Physicians' Online Popularity and Price Premiums for Online Health Consultations: A Combined Signaling Theory and Online Feedback Mechanisms Explanation

Submission Type: Research-in-Progress

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Abstract

Online health consultation communities (OHCCs) provide a digital channel for physicians to signal their professional competence (i.e., credibility) and compassionate care (i.e., benevolence), and for patients to spread word-of-mouth reviews. The valence, volume, and variance of patient reviews may shape the effectiveness of signals transmitted by physicians in OHCCs. We investigate the interactions between the signaling mechanism and the online feedback mechanism through which OHCCs help physicians build online popularity and achieve price premiums for online health consultations. We are using web scraping to collect weekly data for 12 months from a large OHCC in China. Applying mixed effects models on the data collected to date, we find online popularity and price premiums to be two benefits that physicians can derive from OHCCs. Importantly, in the presence of benevolence actions, an absence of consistently favorable online feedback slows down physicians' online popularity and reduces price premiums for online health consultations.

Keywords: Online health consultation communities (OHCCs), popularity, price premiums, signaling theory, online feedback, online trustworthiness

Health Consultation in China

With the change of social structures in China during the past three decades, the central government gradually decentralized its power over the health care system. Hospitals were encouraged to generate revenues on their own and were allowed to retain the surplus, part of which could be paid to their staff, the health professionals, as bonuses. Under such strong economic incentives, hospitals and health professionals were motivated to increase the supply of healthcare to increase economic benefits. The emerging online health consultation communities (OHCCs) in China offer a new platform for physicians to extend their health consultation services, compete for more patients through online consultations, and achieve price premiums for their services. As a new service platform in China's health care market, OHCCs have further increased the competition for patients and profits among physicians.

While physicians market themselves through multiple platforms to gain more patients, patients in China complain that physicians may be too profit driven and do not trust that physicians work for patients' best interests. The trust crisis between patients and physicians in China is now worsening the patient-physician relationship and causing a surge in medical disputes in China in recent years. Under this context, it is critical for Chinese physicians to get prepared for the new reforms and effectively utilize OHCCs to build trust with patients and establish popularity in the competitive health consultation market. Trust building, however, is not an easy task for health consultation services. As a typical type of credence services, health consultation services are suffering from the great information asymmetry between physicians and patients. Without enough professional knowledge, patients can hardly evaluate the trustworthiness of physicians even after their consumption of services. As a result, in order to build online popularity and gain price premiums for their services, physicians have to figure out an effective way to persuade patients to believe in their competent advice, responsible treatment, and compassionate care.

From a theoretical point of view, OHCCs reduce the information asymmetry and facilitate the trust building between patients and physicians through two mechanisms: the signaling mechanism and the online feedback mechanism. The *signaling mechanism* refers to the process that the signaler (i.e., the physician) sends observable signals (i.e., professional information, general knowledge dissemination, online consultation activities) to the receiver (i.e., patients) to convey information about the unobservable attributes (i.e., competence and courtesy) and reduce information asymmetry. Prior research (see a review by Connelly et al., 2011) often assumes that receivers are independent decision makers. In many situations, however, signal receivers are able to exchange information about their interpretations of signals or their perceptions on the signalers. For example, OHCCs allow patients to share their consultation experience with other patients. The shared experience will help potential patients learn about the physicians and consequently influence their choice decisions. Therefore, it is necessary to consider the signal receivers as a social community rather than a group of independent decision makers. Under this situation, the *online feedback mechanism*, typically the word-of-mouth among service consumers about a service, comes into play to reduce the information asymmetry. However, how the online feedback shared among service consumers influences the effectiveness of signals sent by service providers is unclear and important to understand for physicians to be able to effectively leverage OHCCs to relate with patients and offer their services.

