國立臺灣大學管理學院資訊管理學系

碩士論文

Department of Information Management
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Master Thesis

# 透過建構醫療社群平台
# 揭露醫療照護服務提供者的品質資訊
# Revealing Hidden Quality of a Healthcare Provider by Constructing a Healthcare Social Networking Site

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# 摘要

醫療照護服務提供者與病患間的資訊不對稱一直是個重要的議題，而社群平台促進資訊分享與品質揭露的特性，被認為得以有效地緩解這種現象。我們欲研究醫療社群平台是否能夠幫助揭露醫療照護服務提供者的真實品質資訊，即使社群平台上可能存在著錯誤的資訊。

在本篇研究中，我們探討一個醫療照護服務提供者、一個社群平台建置者，以及一群病患之間的資訊不對稱問題。在我們的模型中，病患無法直接地得知醫療照護服務提供者的品質資訊，而平台建置者則有可能知道該品質資訊。我們提出一個賽局理論模型，用以描述病患與平台建置者之間資訊交換的過程，平台建置者會決定其在平台上參與資訊交換的程度，參與度影響社群平台的網絡大小。曾經體驗過該醫療照護服務的病患，會在平台上向不曾體驗過服務的病患傳遞正面或負面的推薦訊息，接著，未曾體驗過服務的病患會根據推薦訊息更新他們對於該醫療照護提供者的認知品質，最後，再依據更新後的認知品質決定他們是否要購買服務。平台建置者的目標是找出其最佳參與度，以最大化病患加入平台的福利，而本研究的目的在於探討此最佳參與度的經濟與管理意涵。

我們發現，即使社群平台上存在著錯誤訊息，醫療社群平台仍可以有效地揭露醫療照護服務提供者的品質資訊，此種平台的存在還是對緩解資訊不對稱有所幫助。


關鍵字：資訊不對稱、品質揭露、醫療照護、社群平台、網路外部性。



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# Abstract

The issue of information asymmetry between healthcare receivers (patients) and healthcare providers has always been of great importance. One feasible way to mitigate this problem is through healthcare social networking sites, which provide a more efficient way to facilitate information sharing and quality disclosure. We examine whether healthcare social networking sites are indeed helpful for revealing the true quality of healthcare providers, though there may be false information (noise) being passed on the sites.

In this study, we discuss an information asymmetry problem among a healthcare provider, a social networking platform, and a group of patients. The quality of the service provided by the healthcare provider cannot be observed by the patients and may or may not be observed by the platform owner. 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 content generation on the site. This affects the network size of the social networking site. Patients who have experienced the service 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 service. We characterize the platform owner's optimal degree of engagement and study the economic and managerial implications of it.

We find that a healthcare social networking site helps reveal the true quality of a healthcare provider. Despite the fact that there may be false information (noise), the existence of the healthcare social networking site is still beneficial.

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



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# Contents





doi:10.6342/NTU201601294

doi:10.6342/NTU201601294

# List of Figures





doi:10.6342/NTU201601294

doi:10.6342/NTU201601294

# List of Tables





doi:10.6342/NTU201601294

doi:10.6342/NTU201601294

# Chapter 1

# Introduction

## 1.1 Background and Motivation

The healthcare industry, which consists 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 receivers. The former involves all kinds of medical specialists providing professional knowledge and suggestions, such as physician, psychiatrist, dentist, nurse, etc. The latter receives healthcare services and therefore cares about the quality of the providers. To facilitate our discussions, we will call all those who deliver medical services the healthcare providers, and all those who receive services the patients.

Information asymmetry between patients and healthcare providers has always been of great importance. As Angst et al. (2014) point out, the extent of information disclosed



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are leading indicators for patients to choose a healthcare provider. On the one hand, patients prefer 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 one instead of being driven out of the market. 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) indicates 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

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



doi:10.6342/NTU201601294

indeed become a prevalent phenomenon.

The emergence of these healthcare social networking sites leads us to some basic questions: Why sharing healthcare information 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, the platform may general educational contents on the platform by itself to foster its network size. Once the network size becomes larger, more patients would join the network and exchange information about the quality of healthcare providers on the site and further mitigate the information asymmetry problem. Is this "strategy" of engaging in social networking sites really helpful for revealing the true quality of a healthcare provider, despite the fact that there may be false information (noise)? If so, is it true for high-quality providers, low-quality providers, or both? Does the existence of a healthcare



doi:10.6342/NTU201601294

social networking site benefit patients? What factors affect the amount of benefits, if any, brought to patients? We examine these questions in this study.



## 1.2 Research Objectives

In this study, we discuss an information asymmetry problem among a healthcare provider, a social networking platform, and a group of patients. The quality of the service provided by the healthcare provider cannot be observed by the patients and may or may not be observed by the platform owner. Our main objective is to examine the strategy for the platform owner to indirectly reveal the hidden quality by facilitating 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 content generation on the site. This affects the network size of the social networking site. Patients who have 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. [2]

[2]Note that the platform we consider in our study is not perfect. Though some people send recommendation messages according to the true quality of the healthcare provider, it is still possible that some patients may send false messages no matter they are intentional or not. In our research, we find that a healthcare SNS helps mitigate information asymmetry in any case.



doi:10.6342/NTU201601294

## 1.3 Research Plan

The remainder of this study is organized as follows. In Chapter 2, we review some related works. In Chapter 3, an economic model is formulated to describe information exchange between a platform owner and patients on a social networking site. We do the analysis and describe our findings for the case that the platform does not know the healthcare provider's quality in Chapter 4. The examination for the case that the platform knows the quality is done is Chapter 5. Chapter 6 concludes. All proofs are in the appendix.



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doi:10.6342/NTU201601294

# Chapter 2

# Literature Review

## 2.1 Provider-Patient Information Asymmetry

The problem of information asymmetry exists nearly everywhere involves 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. Therefore, high-quality sellers leave and the market is filled with low-quality cars (lemons). Under this circumstance, information asymmetry hurts both buyers and sellers, resulting in no good price to sell and thus no fine cars to buy. 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. Information asymmetry once again hurts both sides.



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The same problem exists in the healthcare industry. One typical case is for healthcare providers to know more about their quality information than the patients. Vick and Scott (1998) analyze the factors that patients care the most in doctor-patient relationship. Patients prefer to provide more information to doctors and are willing to know more about their health conditions. Besides, they tend to be involved in decision making rather than letting their doctors to decide for them. This demonstrates the importance of information exchange between healthcare providers, who possess hidden medical information, and patients.

The situation of patients holding more hidden information than healthcare providers is also studied in plenty of literature. 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), where a candidate may turn down an organ despite of the shortage, and the decision depends on his or her current health level. Because only patients know their actual health conditions, an organ cannot be properly allocated to someone who need it the most. Besides, due to humanitarian reason, organ trade is not allowed.

Our main focus in this thesis 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. Through meeting the needs of information, anxiety may be reduced and satisfaction can be generated. Based on this, we will look back to literature addressing social networking and information



doi:10.6342/NTU201601294

sharing in the next section.

## 2.2 Social Networking and Information Sharing

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 association with the mortality rate among people with ischemic heart disease (IHD), cancer, and stroke. Furthermore, among the frequency, scope, and size of a support network, scope has the greatest impact on the mortality rate, meaning that it is how many resources you have or how diversity the people you know that affects mortality rate the most. This leads us to a straightforward belief that people do need as much information as possible, and the prevalence of online social networks can accelerate health information exchange.

The pros and cons of information sharing on social networking sites have been addressed in many works. Eysenbach and Kohler (2003) mentions that the information shared on the virtual communities for cancer patients are mostly about personal opinions, experiences, and supports. By obtaining health information, patients may feel empowered and become more confident. However, the anonymity of the virtual communities could also lead to concerns like unclear or misleading source of information found. Moreover, health information may even cause stress to physicians, for they need to spend more time discussing the information with patients.

Greene et al. (2011) analyse posts and discussion topics from the 15 largest groups for patients with diabetes on Facebook. The result shows that 65.7% of the posts are about



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patients' experiences with diabetes management, 28.8% provide interpersonal support, 26.7% are posted for promotional purpose, and 13.3% request information. It is not surprising that the need for information is again pointed out. However, there comes another issue about healthcare social networking sites that promotional posts could erode patients' trust on the credibility of information.

Wicks et al. (2012) state that most people with epilepsy are isolated without direct relationships with other patients with the same disease. Nevertheless, after joining the social networking site PatientsLikeMe, they are connected with people like them and therefore get the chances to know each other. Besides, the more connections they have, the more benefits they could perceive, which include the extent of helpfulness PatientsLikeMe brings them regarding health condition understanding and management.

