Association for Information Systems
AIS Electronic Library (AISeL)

PACIS 2016 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

Summer 6-27-2016

MAY A HEALTHCARE SOCIAL NETWORKING SITE HELP REVEAL HIDDEN QUALITY OF A HEALTHCARE PROVIDER?

Ling-Chieh Kung
National Taiwan University, lckung@ntu.edu.tw

Ho Ho
National Taiwan University, r03725041@ntu.edu.tw

MAY A HEALTHCARE SOCIAL NETWORKING SITE HELP REVEAL HIDDEN QUALITY OF A HEALTHCARE PROVIDER?

Ling-Chieh Kung, Department of Information Management, National Taiwan University, Taipei, Taiwan, lckung@ntu.edu.tw

Ho Ho, Department of Information Management, National Taiwan University, Taipei, Taiwan, r03725041@ntu.edu.tw

Abstract

In this study, we discuss an information asymmetry problem between a healthcare provider and consumers, and examine the strategy for a platform owner to mitigate this problem. Because the Internet has become a major media for healthcare information sharing, we believe that social networking sites may mitigate the problem of information asymmetry by providing a more efficient way to facilitate information sharing and quality disclosure. We develop a game-theoretic model describing the process of information exchange among healthcare consumers themselves and the platform on a social networking site. We show that this "strategy" of engaging in social networking sites is indeed helpful for revealing the quality information of a healthcare provider, and the existence of a healthcare social networking site does benefit patients. Finally, we discuss factors affecting the platform owner's decision.

Keywords: Information asymmetry, quality disclosure, healthcare, social networking sites, network externality

1 INTRODUCTION

The healthcare industry, which consists of a wide range of sectors including pharmacies, hospitals, nursing, medical device manufacturing, etc., plays a growing important role in the world's economy (Mahmud and Parkhurst, 2007). Two major participants in the industry are healthcare providers and consumers. The former involves all kinds of medical specialists providing professional knowledge and suggestions, such as physicians, psychiatrists, dentists, nurses, babysitters, etc. The latter receives healthcare services and therefore cares about the quality of providers. To facilitate our discussions, in this study we will call all those who deliver medical services as healthcare providers, and all those who receive services as patients.

Information asymmetry between patients and healthcare providers has called researchers' and practitioners' attention. As Angst et al. (2014) point out, the extent of information disclosed are leading indicators for patients to choose a healthcare provider. On the one hand, patients prefer to obtain more information about their health conditions as well as the quality and reputation of a healthcare provider (Vick and Scott, 1998; Angst et al., 2014). On the other hand, high-quality healthcare providers may wish to creditably convey their quality information to the patients, so as to differentiate themselves from the low quality ones. This widely observed problem has given rise to initiatives and policies encouraging healthcare providers to voluntarily disclose their quality information (Angst et al., 2014). It is thus critical for a healthcare provider to reveal its quality to patients.

One popular channel to share healthcare information is healthcare social media. In the past few years, social media has no doubt influenced nearly all aspects of our lives. From casual conversation to professional knowledge, countless messages and information were exchanged upon it every second, every day. Among all kinds of social media, social networking sites focusing on healthcare information sharing particularly play a significant role. Eysenbach and Kohler (2003) indicate that around 4.5% of all search terms are considered health-related. 85% of Americans had access to the Internet, 48% looked at social networking sites at least once per day, and 34% of them read about other people's health experiences (Greaves et al., 2013). The need for healthcare information gives rise to more and more healthcare social networking sites. The most well-known site PatientsLikeMe was founded in 2004 with the goal of providing a platform for patients with similar disease to communicate. It now has more than 400,000 members discussing more than 2,500 conditions.[1] This shows that healthcare information sharing online has indeed become a prevalent phenomenon.

The emergence of these healthcare social networking sites leads us to some basic questions: Why healthcare information sharing is so prevalent? What information is being shared on these sites? According to Eysenbach (2003), patients often feel that the information provided by health professionals is not adequate, and most of them would like to have as much information as possible. He also emphasizes that information acquisition and social support are the two major motives for a cancer patients to join a healthcare social networking site. In a research about online communities for patients with diabetes, around 66% of the posts were patients' personal experiences regarding diabetes management, and 24% seek for interpersonal support (Greene et al., 2011). Obviously, most patients are not satisfied with the information provided by the healthcare providers, and therefore turn to social networking sites to seek for more help.

Because the Internet has become a major media for healthcare information sharing, we believe that social networking sites may mitigate the problem of information asymmetry by providing a more efficient way to facilitate information sharing and quality disclosure. In fact, one may do more than just building a social networking site. For instance, a social media owner may voluntarily join the discussions initiated by patients on online communities, or provide professional suggestions to attract more users and foster its network size. Once the network size becomes large enough, more patients would join the network and exchange information about the quality of healthcare providers on the site and further

[1] Information source: https://www.patientslikeme.com/.

mitigate information asymmetry problem. Is this "strategy" of engaging in social networking sites really helpful for revealing the true quality of a healthcare provider? If so, is it true for high-quality providers, low-quality providers, or both? Does the existence of a healthcare social networking site benefit patients? What factors affect the amount of benefits, if any, brought to patients?