This study aims to bridge this knowledge gap by integrating the online feedback and signaling mechanisms. We investigate how these two mechanisms interactively influence physicians' online popularity and achieve price premiums on their services. In the context of OHCCs, we focus on two dimensions of trustworthiness signals sent by the physicians (i.e., signals of competence and benevolence) and three dimensions of online feedback (i.e., the volume, valence and variance of online word-of-mouth). We formulate the following research question: *how do trustworthiness signals interact with online feedback in OHCCs to help physicians build online popularity and achieve price premiums for their services?*

To address this question, we conceptualized two dimensions of trustworthiness signals (i.e., credibility signal and benevolence signal) and three characteristics of online feedback (i.e., volume, valence, and variance), and synthesized the signaling theory and the word-of-mouth literatures to inform the development of a multi-level model with three interaction hypotheses. We are now using web scraping techniques to collect 12-months weekly data from the Good Doctor website (wwww.haodf.com), the largest OHCC in China. We have completed the formulation of research questions and theory development, and data collection and data analysis are in progress.

Theoretical Background

Signaling Theory

Signaling theory is often applied to describe the process used by decision makers in situations of information asymmetry (Spence, 1973). When one party has more information than the other, the former party (i.e., the signaler) sends observable attributes (i.e., signals) to the latter (i.e., the receiver) to convey information about the unobservable attributes and reduce information asymmetry (Connelly et al., 2011). For example, website quality, as an extrinsic cue of product quality, are found to influence consumers' trust toward online retailers and facilitate consumers' online purchase intentions (e.g., Boulding and Kirmani 1993; Wells et al., 2011; Everard and Galletta 2005; Gregg and Walczak 2008; McKnight et al. 2002). In the context of OHCCs, physicians are providing online consultations for patients when face-to-face meetings are inconvenient, unaffordable, or unnecessary (e.g., consultations to review clinical test results, consultations with elderly patients, consultations with remote patients, etc.). Under these situations, there is remarkable information asymmetry between physicians and patients regarding the quality of online health consultation services. Thus, it is critical for physicians to signal observable information and online actions to attract patients and obtain price premiums for their services.

Although multiple receivers may receive signals sent by a signaler, prior research often assumes that receivers are independent decision makers and simplifies the situation to a one-to-one (i.e., a signaler-receiver dyadic) singling process. In many situations, however, signal receivers are not independent decision makers (Ang et al. 2001; Cox et al. 2009). Instead, they are able to exchange information about their interpretations of signals or their perceptions on the signalers. Such information exchange will in turn influence receivers' perceptions and decisions. In our context, for example, patients may select a physician for online consultation services not only because of the professional information exposed by the physician himself, but also because of the feedback information about consultation experiences shared by other patients in the community. From this perspective, it is necessary to consider the signal receivers as a social community rather than a group of independent decision makers (Bansal and Voyer 2000; Lau and Coiera 2008). Accordingly, signaling theory should be extended from the one-to-one signaling to the one-to-many signaling (Connelly et al. 2011), that is, to investigate how service providers convey information about the unobservable attributes (e.g., their trustworthiness) to the social community signal receivers.

Online Feedback Mechanisms

In addition to signaling behaviors initiated by signalers, prior literature has recognized that informational social feedback among signal receivers is another important component in efficient signaling processes (Dichter 1966; Dellarocas 2003). One commonly investigated information social feedback mechanism is word-of-mouth. Word-of-mouth refers to an interpersonal communication among service consumers, independent of service providers' marketing activities, about a service or its providers (Bone 1995). Prior research found that the impact of informational social feedback, captured by the word of mouth, on consumer behaviors is even stronger than the impact of service providers' marketing activities (Bone, 1995; Herr et al. 1991; Smith and Vogt, 1995). In addition, recent research found that electronic word-of-mouth (eWOM) plays an important role in reducing information asymmetry for investors in the venture financing activities (Aggarwal et al., 2012), influencing viewers' satisfaction with movies (Moon et al., 2010), promoting sales (Chevalier et al. 2006; Chintagunta et al. 2010; Dhar and Chang 2009), and establishing consumers' trust toward online stores (Awad and Ragowsky 2008; Pavlou and Dimoka 2006).

Literature has identified three effects through which online feedback influence online users' decisions and behaviors: the awareness effect (Liu 2006; Duan et al. 2008), the persuasive effect (Duan et al. 2008; Chevalier and Mayzlin 2006), and the dispersion effect (Godes and Mayzlin 2004). In an e-service context, the awareness effect indicates that online feedback toward a service enables consumers to be aware of the existence of the service and thereby put it in their choice set. The persuasive effect indicates that online feedback shapes consumers' attitudes and evaluations towards the service and ultimately influence their consumption decisions (Duan et al. 2008). The dispersion effect indicates the extent to which consumers hold different views toward a particular service (Sun 2012). Moreover, Dellarocas et al. (2007) elaborated that the volume of online feedback captures the awareness effect because the more consumers discuss a service, the higher chance that other consumers become aware of it; the valence of online feedback corresponds with the persuasive effect because positive opinions encourage consumers to purchase a service, whereas negative opinions discourage them; and the variance of online feedback captures the dispersion effect because it captures the degree of disagreement among consumers (Sun 2012).