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 word of mouth effect. In the retailing industry, Chevalier and Mayzlin (2006) analyse the effect of word of mouth on the sales of Amazon and Barnes & Noble. The result shows that word of mouth indeed affects a consumer's online purchase decision, and hence influences firms' sales revenue. For these reasons, we wonder if healthcare providers may also build up credibility through word of mouth online, an effective way of marketing taking place on social media.



doi:10.6342/NTU201601294

## 2.3 Signaling Theory

According to the above discussions, we are well aware of the problem of information asymmetry in the healthcare industry, and the possibility that it could be mitigated through information sharing accelerated by the prevalence of social media. Therefore, the issue now we concern would then be the healthcare providers' signaling strategies.

Since the seminal works by Akerlof (1970) and Spence (1973), people start to discuss how a principal may use signaling strategies to creditably convey quality information to agents. Kalra and Li (2008) show that a firm can signal its quality to consumers through specialization. Desai and Srinivasan (1995) study demand signaling through price contracts. Other mechanisms include advertising (Nelson, 1974; Milgrom and Roberts, 1986; Kihlstrom and Riordan, 1984), warranty offering (Balachander, 2001; Soberman, 2003; Jiang and Zhang, 2011), money-back guarantees (Moorthy and Srinivasan, 1995), selling through reputable retailers (Chu and Chu, 1994), salesforce compensation (Kalra et al., 2003), and online word of mouth (Mayzlin, 2006). Our work can contribute to this stream of literature by discussing the application of signaling in the healthcare domain.

Angst et al. (2014) mention that hospitals with low quality or bad financial conditions are less likely to disclose their quality information. In addition, for hospitals that are non-profitable, information disclosure may be possible. This leaves us the believe that signaling through quality disclosure may be a possible way for higher quality healthcare providers to separate themselves. Due to this and the fact that there is little literature addressing related subject, in this work we would like to develop a feasible strategy for high-quality healthcare providers to signal their quality.



doi:10.6342/NTU201601294

As discussed before, the anonymous character of social networking sites may do harm to users' confidence in the information found. According to Mayzlin (2006), marketers can hire professional posters to take advantage of the power of word of mouth and fake up discussions online in order to promote their own products. Fortunately, it is proved that even though anonymity allows firms to manipulate online discussions, high-quality firms can promote their products by not only generating discussions, but also attracting consumers to disseminate positive reviews. Given that word of mouth effect can still be persuasive under this condition, we believe that even there are false information or advertisements on a healthcare social networking site, its existence may still help mitigate information asymmetry.



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# Chapter 3

# Problem Description and Formulation

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 $\eta$ of joining the SNS for each patient. We assume that $\eta$ is uniformly distributed between 0 and 1, where a patient with a low value of $\eta$ enjoys online networking more than one with a high value of $\eta$ (cf. Figure 3.1). 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 cost $\eta$ to join the site is

$$\mathcal{P}(\eta) = v - \eta + t\eta^*, \tag{3.1}$$



doi:10.6342/NTU201601294

where $v > 0$ is the stand-alone benefit of joining the SNS, $t > 0$ is the degree of network externality, and $\eta^*$ 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 3.1).

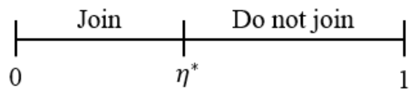


Figure 3.1: Patients' extent of repellence affecting joining decision

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 $\theta$ be the patient's willingness-to-pay, a patient will purchase the service from the healthcare provider if

$$\theta q - p \geq 0, \tag{3.2}$$

where $q$ is his belief on the service quality and $p$ is the price charged for the service. We assume that $\theta$ is uniformly distributed between 0 and 1. Moreover, let $q_i$ for $i \in \{L, H\}$ denotes the service provider's private information. We assume that $q_L < q_H$, so $q_L$ 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 *naive patients*. We use $\alpha \in [0, 1]$ and $1 - \alpha$ to denote the proportion of experienced and naive patients, respectively. It is assumed that whether one is experienced and $\eta$ 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



doi:10.6342/NTU201601294

$\gamma \in [0, 1]$ is his prior distribution 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 naive 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 naive 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 are $h(q)$ 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. For ease of exposition, we will set $h(q) = q$ in our basic model. We relax this assumption in extensions to show that our main findings remain qualitatively true when $h(\cdot)$ is increasing but not linear.

Unfortunately, on an SNS it is also possible that such a message actually comes from a naive 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 naive user to send a positive or negative message. When $k = 0$, a naive user stays honest and does not say anything about the provider. When $k$ goes up, naive users becomes less honest and may randomly promote or demote the provider with no reason. When $k = \frac{1}{2}$, a naive user is never honest and will definitely say something with no proof. $k$ is thus called the



doi:10.6342/NTU201601294

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 naive patient to get a positive and negative message when the true quality is $q_i$ are

$$\begin{aligned}\Pr(\text{positive}|q_i) &= \alpha h(q_i) + (1-\alpha)k \text{ and} \\ \Pr(\text{negative}|q_i) &= \alpha(1-h(q_i)) + (1-\alpha)k,\end{aligned} \tag{3.3}$$

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 naive user who is honest.

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

$$\begin{aligned}\Pr(q_H|\text{positive}) &= \frac{\gamma \Pr(\text{positive}|q_H)}{\gamma \Pr(\text{positive}|q_H) + (1-\gamma)\Pr(\text{positive}|q_L)} \\ &= 1 - \Pr(q_L|\text{positive}).\end{aligned} \tag{3.4}$$

$\Pr(q_H|\text{negative})$ 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

$$q^{post}(\text{positive}) = \Pr(q_H|\text{positive})q_H + \Pr(q_L|\text{positive})q_L. \tag{3.5}$$

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

A naive 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 no message from another naive 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

$$\begin{aligned}A_i = {} & \Pr(\text{positive}|q_i)\Pr\Big(\theta \geq \frac{p}{q^{post}(\text{positive})}\Big) \\ & + \Pr(\text{negative}|q_i)\Pr\Big(\theta \geq \frac{p}{q^{post}(\text{negative})}\Big) + \Pr(\text{no}|q_i)\Pr\Big(\theta \geq \frac{p}{q^{pri}}\Big)\end{aligned} \tag{3.6}$$



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

$$A_N = \Pr\Big(\theta \geq \frac{p}{q^{pri}}\Big) \tag{3.7}$$

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

**Lemma 1.** *$A_H > A_N > A_L$ when $\gamma = \frac{1}{2}$.*

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 her $\frac{\beta m^2}{2}$ to achieve the participation level $m$ with $\beta$ set as a scale factor. 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

$$\mathcal{P}(\eta) = v - \eta + t(\eta^* + m). \tag{3.8}$$

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 the *innocent platform*. In the second one, the platform knows the quality. She is then called the *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



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precisely, the platform owner acts to maximize the ability for the platform to attract naive patients to buy the service when the provider's quality is high and to discourage them from buying 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

$$\mathcal{S}^I = \max_{m \geq 0} \; (1-\alpha)\eta^* \Big\{ \gamma(A_H - A_N) + (1-\gamma)(A_N - A_L) \Big\} - \frac{\beta m^2}{2}. \tag{3.9}$$

The platform chooses a participation level $m$ to maximize its influence minus its cost. $(1-\alpha)\eta^*$ is the number of naive patients who join the SNS. For each of them, the term inside the curly bracket measures the platform's expected influence on him. If the healthcare provider's quality is high (with probability $\gamma$), the influence $A_H - A_N$ is the incremental probability for the naive patient to purchase the service. Otherwise, the provider's quality is low (with probability $1-\gamma$), and the influence is measured by $A_N - A_L$, the reduction in the purchasing probability. Finally, $\frac{\beta m^2}{2}$ is the cost paid by the platform.

**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:

$$\mathcal{S}_H^K = \max_{m_H \geq 0} (1-\alpha)\eta^*(A_H - A_N) - \frac{\beta m_H^2}{2}, \tag{3.10}$$

$$\mathcal{S}_L^K = \max_{m_L \geq 0} (1-\alpha)\eta^*(A_N - A_L) - \frac{\beta m_L^2}{2}. \tag{3.11}$$

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



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messages about the provider's quality, and thus the owner may only send *educational messages* that affects the size of her user base on the SNS. Only patients may send *recommendation messages* to affect others' beliefs on the hidden quality.

The sequence of events 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.