In this study, we discuss an information asymmetry problem among a healthcare provider, a social networking platform, and patients. The quality of the service provided by the healthcare provider can be observed by neither patients nor the platform owner. Our main objective is to examine the strategy for the platform owner to mitigate this problem through engaging in information sharing. We develop a game-theoretic model describing the process of information exchange among patients themselves and the platform owner on a social networking site. The platform owner will decide to what extend to participate in information sharing on the site. This affects the network size of the social networking site. Patients who has experienced the service from the healthcare provider will then pass positive or negative recommendations to unexperienced patients, who then update their beliefs on the healthcare provider's quality. Finally, based on the updated beliefs, unexperienced patients will decide whether to purchase the healthcare service. We characterize the platform owner's optimal degree of engagement and study the implications of it.

The remainder of this study is organized as follows. In Section 2, we review some related works. In Section 3, an economic model is formulated to describe information exchange between a platform owner and patients on a social networking site. We then provide our findings in Section 4. Section 5 discusses extensions of our basic model. Section 6 concludes. All proofs are in the appendix.

2 LITERATURE REVIEW

The problem of information asymmetry exists nearly everywhere involving the principal-agent relationship. Akerlof (1970) studies quality uncertainty in the used-car market and observes that when the sellers (principals) has more information than buyers (agents), high-quality sellers would turn out finding it profitless to stay in the market, which would then be filled with low-quality cars (lemons). Spence (1973) studies quality uncertainty in job market where the employers cannot observe the hidden productivity of employees. This leads to low wages which drive productive people out of the job market and make employers unable to find high-quality workers. The same problem exists in the healthcare industry. Vick and Scott (1998) demonstrate the importance of information exchange between healthcare providers who possess hidden medical information and patients. Su and Zenios (2006) discuss information asymmetry problem in kidney allocation. They point out that in addition to the features of a kidney, transplant candidates also have hidden information about their health conditions. One similar issue is studied by Howard (2002), who shows that a candidate may turn down an organ, despite of the shortage, depending on his or her current health level. Our main focus in this study is on the healthcare providers' hidden quality information, which is more relative with the work of Vick and Scott (1998).

According to Eysenbach and Kohler (2003), a patient's information need is a critical motive for searching health information online or attending social networking sites. In earlier literature, the strong relationship between social support and health condition of a patient has been discussed. Vogt et al. (1992) find that a patient's social support network has negative correlation with the mortality rate among people with ischemic heart disease, cancer, and stroke. Eysenbach and Kohler (2003) mention that by obtaining health information on the virtual communities, patients may feel empowered and become more confident.

Several past works are related to healthcare social media. Greene et al. (2011) highlight the need for information and the role of healthcare social networking sites. However, they also note that promotional posts could erode patients' trust on the credibility of information. Wicks et al. (2012) state that after joining the social networking site PatientsLikeMe, people with epilepsy are connected with each other, and hence help extend their understanding and management about their health conditions. Evaluating healthcare providers is no doubt one of the main reasons for patients to exchange information online.

According to Chaniotakis and Lymperopoulos (2009), a patient's satisfaction toward the service provided by maternities is positively associated with the word of mouth effect. In the retailing industry, Chevalier and Mayzlin (2006) show that word of mouth indeed affects a consumer's online purchase decision on Amazon and Barnes & Noble. For these reasons, we wonder if healthcare providers may also build up credibility through online word of mouth.

Since the seminal works by Akerlof (1970) and Spence (1973), people start to discuss how a principal may use signalling strategies to creditably convey quality information to agents. Desai and Srinivasan (1995) study demand signalling through two-part tariffs. Other mechanisms include advertising (Nelson, 1974; Milgrom and Roberts, 1986; Kihlstrom and Riordan, 1984), warranties (Balachander, 2001; Soberman, 2003; Jiang and Zhang, 2011), returns (Moorthy and Srinivasan, 1995), selling through reputable retailers (Chu and Chu, 1994), and online word of mouth (Mayzlin, 2006). Kalra and Li (2008) show that a firm can signal its quality to consumers through specialization. Angst et al. (2014) mention that hospitals with low quality or bad financial conditions are less likely to disclose their quality information. Though in this study no player really does signalling, our work may still contribute to this stream of literature by discussing the importance of quality disclosure and potential of signalling in the healthcare domain.