A Combination View

As two mechanisms that mitigate information asymmetry and induce consumers' trust in providers, the signaling mechanism (e.g., Aiken and Boush 2006) and the online feedback mechanism (e.g., Ba and Pavlou 2002) have been investigated independently in prior literature. To our best knowledge, how the word of mouth among service consumers influences the effectiveness of signals sent by service providers remains unknown. Given the coexistence of both mechanisms in online communities, t is necessary to take an integrative perspective and investigate the interdependence between the signaling mechanism and the online feedback mechanism in the context of online communities.

Model and Hypotheses

To address the research question, we propose the research model as depicted in Figure 1. Table 1 summarizes the definition of each construct in this model. In the context of OHCCs, we investigate the interactive influence of the signaling mechanism and the online feedback mechanism on physicians' online popularity and price premiums for online health consultation services. We focus on OHCCs and investigates two dimensions of trustworthiness signals sent by the physicians (i.e., signals of competence and signals of benevolence) and three dimensions of online feedback (i.e., the valence, volume and variance of online word of mouth among patients).

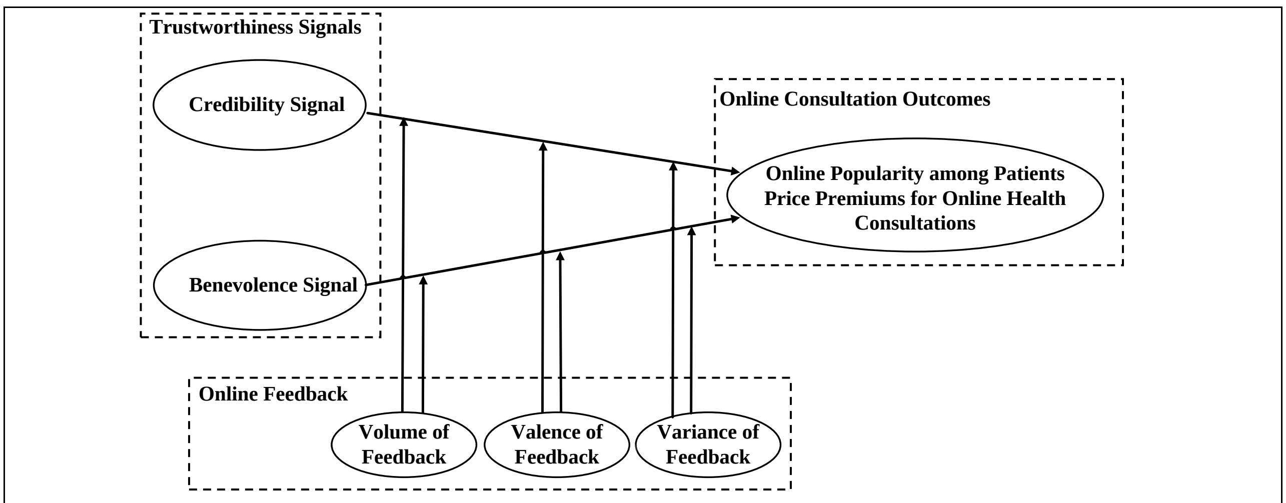


Figure 1. Research Model

Trust is important in building provider-consumer relationships in credence services. In healthcare consultations, for example, the service a physician provides is highly difficulty to judge even after the service is delivered. Given the patients' dependency on physicians and the uncertainties associated with diagnoses and treatments, patients may feel the need to trust their physician to make decisions in their best interest and doing everything possible to obtain desirable treatment outcomes (Holwerda et al., 2013). Therefore, physicians have to convey the information about their trustworthiness in order to reduce the information asymmetry and establish online popularity. Empirical evidence has shown that that physician's trustworthiness in terms of competence and courtesy were the most important criteria that influenced patients' selection of physicians (Crane and Lynch 1988).