A list of notations is provided in Table 3.1 and Table 3.2.

| | Decision variables |
|---|---|
| $m$ | The Innocent platform owner's amount of platform-generated contents. |
| $m_i$ | The Knowledgeable platform owner's amount of platform-generated contents when the healthcare service quality is $q_i$. |

Table 3.1: List of decision variables



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| | Parameters |
|---|---|
| $v$ | A patient's benefit of joining the SNS. |
| $\eta$ | A patient's extent of repellence for technology adoption (joining the SNS). |
| $\eta^*$ | The equilibrium number of patients on the SNS. |
| $t$ | The degree of network externality. |
| $\theta$ | A patient's willingness-to-pay for the healthcare service. |
| $p$ | The price charged for the healthcare service. |
| $\alpha$ | The proportion of experienced patients. |
| $q_i$ | The hidden quality of the healthcare service, $i \in \{H, L\}$. |
| $q^{pri}$ | Patients' prior belief on the service quality. |
| $q^{post}$ | Patients' posterior belief on the service quality. |
| $\gamma$ | Patient's prior distribution for the service quality to be high. |
| $h(q)$ | Probability for receiving a positive message from an experienced patient. |
| $k$ | Probability for a naive patient to send a positive or negative message. |
| $A_i$ | Probability for a naive patient joining the SNS to buy the service with $q_i$. |
| $A_N$ | Probability for a naive patient who does not join the SNS (or receive no message on the SNS) to buy the service. |
| $\beta$ | Scaling factor for the platform owner's cost of participation. |

Table 3.2: List of parameters



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# Chapter 4

# Analysis for Innocent Platform

To highlight the impact of quality difference and network externality on the platform owner's participation decision, in Section 4.1 we will first set $\gamma = \frac{1}{2}$, $k = 0$, and $h(q) = q$. This allows us to obtain clear-cut analytical results to answer our main research questions. We then examine the impact of $\gamma$, $k$, and $h(\cdot)$ in Section 4.2.1, 4.2.2, and 4.2.3, respectively.

## 4.1 Basic Case Analysis

Our first step is to solve the maximization problem by differentiating (3.9) with respect to $m$. Immediately we can derive the first-order solution as

$$m^* = \frac{(1-\alpha)(\frac{t}{1-t})\Big\{\gamma(A_H - A_N) + (1-\gamma)(A_N - A_L)\Big\}}{\beta}, \tag{4.1}$$

which is the optimal amount of platform-generated contents for the provider. $m^*$ is greater than zero, meaning that even though there may be false information (noise) on the SNS, the existence of the healthcare SNS is still beneficial.



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**Proposition 1.** $m^* > 0$ *when* $\gamma = \frac{1}{2}$ *and* $k \in [0, \frac{1}{2}]$.

Besides, $m^*$ can be shown to increase in $q_H$ and decreases in $q_L$. When $q_H$ becomes higher, the difference between $A_H$ and $\Pr(\theta \geq \frac{p}{q^{pri}})$ gets larger, which then raises $m^*$. Same result happens when $q_L$ becomes lower. In other words, large quality difference between the two types of providers gives the platform owner motive to generate more contents. This way, information asymmetry problem can be mitigated, and patients can distinguish between the two types easier. If quality difference is small, the two types of providers becomes similar and thus there is no need for the platform to generate much contents.

**Proposition 2.** $m^*$ *increases in* $q_H$ *and decreases in* $q_L$ *when* $\gamma = \frac{1}{2}$ *and* $k = 0$.

Besides quality, there are other factors which could affect the platform owner's decision. The cost of generating contents apparently has an impact: higher $\beta$ 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. Proposition 3 summarizes how $\beta$ and $t$ affect the degrees of participation.

**Proposition 3.** $m^*$ *decreases in* $\beta$ *and increases in* $t$ *when* $\gamma = \frac{1}{2}$, $k = 0$, *and* $m^* \leq \frac{1-t-v}{t}$.

The impact of $\alpha$, the proportion of patients who are experienced, is somewhat more interesting. We find a nonmonotone relationship between $m^*$ and $\alpha$. Figure 4.1 also illustrates this phenomenon.



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**Proposition 4.** *When $\gamma = \frac{1}{2}$ and $k = 0$, $m^*$ increases in $\alpha$ first until $\alpha = 0.5$. Thereafter, $m^*$ decreases in $\alpha$.*

As $\alpha$ gradually moves from 0 to 0.5, the owner's amount of platform-generated contents increases. However, when $\alpha$ reaches the point 0.5, amount of contents starts to drop. The implication 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 disseminating the true quality of the provider, no matter how large her user base is, naive 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 naive patients' believes becomes too small. Obviously, the optimal participation level then decreases as $\alpha$ becomes even larger.

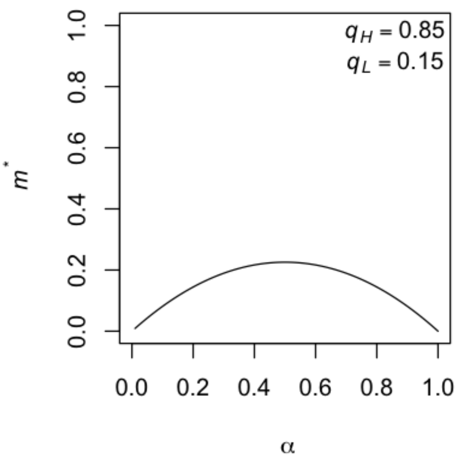


Figure 4.1: The impact of $\alpha$ on $m^*$



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## 4.2 Extensions

The main focus we want to discuss in this section is the impact of the three factors which have not yet been considered: the patients' prior distribution $\gamma$, the noise factor $k$, and the recommendation probability $h(\cdot)$.

### 4.2.1 Impact of Prior Distribution

After relaxing $\gamma$, findings in Proposition 1, 2, 3 and 4 still hold for all $\gamma \in [0, 1]$. Besides, we observed some interesting characters in terms of $\gamma$, which are summarized below.

**Observation 1.** *Proposition 1, 2, 3 and 4 hold for all $\gamma \in [0, 1]$.*

**Observation 2.** *$m^*$ increases in $\gamma$ first until it reaches its peak before $\gamma$ achieves 0.5, and then gradually decreases in $\gamma$.*

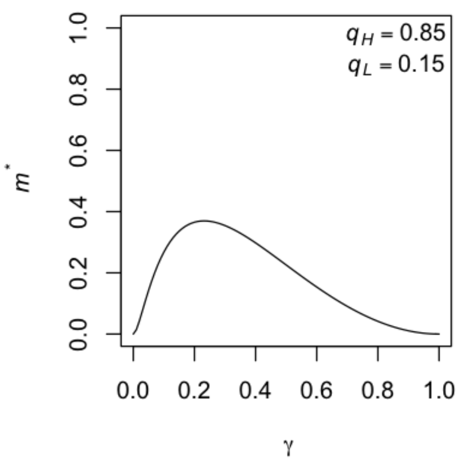


Figure 4.2: The impact of $\gamma$ on $m^*$

As illustrated in Figure 4.2, when $\gamma$ moves from 0 to 1, the platform owner's amount of platform-generated contents increases first, reaches its peak before $\gamma$ achieves 0.5, and



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then gradually decreases. We presume this observation reasonable, because when $\gamma$ is too low, an isolated naive patient who cannot count on any messages to update his belief is extremely pessimistic about the quality of the provider. Similarly, when $\gamma$ is too high, a naive 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.

### 4.2.2 Impact of Noise Factor

In the above discussion, $k$ is still being set as zero. Now we want to see when $k$ becomes any number between 0 and $\frac{1}{2}$, what results it may bring.

**Observation 3.** *Proposition 2 holds for all* $k \in [0, \frac{1}{2}]$.

**Proposition 5.** *Proposition 3 holds for all* $k \in [0, \frac{1}{2}]$.

**Proposition 6.** $m^*$ *decreases in* $k$*, where* $k \in [0, \frac{1}{2}]$.

After relaxing the assumption of $k = 0$, we observe that Proposition 2 holds for all $k \in [0, \frac{1}{2}]$, and find that Proposition 3 holds for all $k \in [0, \frac{1}{2}]$. Furthermore, when the noise factor becomes larger, the platform owner's incentive of generating contents reduces. As mentioned previously, $k$ is the stand-alone probability for a naive patient to send a (dishonest) positive or negative message, which is the noise factor that 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. However, $m^*$ remains greater than zero for all $k \in [0, \frac{1}{2}]$, meaning that even though there may be false information (noise) on the healthcare social networking site, its existence is still beneficial (cf. Figure 4.3).



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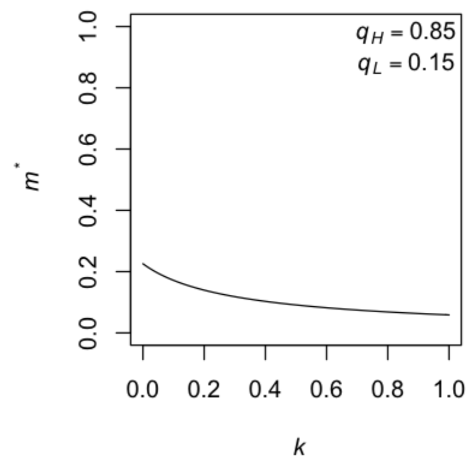


Figure 4.3: The impact of $k$ on $m^*$

### 4.2.3 Impact of Recommendation Probability

Previously, we set $h(q) = q$ throughout the study for ease of exposition. However, the recommendation probability is complicated and cannot be easily estimated. For example, the probability for an experienced patient to send a positive message could be small if the quality of the healthcare service is not that impressive. In other words, he is willing to send a positive message only when superior value of the service is perceived. To discuss the impact of recommendation probability, we set $h(q) = q^z$ for $z \in (0, \infty]$, where $z$ is a factor which adjusts the shape of recommendation probability. We find that Proposition 1, 2, 3, 4, 5, 6 and Observation 1, 2, 3 remain true no matter how $z$ changes.