3 MODEL

We consider a group of patients (for each of them, he) and a platform owner (she) who maintains a social networking site (SNS) on which patients exchange healthcare-related information. Different patients may have different degrees of technology adoption. We model their extent of repellence by assuming a cost η of joining the SNS for each patient. We assume that η is uniformly distributed between 0 and 1, where a patient with a low value of η enjoys online networking more than one with a high value of η. Due to network externality, more patients joining the site will bring more benefits to everyone on it. Collectively, if the platform owner does nothing but building the SNS, the utility function for a patient with η to join the site is

$$\mathcal{P}(\eta) = v - \eta + t\eta^*, \tag{1}$$

where $v > 0$ is the stand-alone benefit of joining the SNS, $t > 0$ is the degree of network externality, and η^* is the equilibrium number of patients on the SNS. It is clear that a patient will join the SNS if and only if $\eta < \eta^*$ (cf. Figure 1).

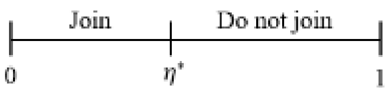

Figure 1. Patients' extent of repellence affecting joining decision.

Besides patients and the platform owner, there is also an exogenous healthcare provider who provides healthcare service with private quality information. Customers are heterogeneous on their willingness to pay for the quality of healthcare service. Let θ be the customer's willingness-to-pay, a patient will purchase the service from the healthcare provider if

$$\theta q - p \geq 0, \tag{2}$$

where q is his belief on the service quality and p is the price charged for the service. We assume that θ is uniformly distributed between 0 and 1. Moreover, we assume that $q \in \{q_L, q_H\}$ is the service provider's private information. We assume that $q_L < q_H$, so $q = q_L$ means that the provider's service is of low quality, and $q = q_H$ otherwise.

Depending on whether one has experienced the service provided by the healthcare provider, patients are divided into two groups: *experienced patients* and *naïve patients*. We use $\alpha \in (0, 1)$ and $1 - \alpha$ to denote the proportion of experienced and naïve patients, respectively. It is assumed that whether one is experienced and η are independent. If a patient has neither experienced the service from the provider nor heard anything from other patients, his prior belief on the service quality is $q^{pri} = \gamma q_H + (1-\gamma)q_L$, where $\gamma \in (0,1)$ is his prior belief for the quality to be high. An experienced customer, who will not purchase the service again, knows the true quality. For the segment of patients who do not join the SNS, because they cannot count on any messages about the provider, they make purchasing decision solely based on expected quality q^{pri}. Therefore, a naïve patient not on the SNS would buy the service if $\theta q^{pri} - p \geq 0$.

For the segment of patients joining the SNS, patients exchange information with each other. Therefore, a naïve patient may obtain some messages from other SNS users and then update his belief on q. We model this updating process by assuming that the patient will obtain one message about the service quality, which may be either positive or negative. If the message comes from an experienced patient, the probability that the message is positive and negative is $h(q)$ and $1 - h(q)$, respectively, where q is the true quality observed by the experienced patient and $h(\cdot)$ is an increasing function whose range is within 0 and 1. In other words, the better the service, the higher the probability for an experienced user to say something good about it.

Unfortunately, on an SNS it is also possible that such a message actually comes from a naïve user, and it may be too hard for one to verify the truthfulness of the message. In this case, we use $k \in [0, \frac{1}{2}]$ to denote the stand-alone probability for a naïve user to send a positive or negative message. When $k = 0$, a naïve user stays honest and does not say anything about the provider. When k goes up, naïve users becomes less honest and may randomly promote or demote the provider with no reason. When $k = \frac{1}{2}$, a naïve user is never honest and will definitely say something with no proof. k is thus called the noise factor in this study. Note that k is not affected by q because the message sender has not experienced the service. Collectively, the probabilities for a naïve patient to get a positive and negative message when the true quality is q_i are

$$\Pr(\text{positive}|q_i) = \alpha h(q_i) + (1-\alpha)k \text{ and } \Pr(\text{negative}|q_i) = \alpha\big(1 - h(q_i)\big) + (1-\alpha)k, \quad (3)$$

respectively. The probability that one gets no message is $\Pr(\text{no}|q_i) = (1-\alpha)(1-2k)$, i.e., the probability of meeting another naïve user who is honest. For ease of exposition, we will set $h(q) = q$ throughout this study. Our main findings remain qualitatively true for any $h(\cdot)$ that is increasing and concave in $[0, 1]$.

Once a naïve patient receives a positive message, he will apply the Bayes' rule to form his posterior beliefs as

$$\Pr(q_H|\text{positive}) = \frac{r\Pr(\text{positive}|q_H)}{r\Pr(\text{positive}|q_H) + (1-r)\Pr(\text{positive}|q_L)} = 1 - \Pr(q_L|\text{positive}). \quad (4)$$

$\Pr(q_H|\text{negative})$ and $\Pr(q_L|\text{negative})$ can be expressed in a similar way. We then have the posterior belief on q upon receiving a positive message as

$$q^{post}(\text{positive}) = \Pr(q_H|\text{positive})q_H + \Pr(q_L|\text{positive})q_L. \quad (5)$$

$q^{post}(\text{negative})$ is expressed similarly.