Table 1. Definitions of Constructs

Constructs	Definition	References
Credibility Signal $_{it}$	The extent to which a physician *i* signals his/her competence and reliability in providing health consultation services at time *t*.	Ganesan (1994)
Benevolence Signal $_{it}$	The extent to which a physician *i* signals an act of kindness in providing health consultation services at time *t*.	
Volume of Feedback $_{it}$	The total amount of feedback provided by patients about physician *i* at time *t*.	Duan et al. (2008)
Valence of Feedback $_{it}$	The rating values (i.e., from negative to positive) assigned by patients to physician *i* at time *t* when they review their online health consultation experience.	Duan et al. (2008)
Variance of Feedback $_{it}$	The extent to which patients hold different opinions about physician *i* at time *t* when they review the physician's online health consultation services (i.e., standard deviation of satisfaction ratings for physician *i* at time *t*).	Godes and Mayzlin (2004)
Online Popularity $_{it}$	The extent to which patients use physician *i* for online health consultation services at time *t*.	Turban and Greening (1997)
Price Premiums $_{it}$	The monetary amount above the average price for a service that is received by physician *i* at time *t*.	Ba and Pavlou (2002)

OHCCs provide a channel for physicians to signal their trustworthiness. The marketing literature identifies two major dimensions of trust: credibility and benevolence (Genesan 1994; Doney and Cannon 1997). First, credibility refers to the extent to which a trustor believes that ability a trustee has the required expertise to provide the service effectively and reliably. In this study, physicians can disclose their professional background in the OHCC. Such background information includes physicians' professional title, education experience and work experience. By disclosing these information, physicians are signaling their credibility in terms of their competence and ability to deliver effective and reliable health consultation services. As a result, physicians who send stronger signals of credibility are at a better position to build online popularity and gain price premiums from patients.

Second, benevolence refers to the extent to which a trustor believes that a trustee is genuinely interested in the other partner's welfare and has intentions and motives beneficial to the trustor. In OHCCs, physicians can answer questions posted by patients, provide medical advice for public audience, and disseminate knowledge concerning specific health conditions. The platform of online communities offers a tool to keep track of these interactions and make details of interactions transparent to all community members. As a result, patients can well observe the way in which physicians care about their patients and help patients deal with their health concerns. Since physicians' benevolence is a key predictor of patient's selection of physicians (Gable 2011), physicians who send stronger signals of benevolence are at a better position to establish online popularity and achieve a higher level of price premiums from patients.

In OHCCs, patients do not only interact with physicians but also network with other patients. According to signaling theory, the networking environment may influence individual patient's detection of signals as well as his interpretation of the received signals (Connelly et al. 2011). Specifically, a large volume of online feedback within OHCCs enable patients to be aware of the provision of online consultations and more favorable and consistent online feedback persuades patients to engage in online health consultations. In addition to the direct impacts on physicians' popularity and price premiums, online feedback also exert moderating impacts and influence the effectiveness of signals sent by physicians.

Signal observability is one important factor that influences signaling effectiveness. Signal observability refers to the extent to which outsiders are able to notice the signal. The effectiveness of signaling mechanisms will be enhanced if the signals become more observable among the target population. Because the volume of online feedback helps spread information among the target receivers and consequently arouses a huge amount of awareness, we expect that the volume of the online feedback will enhance the effectiveness of signals. In our context, physicians who received a large amount of online feedback from patients may take advantage of the awareness effect. As a result, their signals of trustworthiness, both credibility and benevolence, are more likely to attract more patients and generate price premiums. Accordingly, we hypothesize that:

H1: The Volume of Feedback moderates the impacts of Signals of Trustworthiness in such a way that,
H1a: The impact of Credibility Signal on Online Popularity increases with the Volume of Feedback.
H1b: The impact of Credibility Signal on Price Premiums increases with the Volume of feedback.
H1c: The impact of Benevolence Signal on Online Popularity increases with the Volume of Feedback.
H1d: The impact of Benevolence Signal on Price Premiums increases with the Volume of Feedback.

