.001$).

5.2 Robustness checks

The results of the robustness tests are as follows: First, given the abnormal distribution of our dependent variable, we made a log transformation of the same and used ordinary least squares (OLS) to test our hypotheses [23]. The moderating effects of the doctor-patient relationship on the effects of review length and review volume on doctors' consultations were both significant. Consistently, the results of the OLS analysis (robustness test I) were similar to the results of the negative binomial regression analyses. Second, considering other manifestations of the doctor-patient relationship, for example, the sentiment conveyed by patient-generated reviews, might also reflect the doctor-patient relationship. Therefore, we used the average review sentiment corresponding to each doctor as a proxy for the doctor-patient relationship. Specifically, sentiment can be described as "attitude, thought, or judgments prompted by feeling [71]". In OHCs, patients can use review channels to generate comments in a token of gratitude and affection, which is similar to the virtual gift channel to express the doctor-patient relationship. Then, in accordance with a previous study, we employed the SenticNet3 API and SnowNLP to calculate the sentiment strength score [72]. The SenticNet3 API was used to extract the sentiment concepts of each review, and SnowNLP was employed to achieve concept classification and tags. Finally, based on the concept of sentiment strength, the ratio of positive words in each review was calculated to measure the sentiment strength. Similarly, the result (robustness test II) supported our hypotheses as well. Third, under the guidance of previous research, we further verified the robustness of our findings concerning the potential impact of reversed causality by collecting the dependent variable data again on March 7, 2020 [33, 73]. In Table 5 (robustness Test III), we employed the negative binomial regression and proved the robustness of our findings. Fourth, to test the same, we used the review length and review volume of December 11, 2019, as the independent variables and the increase in the number of medical consultations during the time interval between December 11, 2019, and March 7, 2020, as the dependent variables. Given the existence of the zero counts dependent variable observed in our sample, we used a zero-inflation negative binomial regression model. The results also validated the robustness of our findings. Fifth, we conducted another robustness test for the group of doctors whose virtual gift quantity was non-zero, and the results were still robust (robustness test V). Sixth, we used the number of thank-you letters as another proxy variable for

Table 5 Results of robustness test

Variables	Robustness Test I	Robustness Test II	Robustness Test III	Robustness Test IV	Robustness Test V	Robustness Test VI
Scientific article(log)	0.5882***	0.3940***	0.3598***	0.3972***	0.2973***	0.3796***
	(0.0220)	(0.0202)	(0.0203)	(0.0255)	(0.0192)	(0.0204)
Registration time	0.0002***	0.0003***	0.0002***	−0.0004***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Hospital doctor sum (log)	−0.0684	−0.1120*	−0.1589***	−0.3956***	−0.1211**	−0.1467**
	(0.0432)	(0.0459)	(0.0469)	(0.0539)	(0.0432)	(0.0470)
Department	Included	Included	Included	Included	Included	Included
Hospital level	−0.0667	0.0289	0.0060	-0.1992	0.0041	0.0518
	(0.0927)	(0.0658)	(0.0668)	(0.1685)	(0.0609)	(0.0630)
Doctor title	−0.0350	0.0228	0.0281	0.0479	0.0641	0.0277
	(0.0450)	(0.0426)	(0.0441)	(0.0579)	(0.0398)	(0.0424)
Review length(log)	0.2491***	0.2206***	0.2588***	0.6628***	0.1500***	0.1061*
	(0.0417)	(0.0453)	(0.0383)	(0.0526)	(0.0373)	(0.0434)
Review volume	0.0086***	0.0089***	0.0081***	0.0084***	0.0063***	0.0045***
	(0.0006)	(0.0006)	(0.0006)	(0.0007)	(0.0005)	(0.0008)
Virtual gift	0.0014***		0.0018***	0.0011***	0.0017***	
	(0.0003)		(0.0003)	(0.0003)	(0.0003)	
Virtual gift × Length(log)	−0.0009**		−0.0010***	−0.0006**	−0.0009***	
	(0.0003)		(0.0003)	(0.0002)	(0.0002)	
Virtual gift × Volume	−2.43e-06***		−2.07e-06 ***	−2.02e-06 ***	−1.71e-06***	
	(3.96e-07)		(1.72E-07)	(1.89e-07)	(1.57e-07)	
Review sentiment		−0.7572				0.3310
		(0.5803)				(0.5531)

Table 5 (continued)

Variables	Robustness Test I	Robustness Test II	Robustness Test III	Robustness Test IV	Robustness Test V	Robustness Test VI
Review sentiment × Length(log)		−1.9865***				
		(0.4583)				
Review sentiment × Volume		−0.0497***				
		(0.0107)				
The number of thank-you letters						0.0121***
						(0.0015)
Thank-you letters × Length(log)						−0.0068***
						(0.0007)
Thank-you letters × Volume						−4.53e-06***
						(3.84e-07)
Constant	−0.2417*	6.1808***	6.0602***	3.2919***	6.4195***	6.2383***
	(0.1157)	(0.1426)	(0.0997)	(0.0383)	(0.1289)	(0.1428)
Observations	2,865	2,865	2,816	2,816	2,402	2,865
Log pseudolikelihood		−20,070.885	−19,815.77	−10,607.05	−17,815.351	−20,023.085
Wald chi2		1837.85	1837.1		1708.38	1894.22
LR chi2				1081.42		
P-value chi2		0.0000	0.0000	0.0000	0.0000	0.0000
F	199.34					
Prob > F	0.0000					
R-squared	0.539					

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$, +$p < 0.1$

the doctor-patient relationship, and the robustness results (robustness test VI) further confirmed the findings of this research.