**Observation 4.** *Proposition 1, 2, 3, 4, 5, 6 and Observation 1, 2, 3 hold for all* $z \in (0, \infty]$.

Furthermore, we observe that changes of $z$ do not directly affect the platform owners' decision $m^*$ (cf. Figure 4.4). In fact, when $z$ changes, it first affects the difference between $h(q_H)$ and $h(q_L)$, that is, $q_H^z - q_L^z$. Then, the amount of difference affects $m^*$.



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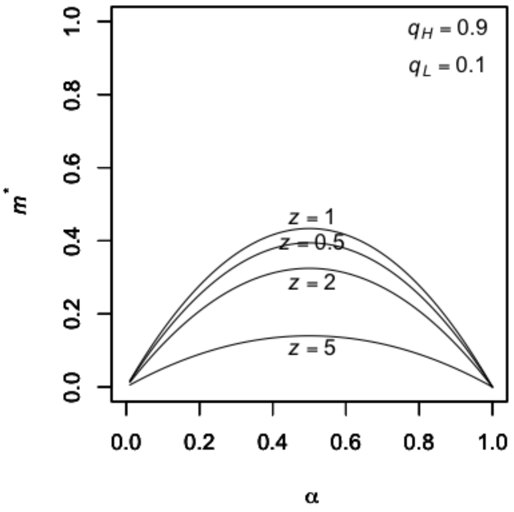


Figure 4.4: The impact of $z$ on $m^*$

As shown in Figure 4.5, the difference between $q_H^z$ and $q_L^z$ depends on both the shape of recommendation probability and the value of $q_i$. When $q_H$ and $q_L$ are set to be 0.3 and 0.1, $q_H - q_L$ is greater than $q_H^2 - q_L^2$. However, when $q_H$ and $q_L$ are set as 0.9 and 0.7, $q_H^2 - q_L^2$ turns out to be greater than $q_H - q_L$. As can be seen, value of $z$ has a knock-on effect on $m^*$.

**Observation 5.** *$m^*$ tends to increase in $z$ when $q_H^z - q_L^z$ increases.*



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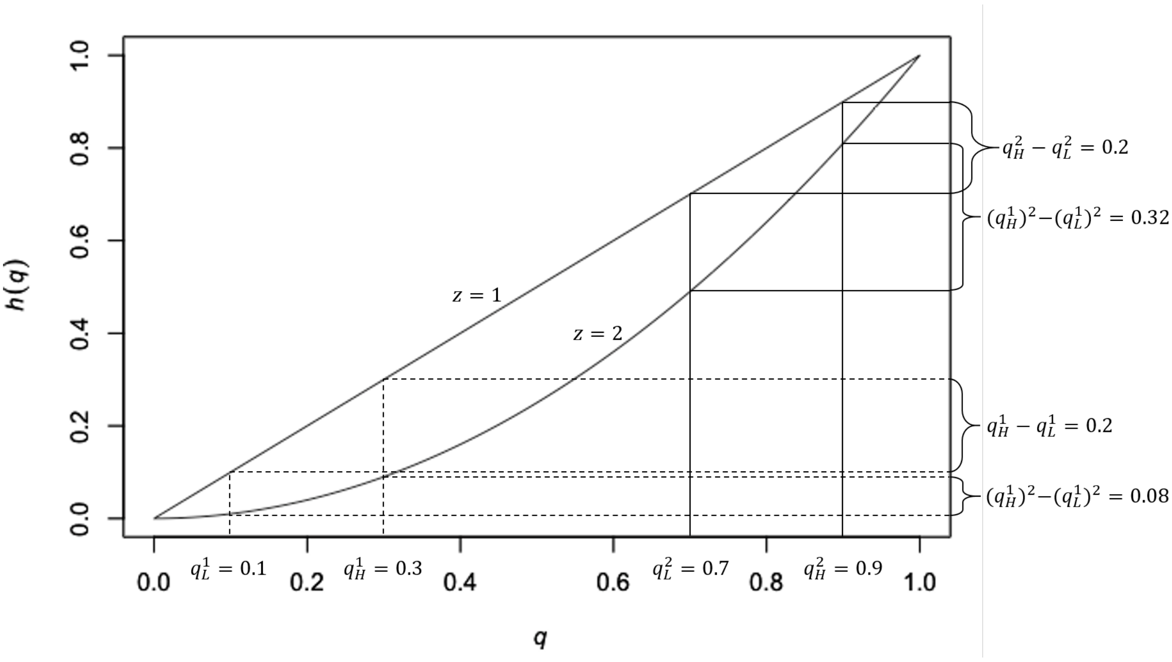


Figure 4.5: The impact of $z$ on $m^*$



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# Chapter 5

# Analysis for Knowledgeable Platform

In Section 5.1, we will first set $\gamma = \frac{1}{2}$, $k = 0$, and $h(q) = q$. We then examine the impact of $\gamma$, $k$, and $h(\cdot)$ in Section 5.2.1, 5.2.2, and 5.2.3, respectively. The main difference between Chapter 4 and Chapter 5 is that the platform owner knows the true quality of the provider now.

## 5.1 Basic Case Analysis

Firstly, we solve the maximization problems by differentiating (3.10) and (3.11) with respect to $m_i$. Immediately we can derive the first-order solutions as

$$m_H^* = \frac{(1-\alpha)(\frac{t}{1-t})(A_H - A_N)}{\beta}, \text{ and} \tag{5.1}$$

$$m_L^* = \frac{(1-\alpha)(\frac{t}{1-t})(A_N - A_L)}{\beta}. \tag{5.2}$$



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$m_H^*$ and $m_L^*$ are then the optimal amounts of platform-generated contents when the provider's service quality is high and low, respectively. Note that both $m_H^*$ and $m_L^*$ are greater than zero, meaning that even though there may be false information (noise) on the SNS, the existence of the healthcare SNS is still beneficial.

**Proposition 7.** *$m_H^* > 0$ and $m_L^* > 0$ when $\gamma = \frac{1}{2}$ and $k \in [0, \frac{1}{2}]$.*

Our first finding is about the magnitudes of $m_H^*$ and $m_L^*$. In particular, in Proposition 8 we show that $m_L^* > m_H^*$. Figure 5.1 provides an illustration.

**Proposition 8.** *$m_L^* > m_H^*$ when $\gamma = \frac{1}{2}$ and $k = 0$.*

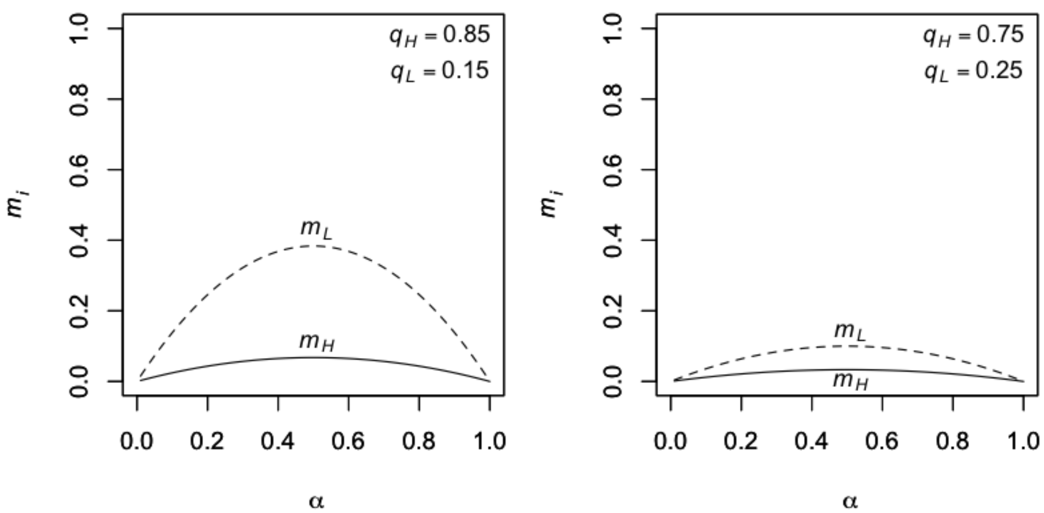


Figure 5.1: $m_L^* > m_H^*$ when $\gamma = \frac{1}{2}$ and $k = 0$

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



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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, similar findings in Proposition 3 and 4 can also be obtained, which are summarized in Proposition 9 and 10 below.

**Proposition 9.** *$m_L^*$ and $m_H^*$ decrease in $\beta$ and increase in $t$ when $\gamma = \frac{1}{2}$, $k = 0$, and $m_i^* \leq \frac{1-t-v}{t}$, $i \in \{L, H\}$.*

**Proposition 10.** *When $\gamma = \frac{1}{2}$ and $k = 0$, $m_L^*$ and $m_H^*$ increase in $\alpha$ first until $\alpha = 0.5$. Thereafter, they decrease in $\alpha$.*

## 5.2 Extensions

As what we have done in Section 4.2, the main focus we want to discuss in this section is the impact of the three factors which have not yet been considered: the patients' prior distribution $\gamma$, the noise factor $k$, and the recommendation probability $h(\cdot)$.