Another important factor that influences the effectiveness of signaling mechanisms is signal consistency. Signal consistency refers to the agreement between multiple signals for the same signaler (Gao et al., 2008). Conflicting signals confuse the receiver, making communication less effective, while consistent signals can help mitigate this problem and reinforce the persuasiveness of signals (Chung and Kalnins 2001; Fischer and Reuber 2007). Serving as responsive signals, negative online feedback reveals information that the physician may not have competence and good intention to help patients. Such information conflicts with trustworthiness signals sent by the physicians, thus impedes signal effectiveness. By contrast, positive online feedback transmits information that is consistent with signals sent by the physician, therefore increases the effectiveness of signaling mechanisms (Miyazaki et al 2005).

H2: The Valence of Feedback moderates the impact of Signals of Trustworthiness in such a way that,
H2a: The impact of Credibility Signal on Online Popularity increases with the Valence of Feedback.
H2b: The impact of Credibility Signal on Price Premiums increases with the Valence of Feedback.
H2c: The impact of Benevolence Signal on Online Popularity increases with the Valence of Feedback.
H2d: The impact of Benevolence Signal on Price Premiums increases with the Valence of Feedback.

Signal consistency can also be reflected by the variance of online feedback. Online feedback with little variance transmits consistent message on the favorable experiences with online health consultation services, and thus reinforces the impacts of trustworthiness signals to a larger extent. However, online feedback with large variance transmits conflicting information that mitigates the signaling effectiveness.

H3: The Variance of Feedback moderates the impacts of Signals of Trustworthiness in such a way that,
H3a: The impact of Credibility Signal on Online Popularity decreases with the Variance of Feedback.
H3b: The impact of Credibility Signal on Price Premiums decreases with the Variance of Feedback.
H3c: The impact of Benevolence Signal on Online Popularity decreases with the Variance of Feedback.
H3d: The impact of Benevolence Signal on Price Premiums decreases with the Variance of Feedback.

Research Design

Research Site

The Good Doctor website (www.haodf.com) is the largest OHCC in China. Founded in 2006, the Good Doctor has collected and shared information of 332,341 physicians from 3,260 regular hospitals across the nation. The website allows physicians to provide online consultations and transfer patients to offline in-person doctor visits. By October 2014, 70,591 physicians have registered in the Good Doctor community and provided online consultations for 2,471,923 patients. Although most online text consultation services are free, physicians may charge for online consultations with the rate ranges from 6 RMB to 40 RMB per minute, which is about ten times higher than the regular doctor visit rates in hospitals. The relatively high consultation rates are acceptable for patients since online consultations remarkably reduce waiting time and long distance transportation expenses of in-person doctor visits.

In addition to the intensive interactions between physicians and patients, the Good Doctor also provides an open platform for patients to exchange information and share experiences about consultation services with each other. By October 2014, patients have shared 1,190,610 consultation experience messages with physicians and other patients, posted 130,076 thank you letters to physicians they consulted, and sent 566,694 virtual gifts with values of 5-100 RMB for physicians in this community. Moreover, patients who consulted with one physician for three times or more will be clustered in a patient group for this physician. In this group, patients can directly network with the physician's other patients, seeking for emotional support and communicating about their health conditions.

Because of the wide user base in both physicians and patients, and the rich interactions between physicians and patients as well as among patients, we view the Good Doctor website as an ideal setting to investigate the effectiveness of signaling mechanism and feedback mechanism on establishing physician's online popularity among patients and on gaining price premiums for online health consultation services.

Sampling

To test the hypotheses, we randomly sampled physicians who are specialists in Obstetrics and Gynecology (OBGYN) or Cardiology. Health conditions in these two specialties have standardized tests for diagnosis and are commonly consulted health conditions in the Good Doctor community. Yet, these two health conditions differ in their danger to the patient's life as well as the complexity of diagnosis. In addition, there is low level of comorbidity between these two health conditions. The sampled physicians will vary in terms of the locations they are working at and the types of hospitals they are working for. We believe these variations would well represent the distributions of physicians we are interested.