A naïve patient on SNS receiving a positive recommendation message would buy the service if $\theta q^{post}(\text{positive}) - p \geq 0$. Similarly, he would buy the service if $\theta q^{post}(\text{negative}) - p \geq 0$ upon receiving a negative message. It is still possible that he receives a neutral message from another naïve patient. In this case, he will buy the service if $\theta q^{pri} - p \geq 0$, just like one not on the SNS. Collectively, we have

$$\begin{aligned} A_i = &\Pr(\text{positive}|q_i)\Pr\left(\theta \geq \frac{p}{q^{post}(\text{positive})}\right) \\ &+ \Pr(\text{negative}|q_i)\Pr\left(\theta \geq \frac{p}{q^{post}(\text{negative})}\right) + \Pr(\text{no}|q_i)\Pr\left(\theta \geq \frac{p}{q^{pri}}\right) \end{aligned} \quad (6)$$

as the probability for a naïve patient joining the SNS to buy the service with quality q_i, and

$$A_N = \Pr\left(\theta \geq \frac{p}{q^{pri}}\right) \tag{7}$$

as the probability for a naive patient who does not join the SNS (or receive no message on the SNS) to buy the service.

The platform owner will decide the amount of platform-generated contents $m \geq 0$, represented by, e.g., the number of articles posted on the SNS every week or the number of educational messages sent to patients for answering their questions. It costs the platform owner $\frac{1}{2}\beta m^2$ to achieve the participation level m. Once the platform owner is highly involved in the SNS, a patient will benefit from the positive network externality by interacting with the owner. In this case, his utility function becomes

$$\mathcal{P}(\eta) = v - \eta + t(\eta^* + m). \tag{8}$$

Note that if the platform owner does not want to generate any contents on the SNS, she will set $m = 0$, and then the patient's utility function will reduce to the one with no platform owner's participation.

Based on whether the platform owner is aware of the quality of the healthcare provider, we have two different scenarios. In the first scenario, the platform is not aware of the quality of the provider. We call such a platform a *innocent platform*. In the second one, the platform knows the quality. She is then called a *knowledgeable platform* in this case. No matter which scenario it is, the platform owner should choose the amounts of platform-generated contents m^* to maximize the influence of the platform. More precisely, the platform owner acts to maximize the ability for the platform to attract naïve patients to buy the service when the provider's quality is high and to discourage them not to buy it when the provider's quality is low.

Scenario 1: Innocent platform. For the innocent platform owner who does not know the quality of the provider, she calculates the expected value of the platform's influence and solves the maximization problem

$$\mathcal{S}^I = \max_{m \geq 0}\ (1-\alpha)\eta^*\{\gamma(A_H - A_N) + (1-\gamma)(A_N - A_L)\} - \frac{\beta m^2}{2}. \tag{9}$$

Scenario 2: Knowledgeable platform. For the knowledgeable platform owner who knows the quality of the provider, she solves two different maximization problems depending on the service quality:

$$\mathcal{S}_H^K = \max_{m \geq 0}\ (1-\alpha)\eta^*(A_H - A_N) - \frac{\beta m^2}{2}, \tag{10}$$

$$\mathcal{S}_L^K = \max_{m \geq 0}\ (1-\alpha)\eta^*(A_N - A_L) - \frac{\beta m^2}{2}. \tag{11}$$

Due to page limit, in this study we only include the analysis for the knowledgeable platform.[2]

Note that while both patients and the platform owner may send messages, these messages are different by nature. We assume that patients will not believe in the owner's messages about the provider's quality, and thus the owner may only send *educational messages* that affects the size the user base of the SNS. Only patients may send *recommendation messages* to affect others' beliefs on the hidden quality.

The sequence of events of the game is as follows. First, the platform owner decides the amount of educational messages she wants to send on the SNS. Second, all patients decide whether to join the SNS simultaneously. Third, each naive patient on SNS receives a positive, a negative, or no recommendation message about the quality of the healthcare provider. Patients then update their beliefs on the provider's quality according to the message received. Finally, all patents make their purchase decisions based on their beliefs simultaneously.

---

[2] Reader who are interested in the analysis for the innocent platform may contact the authors for a full-length manuscript.

4 ANALYSIS

To highlight the impact of quality difference and network externality on the platform owner's participation decision, in this section we will first set $\gamma = \frac{1}{2}$ and $k = 0$. This allows us to obtain clear-cut analytical results to answer our main research questions. We then examine the impact of γ and k in Section 5.

Firstly, we solve the maximization problems by differentiating equation (10) and (11) with respect to m_i. Immediately we can derive the first-order solutions as

$$m_H^* = \frac{(1-\alpha)(\frac{t}{1-t})(A_H - A_N)}{\beta} \text{ and } m_L^* = \frac{(1-\alpha)(\frac{t}{1-t})(A_N - A_L)}{\beta}, \quad (12)$$

whose feasibility may be easily verified by showing $A_H > A_N > A_L$. m_H^* and m_H^* are then the optimal amounts of platform-generated contents when the provider's service quality is high and low, respectively.