### 5.2.1 Impact of Prior Distribution

What would happen if we relax the assumption of $\gamma = \frac{1}{2}$? An interesting finding is shown in Fig 5.2. When $\gamma$ changes from 0.5 to 0.15, $m_L^* > m_H^*$ still hold, though the difference become smaller. However, as $\gamma$ keeps decreasing to, say, 0.05, $m_H^*$ becomes greater than $m_L^*$. A small enough $\gamma$ means that patients have not much confidence in the healthcare provider's quality from the beginning. If the provider does have high quality,



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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 Proposition 11.

**Proposition 11.** *$m_H^* > m_L^*$ if and only if $\gamma < \frac{q_L}{q_H+q_L}$.*

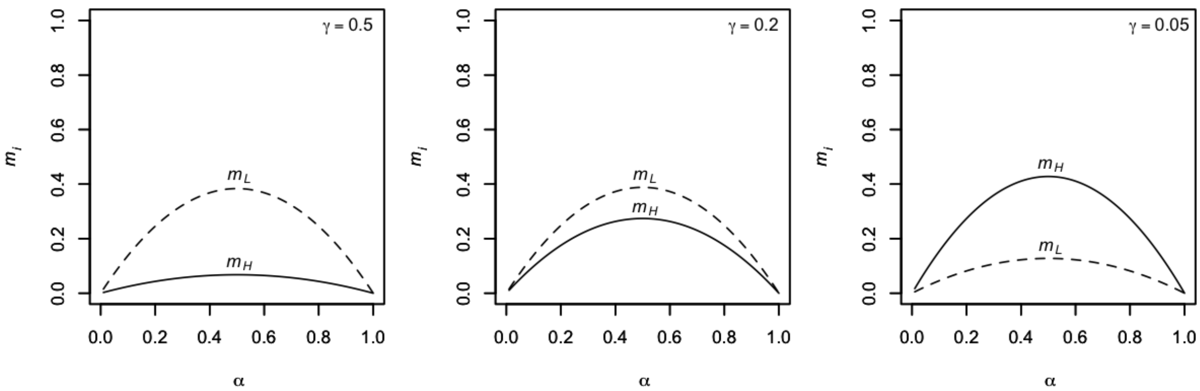


Figure 5.2: $m_L^* < m_H^*$ if $\gamma$ is small. $m_L^* > m_H^*$ if $\gamma$ is not too small

Similar findings to Proposition 7, 9 and 10 are also observed when we relax $\gamma$. Despite the fact that there may be false information (noise), the existence of the platform is still beneficial. The amount of platform-generated contents is obviously affected by the cost and degree of network externality.

**Observation 6.** *Proposition 7, 9 and 10 hold for all $\gamma \in [0, 1]$.*

The impact of $\gamma$ on $m_H^*$ and $m_L^*$ is quite the same as what we observe in Observation 2, Section 4.2.1. When $\gamma$ moves from 0 to 1, the platform owner's amount of platform-generated contents increases first, reaches its peak before $\gamma$ achieves 0.5, and



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then gradually decreases. The difference is that $m_H^*$ reaches its peak before $m_L^*$ does. If the quality of the provider is high while the patients are pessimistic about the service quality (small $\gamma$), platform owner would try harder to generate contents and correct patients' belief. However, when $\gamma$ keeps growing to a certain extent, platform owner would put more effort when the quality of the provider is low (cf. Figure 5.3). The implications are the same as what we have discussed previously regarding Proposition 8 and 11.

**Observation 7.** *$m_H^*$ and $m_L^*$ increase in $\gamma$ first until they reach their peaks before $\gamma$ achieves 0.5 and then gradually decrease in $\gamma$.*

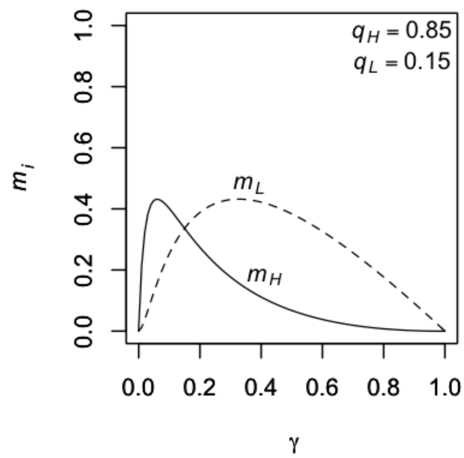


Figure 5.3: The impact of $\gamma$ on $m_i^*$

### 5.2.2 Impact of Noise Factor

**Observation 8.** *Proposition 8 holds for all $k \in [0, \frac{1}{2}]$.*

**Proposition 12.** *Proposition 9 holds for all $k \in [0, \frac{1}{2}]$.*

**Proposition 13.** *$m_H^*$ and $m_L^*$ decrease in $k$, where $k \in [0, \frac{1}{2}]$.*



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After relaxing the assumption of $k = 0$, we observe that Proposition 8 holds for all $k \in [0, \frac{1}{2}]$, and find that Proposition 9 holds for all $k \in [0, \frac{1}{2}]$ Furthermore, we find that when $k$ becomes larger, the platform owner's incentive of generating contents reduces (cf. Figure 5.4). The finding is simlar to what we have discussed previously in Section 4.2.2.

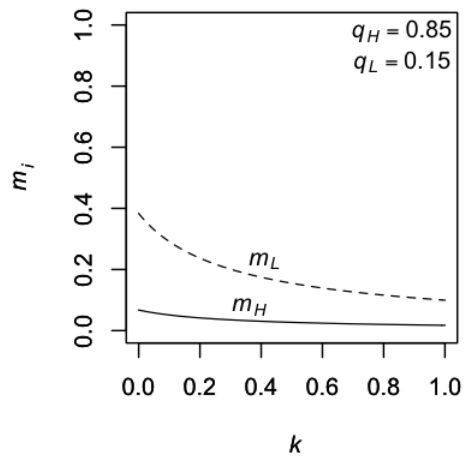


Figure 5.4: The impact of $k$ on $m_i^*$

### 5.2.3 Impact of Recommendation Probability

To discuss the impact of recommendation probability, we set $h(q) = q^z$ for $z \in (0, \infty]$, where $z$ is a factor which adjusts the shape of recommendation probability. We find that Proposition 7, 8, 9, 10, 12, 13 and Observation 6, 7, 8 remain true no matter how $z$ changes.

**Observation 9.** *Proposition 7, 8, 9, 10, 12, 13 and Observation 6, 7, 8 hold for all* $z \in (0, \infty]$.

Again, we observe that changes of $z$ does not directly affect the platform owners' decision $m_i^*$ (cf. Figure 5.5). Instead, changes of $z$ first affect the difference between



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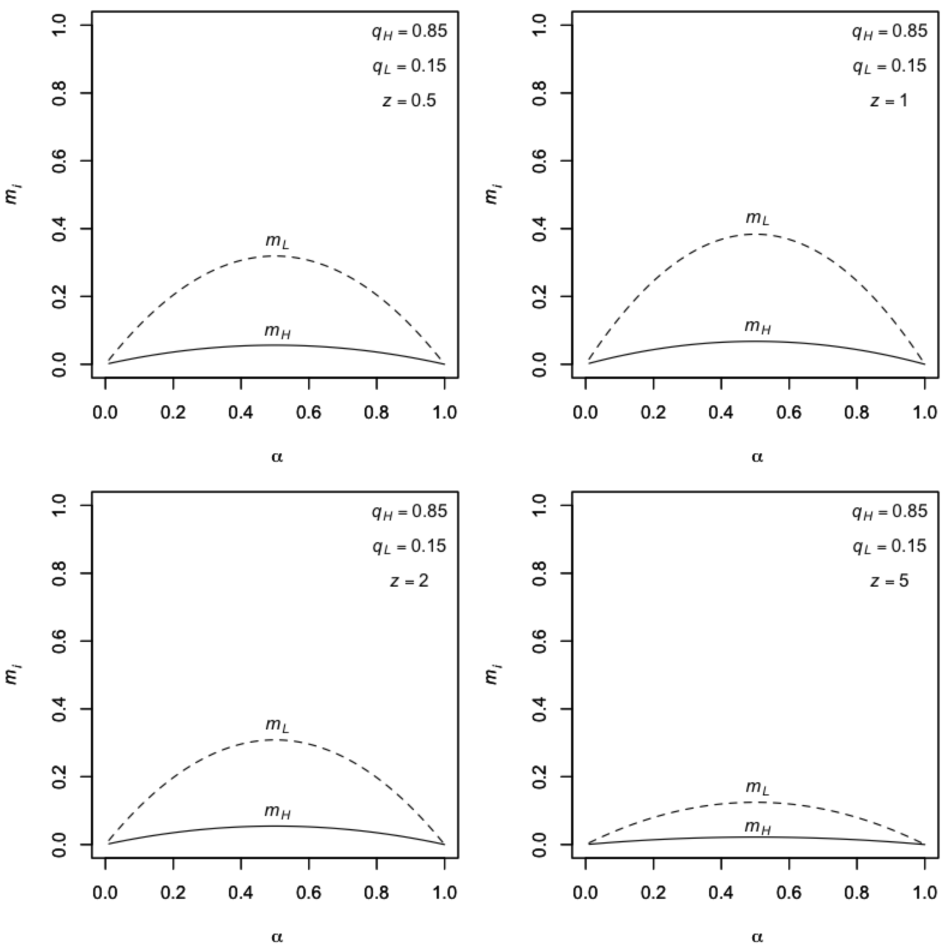


Figure 5.5: The impact of $z$ on $m_i^*$

$h(q_H)$ and $h(q_L)$, that is, $q_H^z - q_L^z$. Then, $q_H^z - q_L^z$ affects $m_i^*$. Value of $z$ has a knock-on effect on $m_i^*$ (cf. Figure 4.5).