Data Collection

We use automated Java scripts to access and parse HTML pages on physician's personal page in the Good Doctor community. Data are being currently gathered on a weekly basis from October 2014 to February 2016 at two levels: the physician level (*i*) and the physician time-varying level (*t*). Physician-level data includes a physician's demographics$_i$, specialty$_i$, and the location of the affiliated hospital$_i$. Physician time-varying level data includes personal page traffic$_{it}$, OHCC use history$_{it}$, Credibility Signal $_{it}$, Benevolence Signal$_{it}$, Volume of Feedback$_{it}$, Valence of Feedback$_{it}$, and Variance of Feedback $_{it}$.(measures of constructs are described in Table 2. We performed natural logarithm transformation on all constructs except Credibility Signal$_{it}$ to fulfill the assumption of normality. We then standardized measures for independent variables (i.e., Credibility Signal$_{it}$, Benevolence Signal$_{it}$) and moderators (i.e., Volume of Feedback$_{it}$, Valence of Feedback$_{it}$, and Variance of Feedback $_{it}$) to facilitate the testing of interaction effects. In addition, we created a relative measure for the two dependent variables (i.e., Online Popularity$_{it}$, Price Premiums$_{it}$) in three steps: (1) calculate the group means for physician *i* at time *t* in each of the two specialty groups (i.e., Cardiology and OBGYN), (2) generate the group-mean centered measures and (3) divide the group-mean centered measures by the group means. We use the transformed measures in the following analyses.

Table 2. Measures of Constructs

Constructs	Measures
Credibility Signal $_{i,t}$	Professional Title for physician *i* at time *t*.
Benevolence Signal $_{i,t}$	The benevolence score provided on the website for physician *i* at time *t*. The benevolence score is calculated based on number of blogs posted by a physician, the frequency of updates on health consultation information, and the frequency of replies to patient's questions.
Volume of Feedback $_{i,t}$	The number of consultation experiences shared by patients.
Valence of Feedback $_{i,t}$	The mean value of patient satisfaction ratings for physician *i* by time *t*.
Variance of Feedback $_{i,t}$	The standard deviation of patient satisfaction ratings for physician *i* by time *t*.
Online Popularity among Patients $_{i,t}$	The number of patients for physician *i* by time *t*.
Price Premiums for Online Health Consultation Services $_{i,t}$	The rate of online consultation services for physician *i* at time *t*.

Preliminary Analyses

Sample Description

We have collected 12,822 physician-weekly observations from October 15, 2014 to February 24, 2015 and use this data in the preliminary analyses reported here. This includes data pertaining to 1,411 physicians (cardiologists, N=603l OBGYN, N=808) for 11 weeks. The sampled physicians are affiliated with 520 hospitals across 29 provinces and show sufficient representativeness of physicians in the two specialties in China. Table 3 summarizes the descriptive statistics of constructs and correlations among constructs.

Table 3. Descriptive Statistics of Constructs

Variable	Mean	Std. Dev.	1	2	3	4	5	6
1. Online Popularity (mean centered)	0.000	3.125	1.000					
2. Price Premiums (mean centered)	0.000	4.926	-0.038	1.000				
3. Credibility Signal	3.428	0.695	0.226	0.296	1.000			
4. Benevolence Signal	4.135	4.571	0.751	-0.221	0.108	1.000		
5. Valence of Feedback	1.483	0.371	0.103	-0.011	-0.003	0.008	1.000	
6. Variance of Feedback	- 1.288	1.244	0.162	0.253	0.271	0.117	-0.301	1.000
7. Volume of Feedback	1.353	1.138	0.351	0.417	0.469	0.135	0.098	0.452
Control variables: age, gender, specialty, location of affiliated hospitals, time, personal page traffic, and OHCC use history.								

Analysis Results

Given the panel data structure, we test the following two mixed effects models:

$$\begin{aligned} Popularity_{it} = {} & \beta_0 + ControlVariables_i + ControlVariables_{it} \\ & + \beta_1 Credibility_{it} + \beta_2 Benevolence_{it} + \beta_3 Volume_{it} + \beta_4 Valence_{it} + \beta_5 Variance_{it} \\ & + \beta_6 Credibility * Volume_{it} + \beta_7 Benevolence * Volume_{it} \\ & + \beta_8 Credibility * Valence_{it} + \beta_9 Benevolence * Valence_{it} \\ & + \beta_{10} Credibility * Variance_{it} + \beta_{11} Benevolence * Variance_{it} \\ & + \mu_{i0} + \varepsilon_{it} \end{aligned}$$

