How does review content contribute to the patients' review helpfulness in online health communities?

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Abstract. This study examines the effects of review content on review helpfulness in OHCs by focusing on two variables: sentiment and informational support description. Given that review helpfulness is a truncated variable, we employ Tobit regression models to evaluate the effects. The results indicate that both positive and negative sentiment contribute to review helpfulness. Moreover, there exists a positive association between informational support description and review helpfulness. When affecting review helpfulness, informational support description negatively moderates the impact of sentiment on review helpfulness.

Keywords: online review helpfulness; sentiment; informational support description.

1. Introduction

The proliferation of information and communication technology has driven individuals to reshape their healthcare behaviors. The utilization of online health communities (OHCs) for consulting physicians is becoming increasingly prevalent. In such case, online review becomes important for patients to evaluate the physician's service. While the role of patients' online review is crucial for both physicians and patients[1, 2], a fundamental question remains: what content factors contribute to the helpfulness of these reviews? Previous researches have extensively examined online review helpfulness across various products such as hotels[3], restaurants[4], apps[5] and electronics[6]. However, there has been insufficient attention given to patients' online review helpfulness in OHCs. Healthcare services offered in OHCs are considered as credence goods[1, 2] with quality information not readily understood by patients themselves[1, 7]. Therefore, previous findings may not be applicable to patients' online review helpfulness in OHCs. To fill this gap, we investigated how does review content affect review helpfulness in OHCs. Specifically, given the uniqueness of OHCs, we focus the following review contents: sentiment and informational support description. We aim to investigate the following questions: (1) How does review sentiment affect patients' online review helpfulness? (2) What role does informational support description play in determining the helpfulness of patients' online reviews? (3) How does sentiment and informational support description interact with each other when affecting review helpfulness?

2. Methods

2.1 Data Collection

The data was collected from Haodf.com[8], a leading online health community in China established in 2006. We utilized a custom Python program to systematically extract review data from Haodf.com in May 2023, obtaining 230164 original records from 13416 physicians at the Department of Internal Medicine focusing on coronary heart disease. We also crawled the data listed in physician's homepage, which including physician's offline information such as affiliated hospital, academic title, professional title, and online information such as ratings, the number of total patients and the number of articles. We excluded the related data which lacks of critical data such as ratings. Finally, we collected a total of 210555 reviews.

2.2 Operationalization of Variables

The independent variables of this research are positive sentiment, negative sentiment and informational support description. Each review is categorized as positive, negative, or neutral. The variable for positive sentiment is assigned a value of 1 if the extraction indicates a positive sentiment; otherwise, it is set to 0. Similarly, the variable for negative sentiment is assigned a value of 1 if the extraction indicates a negative sentiment; otherwise, it is set to 0. For the variable of informational support description, it is calculated based on the total number of the medical-specific words in a review. Two dictionaries are used to identify the medical-specific vocabularies. One dictionary is medical segment dictionary, developed by Wang et al[9] and the other is the THUOCL medical dictionary. For the dependent variable, we use helpfulness vote which can be directly collected from the website. As for the control variables, we include hospital level, physician's professional title, physician's rating, and review age. If the physician is employed by a Grade A hospital, the hospital level was set as 1, otherwise it is set as 0. The professional title of chief physician is assigned a value of 1 while other type of professional titles is assigned a value of 0. The physician's rating is used directly without any further manipulations. We calculated the time duration between the review publishing date and our data collection date to obtain review age. Table 1 shows the definitions of related variables.

Table 1 Description of variables

Variable	Description
Review helpfulness (R_helpfulness)	Patients' helpfulness vote for the related review
Positive sentiment (PosSen)	1 for positive sentiment, 0 for others
Negative sentiment (NegSen)	1 for negative sentiment, 0 for others
Informational support description (Infor_des)	$=\sum MSW$; MSW denotes the medical-specific words
Hospital level (Hosp_level)	1 denotes the hospital is a Grade A hospital, 0 for others
Professional title (Pro_title)	1 denotes the physician is a chief physician, 0 denotes other types of professional title
Patients' ratings (Pa_ratings)	Online recommendations from patients
Review age (R_age)	How many weeks since the review was posted

2.3 Research model

In our dataset, the variable of review helpfulness is a non-negative variable, indicating that it is a censored variable. Therefore, employing an ordinary regression model may introduce bias in the estimated results. To ensure validity, we use the Tobit model to estimate the effects. The Tobit model is particularly suitable for analyzing censored dependent variables. In this study, the dependent variable is non-negative, therefore, the Tobit model can be used to estimate linear relationships between variables.We design two models.The first model is specified as follows:

Model 1 (main effects):

$$R\_helpfulness_i^* = \beta_0 + \beta_1 \times PosSen_i + \beta_2 \times NegSen_i + \beta_3 \times Infor\_des_i + \beta_4 \times Control_i + \varepsilon_i$$

$$R\_helpfulness = max(0, R\_helpfulness_i^*)$$

The second model is designed as follows:

Model 2 (moderating effects):

$$\begin{aligned} R\_helpfulness_i^* = {} & \beta_0 + \beta_1 \times PosSen_i + \beta_2 \times NegSen_i + \beta_3 \times Infor\_des_i + \\ & \beta_4 \times Infor\_des_i \times PosSen_i + \beta_5 \times Infor\_des_i \times NegSen_i + \\ & \beta_6 \times Control_i + \varepsilon_i \end{aligned}$$

$$R\_helpfulness = max(0, R\_helpfulness_i^*)$$

where $R\_helpfulness_i^*$ is a latent variable, $R\_helpfulness_i$ is the dependent variable.

For Model 1, we concentrate on the direct effect of positive sentiment, negative sentiment and informational support description while model 2 is focused on the moderating effect of informational support description. The estimation of these models is performed through Stata 18.

3. Results

Table 2 Descriptive statics

Variable	Mean	SD	Min	Max	VIF[a]
R_helpfulness	0.770	4.220	0	666	--[b]
Sentiment, n (%)					
PosSen	189,500(90)				1.79
NegSen	6,317(3.0)				1.57
Infor_des	3.440	5.250	0	248	1.08
Hosp_level, n (%)					
Grade A hospital	191,605(91.0)				1.07
Pro_title, n (%)					
Chief physician	128,439(61.0)				1.16
Pa_ratings	3.860	0.500	2.500	5	1.50
R_age in weeks	68.78	46.19	5	200	1.73

[a]VIF: variance inflation factor.
--[b]: Not applicable.

Table 2 shows the descriptive static results. Also, we run the VIF test, which indicates no multicollinearity concern for the variables utilized in this study as their VIF values are all below 10.

Table 3 Tobit regression results

	Base model	Model 1	Model 2
PosSen		14.66***	15.07***
		(0.176)	(0.185)
NegSen		17.67***	19.86***
		(0.233)	(0.257)
Infor_des		0.379***	0.726***
		(0.00518)	(0.0228)
Infor_des* PosSen			-0.324***
			(0.0234)
Infor_des* NegSen			-0.536***
			(0.0257)
Hosp_level	1.056***	0.486***	0.493***
	(0.127)	(0.123)	(0.123)
Pro_title	3.240***	2.279***	2.256***
	(0.0842)	(0.0809)	(0.0809)
Pa_ratings	1.691***	1.492***	1.489***
	(0.0968)	(0.0933)	(0.0933)
R_age	0.131***	0.145***	0.145***
	(0.000901)	(0.000917)	(0.000919)
constant	-30.34***	-44.33***	-44.83***
	(0.398)	(0.436)	(0.440)
sigma constant	10.43***	9.687***	9.675***
	(0.0387)	(0.0352)	(0.0351)
N	210555	210555	210555
Log likelihood	-197178.88	-187469.34	-187218.95

Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The regression results are shown in Table 3. Base model only contains control variables. As shown by column 3 of Table 3, supports that positive sentiment in a review has a significant positive association with patients' review helpfulness (β=14.66, $p < 0.01$). According to column 3 of Table 3, negative sentiment in a review is positively and significantly associated with patients' review helpfulness (β=17.67, $p < 0.01$). Furthermore, informational support description has a significant positive relationship with patients' review helpfulness as shown by column 3 of Table 3 (β=0.379, $p < 0.01$).

The moderating effect of informational support description is demonstrated in Column 4 of Table 3. The coefficient of Infor_des * PosSen is significantly negative (β=-0.324, $p < 0.01$), indicating that the positive sentiment's impact is negatively moderated by the informational support description. Similarly, the coefficient of Infor_des * NegSen is significantly negative (β=-0.536, $p < 0.01$), which indicates that as the informational support description increases, the positive effect of negative sentiment on review helpfulness weakens. Hence, the positive relationship between negative sentiment and review helpfulness is negatively moderated by the informational support description.

4. Conclusion

The present study illustrates how review contents in OHCs, in terms of sentiment and informational support description, can be utilized to examine the review helpfulness in OHCs. The results show that both positive and negative sentiment have positive effect on review helpfulness. Informational support description plays a similar positive role when affecting review helpfulness. Additionally, informational support description negatively moderates the positive effect of both positive sentiment and negative sentiment on patients' online review helpfulness.

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