**Observation 10.** *$m_H^*$ and $m_L^*$ tend to increase in $z$ when $q_H^z - q_L^z$ increases.*



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# Chapter 6

# Conclusions and Future Works

## 6.1 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, despite the fact that there may be false information (noise). 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. We develope two different scenarios, innocent platform and knowledgeable platform, based on whether the platform owner is aware of the quality of the healthcare provider. For the innocent platform, large quality difference between the two types of providers gives the platform owner motive to generate more contents. For the knowledgeable platform, 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



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be aware of the low quality healthcare provider. Besides, despite the fact that there may be false information (noise), the existence of the healthcare SNS is still beneficial. These results fit 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 naive 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.

Naive patients' prior distribution and noise factor have impact on the owner's decision too. For the former, we find that platform owner has more incentives to generate contents when patients are pessimistic while the service quality is actually high. 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.



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## 6.2 Future Works

For future works, healthcare service providers' action should be included in the model. They can send messages to promote themselves, and therefore affect naive patients' beliefs on the messages received. In addition, healthcare provider's signalling problem can be modeled to discuss whether it is possible to differentiate a high quality provider from a low quality one.

Number of healthcare providers and the quality difference between them may affect the decision of the platform owner as well. This leaves us an interesting question that when there are more than one providers with different quality competing in healthcare industry, how a social networking site may react to it and play a role in reducing information asymmetry.



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# Appendix A

# Proofs of Propositions

**Proof of Lemma 1.** To prove that $A_H - A_N > 0$ when $\gamma = \frac{1}{2}$, we combine 3.3, 3.4, and 3.5, and obtain $A_H - A_N =$

$$(\alpha q_H + (1-\alpha)k)\mathcal{B}_{pos} + (\alpha(1-q_H) + (1-\alpha)k)\mathcal{B}_{neg} + (-\alpha + 2\alpha k - 2k)(1 - \frac{2p}{q_H + q_L})$$

where

$$\begin{aligned}
\mathcal{B}_{pos} =& \frac{(q_H - p)(\alpha q_H + (1-\alpha)k) + (q_L - p)(\alpha q_L + (1-\alpha)k)}{q_H(\alpha q_H + (1-\alpha)k) + q_L(\alpha q_L + (1-\alpha)k)} \\
\mathcal{B}_{neg} =& (\alpha(1-q_H) + (1-\alpha)k) \\
& \frac{(q_H - p)(\alpha(1-q_H) + (1-\alpha)k) + (q_L - p)(\alpha(1-q_L) + (1-\alpha)k)}{q_H(\alpha(1-q_H) + (1-\alpha)k) + q_L(\alpha(1-q_L) + (1-\alpha)k)}.
\end{aligned}$$

After some arithmetic, we have $A_H - A_N =$

$$-\frac{\alpha^2\left((2\alpha - 2)k - \alpha\right)q_L\left(q_L - q_H\right)^3 p}{\begin{array}{c}\left(q_L + q_H\right)\left(\alpha q_L^2 + (1-\alpha)kq_L + (1-\alpha)q_H k + \alpha q_H^2\right) \\ \left(\alpha q_L^2 + ((\alpha - 1)k - \alpha)l + (\alpha - 1)q_H k + \alpha q_H^2 - \alpha q_H\right)\end{array}},$$

which is greater than zero. $A_N > A_L$ can be proved in a similar way. $\square$

**Proof of Proposition 1.** The statement is the direct result of Lemma 1. $\square$



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**Proof of Proposition 2.** After differentiating $m^*$ with respect to $q_H$, we have

$$\frac{\partial m^*}{\partial q_H} = \frac{(1-\alpha)\alpha pt}{2\beta(1-t)}\left\{\frac{f(q_H)}{(q_H^2+q_L^2)^2(q_H^2-q_H+q_L^2-q_L)^2}\right\},$$

where $f(q_H) = q_H^6 - 6q_Lq_H^5 + (7q_L^2+4q_L)q_H^4 + (-4q_L^3-4q_L^2)q_H^3 + 3q_L^4q_H^2 + (2q_L^5-4q_L^4)q_H - 3q_L^6 + 4q_L^5$. We want to show $f(q_H) > 0$. Note that $f(q_H) = (q_H - q_L)(q_H^5 - 5q_Lq_H^4 + (2q_L^2+4q_L)q_H^3 - 2q_L^3q_H^2 + q_L^4q_H + 3q_L^5 - 4q_L^4)$. Let $f(q_H) = (q_H - q_L)h(q_H)$, we have to show $h(q_H) > 0$ for all $q_H \in [q_L, 1]$ and $q_L \in [0,1]$.

(a) $h(q_L) = q_L^5 - 5q_L^5 + 2q_L^5 + 4q_L^4 - 2q_L^5 + q_L^5 + 3q_L^5 - 4q_L^4 = 0$. Therefore, all we need is to show that $h'(q_H) > 0$ for all $q_H \in [q_L, 1]$ and $q_L \in [0,1]$.

(b) Split $h'(q_H)$ into $h_1'(q_H) + h_2'(q_H)$, where

$$h_1'(q_H) = 5q_H^4 - 20q_Lq_H^3 + (5q_L^2+10q_L)q_H^2,$$
$$h_2'(q_H) = (q_L^2+2q_L)q_H^2 - 4q_L^3q_H + q_L^4.$$

(c) $h_1'(q_H) = 5q_H^2(q_H^2 - 4q_Lq_H + q_L^2 + 2q_L) = 5q_H^2((q_H-q_L)^2 + 2q_L(1-q_H)) > 0$ for all $q_H \in [q_L, 1]$ and $q_L \in [0,1]$.

(d) $h_2'$ is a quadratic function of $q_H$ having a positive cofficient for $q_H^2$. Therefore, consider its roots

$$\frac{4q_L^3 \pm \sqrt{16q_L^6 - 4q_L^4(q_L^2+2q_L)}}{2(q_L^2+2q_L)} = \frac{2q_L^2 \pm q_L\sqrt{3q_L^2-2q_L}}{q_L+2}.$$

If $3q_L^2 - 2q_L < 0$, we know $h_2'(q_H) > 0$ for all $q_H$. Otherwise, all we need to show is $\frac{2q_L^2+q_L\sqrt{3q_L^2-2q_L}}{q_L+2} < q_L$. As long as this is true, then $h_2'(q_H) > 0$ for all $q_H > q_L$. To



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show that $\frac{2q_L^2+q_L\sqrt{3q_L^2-2q_L}}{q_L+2} < q_L$:

$$\Longleftrightarrow 2q_L + \sqrt{3q_L^2 - 2q_L} < q_L + 2$$

$$\Longleftrightarrow \sqrt{3q_L^2 - 2q_L} < -q_L + 2$$

$$\Longleftrightarrow 3q_L^2 - 2q_L < 4 - 4q_L + q_L^2$$

$$\Longleftrightarrow 2q_L^2 + 2q_L - 4 < 0$$

$$\Longleftrightarrow 2(q_L - 1)(q_L + 2) < 0$$

$$\Longleftrightarrow -2 < q_L < 1,$$

which is true. $m^*$ decreasing in $q_L$ can be proved in a similar way. □

**Proof of Proposition 3.** We have

$$\frac{\partial m^*}{\partial \beta} = -\frac{(1-\alpha)(\frac{t}{1-t})\Big\{\gamma(A_H - A_N) + (1-\gamma)(A_N - A_L)\Big\}}{\beta^2} < 0,$$

$$\frac{\partial m^*}{\partial t} = \frac{(1-\alpha)\Big\{\gamma(A_H - A_N) + (1-\gamma)(A_N - A_L)\Big\}}{\beta}\Big(\frac{1}{(1-t)^2}\Big) > 0.$$