$$\begin{aligned} Price_{it} = {} & \beta_0 + ControlVariables_i + ControlVariables_{it} \\ & + \beta_1 Credibility_{it} + \beta_2 Benevolence_{it} + \beta_3 Volume_{it} + \beta_4 Valence_{it} + \beta_5 Variance_{it} \\ & + \beta_6 Credibility * Volume_{it} + \beta_7 Benevolence * Volume_{it} \\ & + \beta_8 Credibility * Valence_{it} + \beta_9 Benevolence * Valence_{it} \\ & + \beta_{10} Credibility * Variance_{it} + \beta_{11} Benevolence * Variance_{it} \\ & + \mu_{i0} + \mu_{i1} Time + \varepsilon_{it} \end{aligned}$$

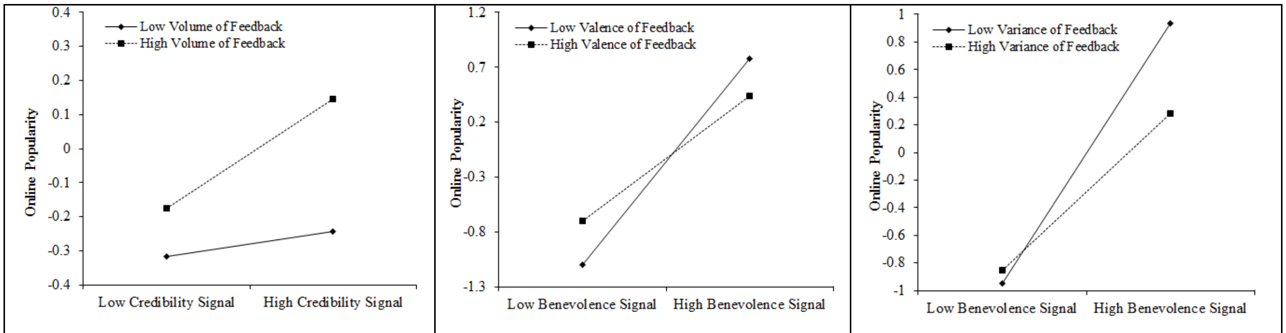
As shown in Table 4, we first included the control variables at both physician level and physician-time level in the Online Popularity and Price Premiums models. In the second step, we added the direct effects of independent variables and moderators into the models. We found that Credibility Signal, Benevolence Signal, Volume of Feedback and Variance of Feedback have significant impacts on Online Popularity; while Credibility Signal and Volume of Feedback also have significant impacts on Price Premiums. In the third step, we entered the hypothesized interactions into the models. Volume of Feedback significantly moderates the impact of Credibility Signal on Online Popularity (H1a is supported; H1b, H1c, and H1d are not supported), Valence of Feedback significantly moderates the impacts of Benevolence Signal on Online Popularity and Price Premiums(H2c and H2d are supported; H2a and H2b are not supported), and Variance of Feedback significantly moderates the impacts of Benevolence Signal on online Popularity and Price Premiums (H3c and H3d are supported; H3a and H3b are not supported).

Table 4. Results of Mixed Effects Models

	Online Popularity				**Price Premiums**			
	Direct Effects		**Interaction Effects**		**Direct Effects**		**Interaction Effects**	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Credibility Signal $_{it}$	0.088***	0.015	0.099***	0.015	0.129***	0.033	0.133***	0.035
Benevolence Signal $_{it}$	0.748***	0.006	0.754***	0.006	0.001	0.019	0.006	0.022
Volume of Feedback $_{it}$	0.134***	0.010	0.132***	0.010	0.067***	0.020	0.083***	0.031
Valence of Feedback $_{it}$	0.001	0.004	0.003	0.007	-0.012	0.028	-0.021	0.029
Variance of Feedback $_{it}$	-0.018***	0.006	-0.028***	0.006	0.037	0.029	-0.014	0.044
Credibility*Volume $_{it}$			0.062*** (H1a)	0.009			0.014 (H1b)	0.021
Benevolence*Volume $_{it}$			-0.012 (H1c)	0.007			-0.026 (H1d)	0.027
Credibility *Valence $_{it}$			0.005 (H2a)	0.009			-0.033 (H2b)	0.046
Benevolence*Valence $_{it}$			-0.037*** (H2c)	0.007			0.046** (H2d)	0.027
Credibility*Variance $_{it}$			-0.003 (H3a)	0.007			-0.041 (H3b)	0.038
Benevolence*Variance $_{it}$			-0.037*** (H3c)	0.005			0.089** (H3d)	0.039
_cons	-0.130	0.075	-0.147**	0.075	0.180	0.128	0.149	0.131
Random-effects								
var(_cons)	0.373***	0.015	0.370***	0.015	0.162***	0.016	0.169***	0.017
var(Residual)	0.004	0.000	0.004	0.000	0.001	0.000	0.001	0.000
Number of observations	13168.00				2210.000			
Number of physicians	1347.000				232.000			
Log Likelihood	12581.211		12660.337		3324.929		3328.339	