Our first finding is about the magnitudes of m_H^* and m_H^*. In particular, in Proposition 1 we show that $m_L^* \geq m_H^*$. Figure 2 provides an illustration.

Proposition 1. *$m_L^* > m_H^*$ when $\gamma = \frac{1}{2}$ and $k = 0$.*

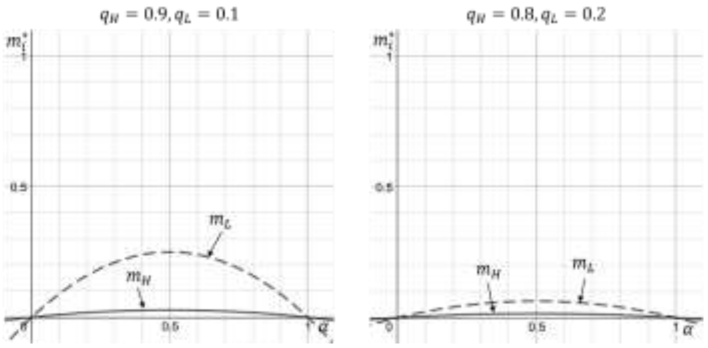

Figure 2. Impact of q_i and α on m_i^*.

No matter how q_H and q_L change, m_L^* always remains greater than m_H^*. We find this result interesting while reasonable. It shows that the platform owner would become more drastic in generating contents when the service quality of the healthcare provider is low. She would try hard to grow her user base in order to let more patients be aware of the low-quality service. However, if the service quality is high, she would then devote less effort. As long as the quality difference between the two types of providers gets smaller, the efforts she makes for each type become more similar.

Besides quality, there are other factors which could affect the platform owner's decision. Proposition 2 summarizes how β and t affect the degrees of participation.

Proposition 2. *m_H^* and m_L^* decreases in β and increases in t when $\gamma = \frac{1}{2}$ and $k = 0$.*

The cost of generating contents apparently has an impact: higher β forces the owner to send fewer messages. The degree of network externality plays a part as well. When t becomes larger, patients in the SNS gain more benefits with the same number of patients on it. Engaging in the SNS can be more efficient, and the same effect can be achieved with less effort, giving the owner more incentives to send messages.

The impact of α, the proportion of patients who are experienced, is somewhat more interesting. For both m_H^* and m_H^*, we find a nonmonotone relationship between each of them and α. Figure 2 also illustrates this phenomenon.

Proposition 3. *When $\gamma = \frac{1}{2}$ and $k = 0$, m_H^* and m_L^* increase in α first until $\alpha = 0.5$. Thereafter, they decrease in α.*

As α gradually moves from 0 to 0.5, the owner's amount of platform-generated contents increases. However, when α reaches the point 0.5, the amount of contents starts to drop. The intuition is as follows. Note that the owner may only send educational messages which affects user base of the SNS rather than recommendation messages which affects patients' beliefs on the hidden quality. If there are not enough experienced patients disseminate the true quality of the provider, no matter how large her user base is, naïve patients' beliefs, that is, q^{pri}, will always remain the same. On the contrary, if the proportion of experienced patients in the SNS is too large, the benefit of affecting naïve patients' believes becomes too small. Obviously, the optimal participation level then decreases as α becomes even larger.

5 EXTENSIONS

As the impact of the patients' prior distribution γ and the noise factor k have not yet been considered, the main focus we want to discuss in Section 5 is the impact of these two parameters.

5.1 Impact of prior distribution

What would happen if we relax the assumption of $\gamma = \frac{1}{2}$? An interesting finding is shown in Figure 3. When γ changes from 0.5 to 0.15, $m_L^* \geq m_H^*$ still hold, though the difference become smaller. However, as γ keeps decreasing to, say, 0.05, m_H^* become greater than m_L^*. A small γ means that patients have no confidence in the healthcare provider's quality from the beginning. If the provider does have high quality, the platform would need to generate more contents so as to indirectly persuade patients that the service quality is high. On the contrary, if the provider indeed has low quality, it would be unnecessary for the platform to generate contents and grow user base, because patients are already pessimistic about the quality and probably would not purchase the service. We summarize this finding in Observation 1.