□

**Proof of Proposition 4.** First of all, differentiate $m^*$ with respect to $\alpha$, we have

$$\begin{aligned}\frac{\partial m^*}{\partial \alpha} =& \frac{t}{2\beta(1-t)}\Big\{(1-2\alpha)(q_H + q_L)\Big(1 - \frac{p(q_H+q_L)}{q_H^2+q_L^2}\Big)\\ &+(1-2\alpha)(2-q_H-q_L)\Big(1-\frac{p(2-q_H-q_L)}{q_H(1-q_H)+q_L(1-q_L)}\Big)\\ &+(-4+4\alpha)\Big(1-\frac{2p}{q_H+q_L}\Big)+1-\frac{2p}{q_H+q_L}\Big\}.\end{aligned}$$

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 $\alpha^2$ is negative to make sure that it is a concave function. After some arithmetic, the coefficient for $\alpha^2$ is

$$-\frac{t}{2\beta(1-t)} \cdot \frac{p(q_L - q_H)^3}{q_L^4 - q_L^3 + (2q_H^2 - q_H)q_L^2 - q_H^2 q_L + q_H^4 - q_H^3}.$$



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The numerator of the second term is negative, thus its denominator has to be negative as well. Let the denominator of the second term be denoted by

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

We need to make sure that for all $q_L \in [0, q_H]$, $h(q_L)$ is less than or equal to zero. We have $h(0) \leq 0$. Let $t(q_H)$ denote $h(1) = q_H^4 - q_H^3 + q_H^2 - q_H$. The fact that both $t(0)$ and $t(1)$ are zero and S.O.C. of $t(q_H) > 0$ show convexity of $t(q_H)$, meaning $h(1) \leq 0$ for $q_H \in [0, 1]$. Besides, we find that the slope of $h(q_L)$ at point 0 is less than or equal to zero, and the slope of $h(q_L)$ at point 1 is $4q_H^2 - 2q_H + 1$, which is greater than zero. Finally, by differentiating $h(q_L)$ with respect to $q_L$, we have

$$\frac{\partial h(q_L)}{\partial q_L} = 4q_L^3 - 3q_L^2 + 2(2q_H^2 - q_H)q_L - q_H^2.$$

It can be verifed that $\frac{\partial h(q_L)}{\partial q_L}$ has exactly one real root in $[0, q_H]$. Thus, $h(q_L)$ is less than or equal to zero for $q_L \in [0, q_H]$, indicating that the coefficient of $\alpha^2$ is negative and $\frac{\partial m^*}{\partial \alpha}$ is a concave function. □

**Proof of Proposition 5.** The proof is similar to that for Proposition 3. □



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**Proof of Proposition 6.** After differentiating $m^*$ with respect to $k$, we have

$$\frac{\partial m^*}{\partial k} = \frac{\alpha(1-\alpha)\frac{t}{2(1-t)}(q_H - q_L)\cdot \mathcal{N}}{\beta \cdot \mathcal{D}},$$

where

$$\begin{aligned}
\mathcal{N} =&(\alpha-1)\alpha(q_L-q_H)^2 p(((2(\alpha-1)^2 q_L^2 + 4(\alpha-1)^2 q_H q_L + 2(\alpha-1)^2 q_H^2)k^2 \\
&+((2\alpha-2\alpha^2)q_L^2 + (4\alpha-4\alpha^2)q_H q_L + (2\alpha-2\alpha^2)q_H^2)k \\
&+2\alpha^2 q_L^4 - 2\alpha^2 q_L^3 + (4\alpha^2 q_H^2 - 2\alpha^2 q_H + \alpha^2)q_L^2 \\
&+(2\alpha^2 q_H - 2\alpha^2 q_H^2)q_L + 2\alpha^2 q_H^4 + 2\alpha^2 q_H^3 + \alpha^2 q_H^2) \\
\mathcal{D} =&(((\alpha-1)q_L + (\alpha-1)q_H)k - \alpha q_L^2 - \alpha q_H^2)^2 \\
&(((\alpha-1)q_L + (\alpha-1)q_H)k + \alpha q_L^2 - \alpha q_L + \alpha q_H^2 - \alpha q_H)^2.
\end{aligned}$$

Let $\mathcal{N} = (\alpha-1)\alpha(q_L-q_H)^2 p h(k)$. Because $\mathcal{D} > 0$ and $(\alpha-1)\alpha(q_L-q_H)^2 p < 0$, all we need is to show that $h(k) > 0$. By applying the F.O.C. and S.O.C., we know that $h(k)$ is a convex function, and the global minimum $\bar{k}$ satisfying $h(\bar{k}) = 0$ is $\bar{k} = \frac{\alpha}{2\alpha-2} < 0$. Therefore, all we need is to prove that $h(0) \geq 0$. We have

$$\begin{aligned}
h(0) &= \alpha^2(2q_L^4 - 2q_L^3 + (4q_H^2 - 2q_H + 1)q_L^2 + (2q_H - 2q_H^2)q_L + 2q_H^4 + 2q_H^3 + q_H^2) \\
&= \alpha^2(q_L^2(2q_L^2 - 2q_L + (4q_H^2 - 2q_H + 1)) + 2q_L(1-q_H)q_H + q_H^2(q_H-1)^2 + q_H^4).
\end{aligned}$$

The last two terms, $2q_L(1-q_H)q_H$ and $q_H^2(q_H-1)^2 + q_H^4$, are positive. As for the first term, the quadratic function of $q_L$, we find its global minimum $q_L = \frac{1}{2}$ and plug it into the term to form the following inequality:

$$\begin{aligned}
q_L^2(2q_L^2 - 2q_L + (4q_H^2 - 2q_H + 1)) &\geq q_L^2\left(4q_H^2 - 2q_H + \frac{1}{2}\right) \\
&= q_L^2\left(\frac{1}{2}(2q_H-1)^2 + 2q_H^2\right) \geq 0.
\end{aligned}$$

□

**Proof of Proposition 7.** The statement is the direct result of Lemma 1. □



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**Proof of Proposition 8.** To prove that $m_L^* > m_H^*$, we only need $A_N - A_L > A_H - A_L$ to be satisfied when $\gamma = \frac{1}{2}$ and $k = 0$.

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

Simplify the above inequality, we have $\alpha q_H^2 - 2\alpha q_H q_L + \alpha q_L^2 = \alpha(q_H - q_L)^2 > 0$, which holds. □

**Proof of Proposition 9.** We have

$$
\begin{aligned}
\frac{\partial m_H^*}{\partial \beta} &= -\frac{(1-\alpha)(p-c)(\frac{t}{1-t})(A_H - A_N)}{\beta^2} < 0, \\
\frac{\partial m_H^*}{\partial t} &= \frac{(1-\alpha)(p-c)(A_H - A_N)}{\beta}\Big(\frac{1}{(1-t)}^2\Big) > 0.
\end{aligned}
$$

Impact of $\beta$ and $t$ on $m_L^*$ can be proved in a similar way. □

**Proof of Proposition 10.** To begin with, differentiate $m_H^*$ with respect to $\alpha$:

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

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 $\alpha^2$ is negative to make sure that it is a concave function. After some arithmetic, the coefficient for $\alpha^2$ is

$$
-\frac{t}{\beta(1-t)} \cdot \frac{p q_L (q_L - q_H)^3}{q_L^5 + (q_H - 1)q_L^4 + (2q_H^2 - 2q_H)q_L^3 + (2q_H^3 - 2q_H^2)q_L^2 + (q_H^4 - 2q_H^3)q_L + q_H^5 - q_H^4}.
$$



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The numerator of the second term is negative, thus its denominator has to be negative as well. Let the denominator of the second term 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 $q_L \in [0, q_H]$, $h(q_L)$ 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 convex 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 convex 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 fo $\alpha^2$ is negative and $\partial m_H^*/\partial\alpha$ is a concave function. Impact of $\alpha$ on $m_L^*$ can be proved in a similar way. $\square$



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**Proof of Proposition 11.** We want to find $\gamma$ which satisfies $m_H^* = m_L^*$. After some arithmetic, we have the following equation:

$$A_H + A_L - 2A_N = \Big(\frac{p}{\gamma q_H + (1-\gamma) q_L} - \frac{p\gamma q_H + p(1-\gamma)q_L}{q_H^2\gamma + q_L^2(1-\gamma)}\Big)\alpha(q_H + q_L)$$
$$+ \Big(\frac{p}{\gamma q_H + (1-\gamma) q_L} - \frac{p\gamma(1-q_H) + p(1-\gamma)(1-q_L)}{q_H(1-q_H)\gamma + q_L(1-q_L)(1-\gamma)}\Big)\alpha(2 - q_H - q_L) = -\frac{\mathcal{N}}{\mathcal{D}},$$

where

$$\mathcal{N} = \alpha p((q_L^4 - 2q_Hq_L^3 + 2q_H^3q_L - q_H^4)\gamma^3 + (-2q_L^4 + 5q_Hq_L^3 - 3q_H^2q_L^2 - q_H^3q_L + q_H^4)\gamma^2$$
$$+ (q_L^4 - 3q_Hq_L^3 + 3q_H^2q_L^2 - q_H^3q_L))$$
$$\mathcal{D} = (q_L^5 - (1+q_H)q_L^4 + (1-q_H)2q_Hq_L^3 + 2q_H^3q_L^2 + (q_H-2)q_H^3q_L - q_H^5 + q_H^4)\gamma^3$$
$$+ (-3q_L^5 + (2q_H+3)q_L^4 + (q_H-1)4q_Hq_L^3 - (2q_H+1)q_H^2q_L^2 + (2-q_H)q_H^3q_L)\gamma^2$$
$$+ (3q_L^5 - (q_H+3)q_L^4 + (1-q_H)2q_Hq_L^3 + q_H^2q_L^2)\gamma - q_L^5 + q_L^4.$$