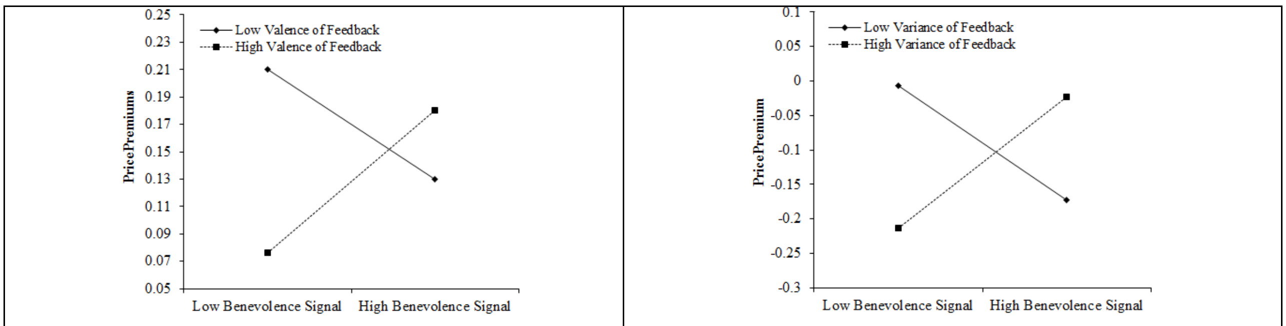
Control variables: age, gender, specialty, location of affiliated hospitals, time, personal page traffic, and OHCC use history.
One-tailed tests are reported for theorized effects: *** p<0.01, ** p<0.05

To develop a more nuanced understanding, we performed simple slope tests and plotted the interaction effects (Figure 2 and Figure 3). Physicians with higher credibility tend to benefit to a greater extent in establishing online popularity among patients when they receive a larger volume of feedback (Figure 2a). More interestingly, for physicians who exhibit more benevolent behaviors in OHCCs, less favorable or less consistent feedback tends to slow down the establishment of online popularity (Figure 2b and Figure 2c) and lead to a decline in price premiums for their online health consultations (Figure 3a and Figure 3b).



a. Credibility*Volume (H1a)	b. Benevolence*Valence (H2c)	c. Benevolence*Variance (H3c)

Figure 2. The Moderating Effect of Volume



a. Benevolence*Valence (H2d)	b. Benevolence*Variance (H3d)

Figure 3. Interaction Effects for Price Premiums

Conclusion and Planned Extensions

This study elaborates our understanding about how online feedback (i.e., the valence, volume, and variance of feedback) influences the effectiveness of signaling mechanism, specifically competence and benevolence, in physicians establishing online popularity and gaining price premiums for online health consultation services. It demonstrates the role of OHCCs in helping physicians to establish professional popularity online and to establish a base of patients and price premiums for their online consultation services. With the analyses of mixed effects models, we found that online popularity and price premiums are two distinct outcomes that physicians can benefit from OHCCs. More importantly, in the presence of benevolence actions, an absence of consistently favorable online feedback would slow down the physicians' online popularity and would lead to a decline in the price premiums of online health consultation services. We are elaborating the analysis to address the endogeneity concerns on our model. We also plan to conduct robustness tests and investigate heterogeneity in the interaction between signaling and online feedback mechanisms in subsegments of physicians with different specialties. With these extensions, we expect to develop a more complete picture of how physicians establish online popularity and price premiums for their services through a combined signaling and online feedback mechanism.

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