Observation 1. *$m_L^* < m_H^*$ if γ is small. $m_L^* > m_H^*$ if γ is not too small.*

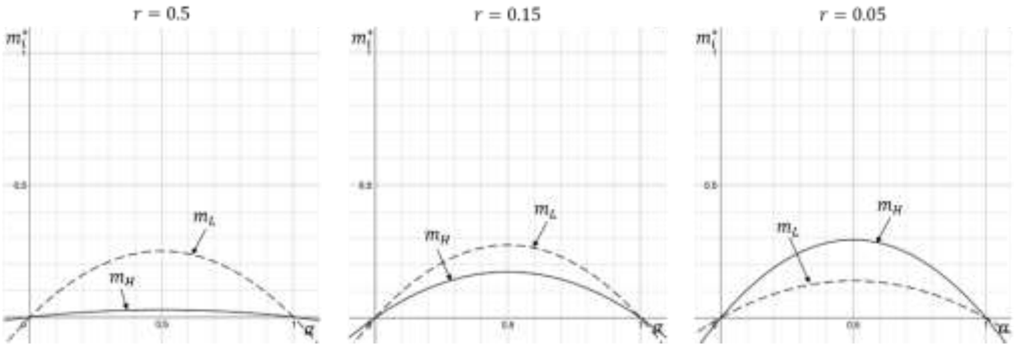

Figure 3. $m_L^* \geq m_H^*$ *holds if γ is not too small.*

Similar findings to Proposition 2 and 3 are summarized in Observation 2. The amount of platform-generated contents is obviously affected by the cost and degree of network externality. Besides, it increases in α until α reaches 0.5. After that, it decreases in α.

Observation 2. *Proposition 2 and 3 hold for all $\gamma \in [0, 1]$.*

As one can see in Figure 4, when γ moves from 0 to 1, the platform owner's amount of platform-generated contents increases first, reaches its peak before γ achieves 0.5, and then gradually decreases. We presume this observation reasonable, because when γ is too low, an isolated naïve patient who cannot count on any messages to update his belief is extremely pessimistic about the quality of the provider. Similarly, when γ is too high, a naïve patient is extremely optimistic. These two extreme situations make it harder for the platform owner to affect patients' prior belief, and thus less effort would be put into. Note that m_H^* reaches its peak before m_L^* does. If the quality of the provider is high, platform owner becomes more sensitive to γ and would try harder to correct patients' low prior belief while γ is really small. However, when γ keeps growing to a certain extent, platform owner would put more effort when the quality of the provider is low. The implication is the same as what we have discussed previously regarding Proposition 1 and Observation 1.

Observation 3. *m_H^* and m_L^* increase in γ first until they reach their peaks before γ achieves 0.5 and then decrease in γ.*

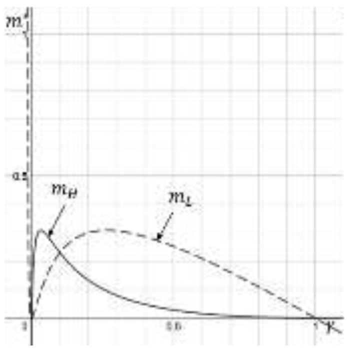

Figure 4. The impact of γ on m_i^*: As γ moves from 0 to 1, the high quality provider's degree of participation increases first, and then gradually decreases before γ reaches 0.5.

5.2 Impact of noise factor

Observation 4. *Proposition 1 and 2 hold for all $k \in \left[0, \frac{1}{2}\right]$. m_H^* and m_L^* decrease in k.*

After relaxing the assumption of $k = 0$, we observe that Proposition 1 and 2 hold for all $k \in \left[0, \frac{1}{2}\right]$. Furthermore, we find that when k becomes larger, the platform owner's incentive of generating contents reduces (cf. Figure 5). As mentioned previously, k is the stand-alone probability for a naïve user to send a (dishonest) positive or negative message. In other words, k is the noise factor which could reduce the objectivity of recommendation messages sent by experienced patients. In this case, no matter how large the user base is, true quality cannot be revealed effectively, thus the owner has less incentive to generate contents.

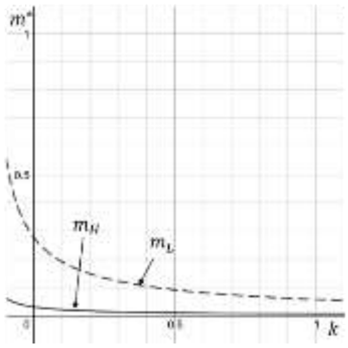

Figure 5. The impact of k on m_i^*.

6 CONCLUSIONS

In this study, our main concern is whether a healthcare social networking site could help reveal the true quality of healthcare provider and thus mitigate information asymmetry problems. Most importantly, we want to know if it is possible to differentiate a high quality provider from a low quality one, and at the same time benefits patients. The platform owner plays an important role in fostering her network size through generating healthcare-related contents. Our findings show that as long as patients' prior belief is not too small, platform owner would try harder to generate contents when the service quality is low in order to let more patients be aware of the low quality healthcare provider. This result fits with our expectation that through participating the SNS, the problem of information asymmetry is eased up, and therefore benefits the high quality provider. Although the provider cannot promote herself, patients can still be well aware of the true quality, as long as the owner knows what the suitable amount of platform-generated contents should be sent.