6 Discussion and conclusions

6.1 Summary of findings

Based on cue diagnosticity theory, the current research investigates the influence of review length, review volume, and doctor-patient relationship on doctors' consultations. From the perspective of low-scope cues, our findings suggest that both review volume and review length positively influence doctors' consultations, consistent with findings of studies in other industries [14–17]. From the perspective of high-scope cues, we found that the novel information cue, doctor-patient relationship, positively influences doctors' consultations. Overall, the present research not only enriches the applications of cue diagnosticity theory in OHCs but also reveals the unique information cues in OHCs.

Moreover, the present research confirms the attenuated effects of various cues, indicating that the doctor-patient relationship negatively moderates the effects of review volume and review length on doctors' consultations. This rationale can be interpreted as follows: Based on cue diagnosticity theory, a few key diagnostic cues are employed for information processing in decision making and judgments. Compared to low-scope cues, high-scope cues are more diagnostic and may possess dominant characteristics [26]. Additionally, given the urgency of the illness, patients may be more likely to use high diagnostic cues, such as doctor-patient relationships, to choose consulted doctors more efficiently.

6.2 Theoretical implications

First, utilizing cue diagnosticity theory, this research enriches the information processing research in OHCs by bridging and investigating the effects of specific information cues: patient-generated reviews and doctor-patient relationships on doctors' online consultations in OHCs. Whereas cue diagnosticity theory has been widely used to explain consumers' decision-making behavior in information systems in various industries [9, 25, 26], the application of the theory to explore patients' decision-making behavior in OHCs is still insufficient [2]. This research deepens the understanding of cue diagnosticity theory by investigating the specific information cues in OHCs, thus paving the way for further studies on OHCs. The current research also investigates the novel information cue in OHCs: doctor-patient relationship, by applying negative binomial regression, which provides empirical evidence of the significance of the doctor-patient relationship in OHCs. In summary, our research not only provides empirical support for the development of cue diagnosticity theory in emerging field OHCs but also highlights the significance of novel characteristics in OHCs: doctor-patient relationships in information processing.

Second, our research enriches the understanding of the mechanism of information cues in OHCs by distinguishing the attenuating effects rather than the synergistic effect of the doctor-patient relationship with review length or review volume. Based on previous related studies from multiple perspectives [1, 7, 74], this study furthers the understanding of doctor-patient relationships by studying their moderating effects in OHCs. Moreover, in the conflict about the synergistic or attenuating effects between different cues, this study supports the attenuated role of the doctor-patient relationship in information processing, which is contrary to the synergy in the previously related information cues [56, 75]. In summary, our study contributes to the understanding of the attenuated role of the doctor-patient relationship in the complicated context of patient-generated review information processing in OHCs.

6.3 Practical implications

The following are the practical implications of the current research, from the perspectives of patients, doctors, and platform managers. For patients, while mentioned novel cues in OHCs may help them simplify the information processing in decision-making, they should be fully considered for further optimization as well. For doctors, it is worth noting that creating a good doctor-patient environment is a win–win situation for both doctors and patients. During the consultation, the doctor must emphasize considerably on maintaining a good doctor-patient relationship. Finally, platform managers should pay attention to the layout of relevant information cues, such as patient-generated reviews and virtual gifts. Moreover, it is suggested that platforms use their own information and resource advantages to promote the said relationship.

6.4 Limitations and future research

This study has some limitations. First, it mainly focused on studying three cues to investigate the mechanism of patient information processing. However, additional cues also exist in OHCs. Thus, future research should investigate the influence of other cues such as platform characteristics, review valence. Second, this research considered one representational website, GoodDoctor (www.haodf.com), in China as the dataset. However, there exist other OHC platforms, such as Vitals.com, RateMDs.com, and GuaHao.com. Future studies could therefore examine the effects across different platforms and countries. Third, by analyzing the collected data, the model in this article was verified, and the results explained the relationship between patient-generated reviews and doctor-patient relationships on doctors' consultations. Although we provided informational evidence for the relationship between variables, future research should use experimentation methods.

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Authors and Affiliations

Yajie Hu[1] · Huiwen Zhou[1] · Yuangao Chen[2] · Jianrong Yao[2] · Jiangwu Su[2]

Yajie Hu
huyajie77@126.com

Yuangao Chen
chenyg@zufe.edu.cn

Jianrong Yao
yjr@zufe.edu.cn

Jiangwu Su
sujiangwu163@163.com

[1] School of Public Administration, Zhejiang University of Finance and Economics, 18, Xueyuan St., 310018 Hangzhou, China

[2] School of Information Management and Artificial Intelligence, Zhejiang University of Finance and Economics, 18, Xueyuan St., 310018 Hangzhou, China