Solve the equation, we obtain three real roots which are: $\gamma = 0$, $\gamma = 1$, and $\gamma = \frac{q_L}{q_H + q_L}$. □

**Proof of Proposition 12.** The proof is similar to that for Proposition 9. □

**Proof of Proposition 13.** The proof is similar to that for Proposition 6. □



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# Appendix B

# Summary of Closed-Form, Propositions, and Observations

**Innocent Platform: Closed-Form**

∘ The optimal amount of platform-generated contents:

$$m^* = \frac{(1-\alpha)(\frac{t}{1-t})\Big\{\gamma(A_H - A_N) + (1-\gamma)(A_N - A_L)\Big\}}{\beta}.$$

∘ Differentiating $m^*$ with respect to the high service quality $q_H$:

$$\frac{\partial m^*}{\partial q_H} = \frac{(1-\alpha)\alpha pt}{2\beta(1-t)}\Big\{\frac{f(q_H)}{(q_H^2 + q_L^2)^2(q_H^2 - q_H + q_L^2 - q_L)^2}\Big\}.$$

∘ Differentiating $m^*$ with respect to the scaling factor for cost of participation $\beta$:

$$\frac{\partial m^*}{\partial \beta} = -\frac{(1-\alpha)(\frac{t}{1-t})\Big\{\gamma(A_H - A_N) + (1-\gamma)(A_N - A_L)\Big\}}{\beta^2}.$$

∘ Differentiating $m^*$ with respect to the degree of network externality $t$:

$$\frac{\partial m^*}{\partial \beta} = -\frac{(1-\alpha)(\frac{t}{1-t})\Big\{\gamma(A_H - A_N) + (1-\gamma)(A_N - A_L)\Big\}}{\beta^2}.$$



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∘ Differentiating $m^*$ with respect to the proportion of experienced patients $\alpha$:

$$\begin{aligned}\frac{\partial m^*}{\partial \alpha} =& \frac{t}{2\beta(1-t)}\Big\{(1-2\alpha)(q_H+q_L)\Big(1-\frac{p(q_H+q_L)}{q_H^2+q_L^2}\Big) \\ &+(1-2\alpha)(2-q_H-q_L)\Big(1-\frac{p(2-q_H-q_L)}{q_H(1-q_H)+q_L(1-q_L)}\Big) \\ &+(-4+4\alpha)\Big(1-\frac{2p}{q_H+q_L}\Big)+1-\frac{2p}{q_H+q_L}\Big\}.\end{aligned}$$

∘ Differentiating $m^*$ with respect to the noise factor $k$:

$$\frac{\partial m^*}{\partial k} = \frac{\alpha(1-\alpha)\frac{t}{2(1-t)}(q_H-q_L)\cdot\mathcal{N}}{\beta\cdot\mathcal{D}},$$

where

$$\begin{aligned}\mathcal{N} =& (\alpha-1)\alpha(q_L-q_H)^2p(((2(\alpha-1)^2q_L^2+4(\alpha-1)^2q_Hq_L+2(\alpha-1)^2q_H^2)k^2 \\ &+((2\alpha-2\alpha^2)q_L^2+(4\alpha-4\alpha^2)q_Hq_L+(2\alpha-2\alpha^2)q_H^2)k \\ &+2\alpha^2q_L^4-2\alpha^2q_L^3+(4\alpha^2q_H^2-2\alpha^2q_H+\alpha^2)q_L^2 \\ &+(2\alpha^2q_H-2\alpha^2q_H^2)q_L+2\alpha^2q_H^4+2\alpha^2q_H^3+\alpha^2q_H^2) \\ \mathcal{D} =& (((\alpha-1)q_L+(\alpha-1)q_H)k-\alpha q_L^2-\alpha q_H^2)^2 \\ &(((\alpha-1)q_L+(\alpha-1)q_H)k+\alpha q_L^2-\alpha q_L+\alpha q_H^2-\alpha q_H)^2.\end{aligned}$$



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**Innocent Platform: Propositions and Observations**

| | |
|---|---|
| **Proposition 1** | *$m^* > 0$ when $\gamma = \frac{1}{2}$ and $k \in [0, \frac{1}{2}]$.* |
| **Proposition 2** | *$m^*$ increases in $q_H$ and decreases in $q_L$ when $\gamma = \frac{1}{2}$ and $k = 0$.* |
| **Proposition 3** | *$m^*$ decreases in $\beta$ and increases in $t$ when $\gamma = \frac{1}{2}$, $k = 0$, and $m^* \leq \frac{1-t-v}{t}$.* |
| **Proposition 4** | *When $\gamma = \frac{1}{2}$ and $k = 0$, $m^*$ increases in $\alpha$ first until $\alpha = 0.5$. Thereafter, $m^*$ decreases in $\alpha$.* |
| **Proposition 5** | *Proposition 3 holds for all $k \in [0, \frac{1}{2}]$.* |
| **Proposition 6** | *$m^*$ decreases in $k$, where $k \in [0, \frac{1}{2}]$.* |
| **Observation 1** | *Proposition 1, 2, 3 and 4 hold for all $\gamma \in [0, 1]$.* |
| **Observation 2** | *$m^*$ increases in $\gamma$ first until it reaches its peak before $\gamma$ achieves 0.5, and then gradually decreases in $\gamma$.* |
| **Observation 3** | *Proposition 2 holds for all $k \in [0, \frac{1}{2}]$.* |
| **Observation 4** | *Proposition 1, 2, 3, 4, 5, 6 and Observation 1, 2, 3 hold for all $z \in (0, \infty]$.* |
| **Observation 5** | *$m^*$ tends to increase in $z$ when $q_H^z - q_L^z$ increases.* |



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**Knowledgeable Platform: Closed-Form**

- The optimal amount of platform-generated contents:

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

- Differentiating $m^*$ with respect to the scaling factor for cost of participation $\beta$:

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

- Differentiating $m^*$ with respect to the degree of network externality $t$:

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

- Differentiating $m^*$ with respect to the proportion of experienced patients $\alpha$:

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



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**Knowledgeable Platform: Propositions and Observations**

| | |
|---|---|
| **Proposition 7** | $m_H^* > 0$ *and* $m_L^* > 0$ *when* $\gamma = \frac{1}{2}$ *and* $k \in [0, \frac{1}{2}]$. |
| **Proposition 8** | $m_L^* > m_H^*$ *when* $\gamma = \frac{1}{2}$ *and* $k = 0$. |
| **Proposition 9** | $m_L^*$ *and* $m_H^*$ *decrease in* $\beta$ *and increase in* $t$ *when* $\gamma = \frac{1}{2}$, $k = 0$, *and* $m_i^* \leq \frac{1-t-v}{t}$, $i \in \{L, H\}$. |
| **Proposition 10** | *When* $\gamma = \frac{1}{2}$ *and* $k = 0$, $m_L^*$ *and* $m_H^*$ *increase in* $\alpha$ *first until* $\alpha = 0.5$. *Thereafter, they decrease in* $\alpha$. |
| **Proposition 11** | $m_H^* > m_L^*$ *if and only if* $\gamma < \frac{q_L}{q_H + q_L}$. |
| **Proposition 12** | *Proposition 9 holds for all* $k \in [0, \frac{1}{2}]$. |
| **Proposition 13** | $m_H^*$ *and* $m_L^*$ *decrease in* $k$, *where* $k \in [0, \frac{1}{2}]$. |
| **Observation 6** | *Proposition 7, 9 and 10 hold for all* $\gamma \in [0, 1]$. |
| **Observation 7** | $m_H^*$ *and* $m_L^*$ *increase in* $\gamma$ *first until they reach their peaks before* $\gamma$ *achieves 0.5 and then gradually decrease in* $\gamma$. |
| **Proposition 8** | *Proposition 8 holds for all* $k \in [0, \frac{1}{2}]$. |
| **Observation 9** | *Proposition 7, 8, 9, 10, 12, 13 and Observation 6, 7, 8 hold for all* $z \in (0, \infty]$. |
| **Observation 10** | $m_H^*$ *and* $m_L^*$ *tend to increase in* $z$ *when* $q_H^z - q_L^z$ *increases.* |



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