Beside the cost, there are other factors which could affect a platform owner's content amount decision. Network externality no doubt plays an important role. If user base of a SNS is not large enough, no matter how superior a provider is, quality information cannot be effectively disseminated, and naïve patients cannot make their purchasing decision with thorough messages. Maintaining reputation is of great importance as well, because a high quality provider should attract experienced patients to the site and disseminate good quality for her. Maximum effect would be reached if fostering network size of the SNS and keeping reputation could be proceeded at the same time.

Naïve patients' prior belief and noise factor have impact on the owner's decision too. For the former, it could be related to circumstance at present. For the latter, it is necessary in our model considering the massive information produced every second which is out of order and can hardly be traced back to the source. If a naive patient who has not bought the service from the provider sends recommendation messages on the SNS, the owner's decision would definitely be affected.

Appendix

Proof of Proposition 1. To prove that $m_L^* \geq m_H^*$, we only need $A_N - A_L \geq A_H - A_N$ $(2A_N - A_L - A_H \geq 0)$ to be satisfied when $r = \frac{1}{2}$ and $k = 0$.

$$\begin{aligned}2A_N - A_L - A_H &= \alpha(q_H + q_L)\left(1 - \frac{2p}{q_H + q_L}\right) + \alpha(2 - q_H - q_L)\left(1 - \frac{2p}{q_H + q_L}\right) \\ &\quad + 2(1-\alpha)\left(1 - \frac{2p}{q_H + q_L}\right) - \alpha(q_H + q_L)\left(1 - \frac{p(q_H + q_L)}{q_H^2 + q_L^2}\right) - \alpha(2 - q_H - q_L)(1 \\ &\quad - \frac{p(2 - q_H - q_L)}{q_H(1 - q_H) + q_L(1 - q_L)} - 2(1-\alpha)\left(1 - \frac{2p}{q_H + q_L}\right) \\ &= -\frac{\alpha(q_H + q_L)}{q_H^2 + q_L^2} + \frac{\alpha(2 - q_H - q_L)}{q_H + q_L - q_H^2 - q_L^2} \geq 0.\end{aligned}$$

Simplify the above inequality, we have

$$\alpha q_H^2 - 2\alpha q_H q_L + \alpha q_L^2 = \alpha(q_H - q_L)^2 \geq 0,$$

which holds.

Proof of Proposition 2. We have

$$\frac{\partial m_H^*}{\partial \beta} = -\frac{(1-\alpha)(p-c)\left(\frac{t}{1-t}\right)(A_H - A_N)}{\beta^2} < 0.$$

$$\frac{\partial m_H^*}{\partial t} = \frac{(1-\alpha)(p-c)(A_H - A_N)}{\beta}\left(\frac{1}{(1-t)^2}\right) > 0.$$

Impact of β and t on m_L^* can be proved in a similar way.

Proof of Proposition 3. To begin with, differentiate m_H^* with respect to α:

$$\begin{aligned}\frac{\partial m_H^*}{\partial \alpha} = \frac{t}{(1-t)\beta}\Bigg\{&(1-2\alpha)q_H\left(1 - \frac{p(q_H + q_L)}{q_H^2 + q_L^2}\right) \\ &+ (1-2\alpha)(1-q_H)\left(1 - \frac{p(2 - q_H - q_L)}{q_H(1-q_H) + q_L(1-q_L)}\right) + (-2+2\alpha)\left(1 - \frac{2p}{q_H + q_L}\right) \\ &+ 1 - \frac{2p}{q_H + q_L}\Bigg\}.\end{aligned}$$

Then, substitute $\alpha = 0.5$ into the above expression, and find that the slope at point 0.5 is zero. Now we only need to know if the coefficient sign for the quadratic term α^2 is negative to make sure that it is a concave function. After some arithmetic, the coefficient for α^2 is

$$-\frac{pq_L(q_L - q_H)^3}{q_L^5 + (q_H - 1)q_L^4 + (2q_H^2 - 2q_H)q_L^3 + (2q_H^3 - 2q_H^2)q_L^2 + (q_H^4 - 2q_H^3)q_L + q_H^5 - q_H^4}.$$

The numerator is negative, thus the denominator has to be negative as well. Let the denominator be denoted by $h(q_L)$:

$$h(q_L) = q_L^5 + (q_H - 1)q_L^4 + 2q_H(q_H - 1)q_L^3 + 2q_H^2(q_H - 1)q_L^2 + q_H^3(q_H - 2)q_L + q_H^4(q_H - 1).$$

According to Descartes' rule of signs, $h(q_L)$ has one sign change between the first and second terms. Therefore, it has exactly one positive root. Besides, $h(0) = q_H^4(q_H - 1) \leq 0$, which indicates that $h(1)$ must be less than or equal to zero so as to satisfy Descartes' rule of signs while make sure that when $q_L \in [0, 1]$, $h(q_L)$ would be less than or equal to 0. To confirm that, we apply S.O.C , differentiate $h(1)$ with respect to q_H twice, and have $h''(1) = 20q_H^3 > 0$, which implies that $h(1)$ is a concave function. Let $t(q_H) = h(1)$. Because $t(0) = 0$ and $t(1) = 0$, in addition to the fact that $h(1)$ is a concave function, we are now certain that $h(1)$ is less than or equal to zero for $q_H \in [0, 1]$. Therefore, $h(q_L)$ is less than or equal to zero, indicating that the coefficient for α^2 is negative and $\partial m_H^*/\partial\alpha$ is a concave function. Impact of α on m_L^* can be proved in a similar way.

References

Akerlof, G.A. (1970). The market for" lemons": Quality uncertainty and the market mechanism. The quarterly journal of economics, 84(3), 488-500.

Angst, C., R. Agarwal, G. Gao, J. Khuntia, J.S. McCullough. (2014). Information technology and voluntary quality disclosure by hospitals. Decision Support Systems, 57, 367-375.

Balachander, S. (2001). Warranty signalling and reputation. Management Science, 47(9), 1282-1289.

Chaniotakis, I.E., C. Lymperopoulos. (2009). Service quality effect on satisfaction and word of mouth in the health care industry. Managing Service Quality: An International Journal, 19(2), 229-242.

Chevalier, J.A., D. Mayzlin. (2006). The effect of word of mouth on sales: Online book reviews. Journal of marketing research, 43(3), 345-354.

Chu, W., W. Chu. (1994). Signalling quality by selling through a reputable retailer: An example of renting the reputation of another agent. Marketing Science, 13(2), 177-189.

Desai, P.S., K. Srinivasan. (1995). Demand signalling under unobservable effort in franchising: Linear and nonlinear price contracts. Management Science, 41(10), 1608-1623.

Eysenbach, G. (2003). The impact of the internet on cancer outcomes. CA: A Cancer Journal for Clinicians, 53(6), 356-371.

Eysenbach, G., C. Kohler. (2003). What is the prevalence of health-related searches on the world wide web? qualitative and quantitative analysis of search engine queries on the internet. American Medical Informatics Association Annual Symposium Proceedings Archive. American Medical Informatics Association, 225-229.

Greaves, F., D. Ramirez-Cano, C. Millett, A. Darzi, L. Donaldson. (2013). Harnessing the cloud of patient experience: using social media to detect poor quality healthcare. BMJ quality & safety, 22(3), 251-255.

Greene, J.A., N.K. Choudhry, E. Kilabuk, W.H. Shrank. (2011). Online social networking by patients with diabetes: a qualitative evaluation of communication with facebook. Journal of general internal medicine, 26(3), 287-292.

Howard, D.H. (2002). Why do transplant surgeons turn down organs? A model of the accept/reject decision. Journal of Health Economics, 21(6), 957-969.

Jiang, B., X. Zhang. (2011). How does a retailer's service plan affect a manufacturer's warranty? Management Science, 57(4), 727-740.

Kalra, A., S. Li. (2008). Signalling quality through specialization. Marketing Science, 27(2), 168-184.

Kihlstrom, R.E., M.H. Riordan. (1984). Advertising as a signal. The Journal of Political Economy, 92(3), 427-450.
Mahmud, A., M. Parkhurst. (2007). Expanding economic opportunity: The role of pharmaceutical companies. Corporate Social Responsibility Initiative Report (21). Cambridge, MA: Kennedy School of Government, Harvard University.
Mayzlin, D. (2006). Promotional chat on the internet. Marketing Science, 25(2), 155-163.
Milgrom, P., J. Roberts. (1986). Price and advertising signals of product quality. The Journal of Political Economy, 94(4), 796-821.
Moorthy, S., K. Srinivasan. (1995). Signaling quality with a money-back guarantee: The role of transaction costs. Marketing Science, 14(4), 442-466.
Nelson, P. (1974). Advertising as information. The journal of political economy, 82(4), 729–754.
Soberman, D.A. (2003). Simultaneous signaling and screening with warranties. Journal of Marketing Research, 40(2), 176-192.
Spence, M. (1973). Job market signaling. The quarterly journal of Economics, 87(3), 355-374.
Su, X., S.A. Zenios. (2006). Recipient choice can address the efficiency-equity trade-off in kidney transplantation: A mechanism design model. Management Science, 52(11), 1647-1660.
Vick, S., A. Scott. (1998). Agency in health care. Examining patients' preferences for attributes of the doctorpatient relationship. Journal of Health Economics, 17, 587-605.
Vogt, T.M., J.P. Mullooly, D. Ernst, C.R. Pope, J.F. Hollis. (1992). Social networks as predictors of ischemic heart disease, cancer, stroke and hypertension: incidence, survival and mortality. Journal of clinical epidemiology, 45(6), 659-666.
Wicks, P., D.L. Keininger, M.P. Massagli, C. Loge, C. Brownstein, J. Isojarvi, J. Heywood. (2012). Perceived benefits of sharing health data between people with epilepsy on an online platform. Epilepsy & Behavior, 23, 16-23.