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The Economics of Online Subsidiary Healthcare Systems

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Completed Research Paper

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Abstract

During the era of COVID-19, many hospitals start to build their own online healthcare systems (hereafter referred to as online subsidiary healthcare systems). The presence of online subsidiary healthcare systems brings hospitals an additional traffic source; however, in the meanwhile, it cannibalizes hospitals' traditional offline traffic. Using a game-theoretic model, we obtain the optimal design of such an online healthcare system and investigate its impact on the traditional offline healthcare system. Surprisingly, we find that instead of reducing the offline traffic, such an online subsidiary healthcare system actually incentivizes more patients to visit the hospital offline, failing to fulfill the purpose of adopting online healthcare during COVID-19. Moreover, we find that online healthcare systems do not necessarily improve the profitability of the hospital and the surplus of patients. Our findings provide important implications regarding the management and regulation of such online subsidiary healthcare systems.

Keywords: Online healthcare, telemedicine, healthcare economics, game theory

Introduction

The online healthcare market has been proliferating during the era of COVID-19 (Webster 2020). In 2019, the global digital health market was worth 106 billion U.S. dollars. With an expected compound annual growth rate of 28.5 percent from 2020 to 2026, the digital health market will enjoy an almost six-fold increase and amount to nearly 640 billion U.S. dollars by 2026 (Stewart 2021). In the online healthcare market, there are many third-party platforms (e.g., Best Doctors, Buoy Health, Chunyu Doctor, and Practo Health) connecting patients and doctors to facilitate online diagnosis. Apart from such third-party platforms, another large portion of the online healthcare market is healthcare systems subsidiary to brick-and-mortar hospitals (e.g., Rush Oak Park Hospital, Huaxi Hospital, and Beijing Xiehe Hospital). For convenience, we refer to this type of healthcare system as *online subsidiary healthcare systems*. Accelerated by the global pandemic of COVID-19, the number of online subsidiary healthcare systems has been increasing rapidly in recent years. According to the National Health Commission of China[1], by the end of 2020, there were more than 7,700 hospitals in China offering their own online healthcare services. In addition, during the period from June 26, 2020 to November 6, 2020, 30.2% of weekly health center visits occurred via online subsidiary healthcare systems (Demeke 2021).

Despite the growing popularity of online subsidiary healthcare systems, it remains unclear as to how and to what extent they can impact the patients as well as the brick-and-mortar hospitals that they are subsidiary

[1] See http://www.nhc.gov.cn.

to. For patients, the online subsidiary healthcare systems do offer them a more convenient way to seek medical treatment, which may save the opportunity cost of visiting hospitals offline (Ortholive 2018); however, at the same time, patients need to pay an additional online healthcare fee for the online healthcare service, the reliability of which still remains a big concern (NIA 2018). Thus, whether patients can benefit from the online subsidiary healthcare system remains an open question.

Besides, it is also unclear whether having an online subsidiary healthcare system can indeed help increase the hospital's profitability. On the one hand, the adoption of an online healthcare system can help the hospital obtain more traffic from remote areas (Ortholive 2018), so the hospital can generate additional revenue from the online healthcare fees. In addition, part of such online traffic can be converted to the hospital's offline traffic, which can help the hospital generate additional revenue. On the other hand, the presence of an online healthcare system may cannibalize the hospital's offline traffic. In particular, fewer patients would directly go to the hospital in the presence of online healthcare since they might think it is better first to seek an online medical diagnosis. Thus, there is no immediate answer to the question of whether the online subsidiary healthcare system can indeed help enhance the hospital's profitability.

In addition, the online healthcare system is widely considered an effective way to reduce the hospital's offline traffic, especially during the ongoing pandemic COVID-19 (Webster 2020). However, it remains uncertain whether the online subsidiary healthcare system can indeed serve this purpose. This is because although the online healthcare system can address some patients' needs online, it also attracts more patients from remote areas to use the online healthcare system and these patients may, later on, be converted to offline traffic of the hospital. Yet, it is crucial for policymakers and hospitals to better understand the impact of the online subsidiary healthcare systems on the hospital's offline traffic; otherwise, the effort of reducing offline traffic by introducing an online healthcare system may even turn out to be counterproductive.

Despite their importance, the questions above still remain largely unanswered in the literature. In this paper, using the lens of game-theoretic modeling, we aim to fill the critical gap in the literature by investigating those puzzling problems brought about by the presence of online subsidiary healthcare systems.

Motivation

Hospitals typically have standardized offline medical treatment procedures. For example, according to the webpages of Capital Health Hospitals (USA) and Beijing Xiehe Hospital (China),[2] in the first stage of the treatment process, patients need to register and pay an outpatient fee for diagnosis; in the second stage, doctors make their diagnosis and prescribe the subsequent test or treatment; in the third stage, based on the diagnosis results and prescription, patients decide whether to take the medical treatment and, if so, which treatment to take. Patients consider the outpatient fee, the hospital's service quality, and their own opportunity cost of visiting the hospital (e.g., physical distance, time cost) when deciding whether to visit the hospital or choose other alternative options (e.g., self-medication). For example, individuals in remote areas seldom visit the hospital due to the relatively long distance (Ortholive 2018).

The presence of online healthcare provides patients with an additional option. That is, in the presence of an online healthcare system, instead of directly going to the hospital, patients could first use the online healthcare system to consult doctors about whether they must visit the hospital offline, which costs them online healthcare fees but can sometimes save their opportunity cost of visiting the hospital (Brody 2020). Compared to the case wherein only the offline hospital is available, with an online healthcare system, patients also consider the online healthcare fee and the accuracy of the online healthcare systems when deciding whether to visit the hospital offline, use an online healthcare system, or choose alternative options. For example, making a tradeoff between the online healthcare fee and the opportunity cost of visiting a hospital offline, patients in rural areas may think it is better to use the online healthcare system to save the cost of traveling to the hospital (Harrison 2019).

[2] See https://www.capitalhealth.org/medical-services/cyberknife/why-cyberknife/patient-treatment-process for Capital Health Hospitals and https://www.pumch.cn/medical_notice.html for Beijing Xiehe Hospital.

Research Question and Key Findings

There has been a growing concern over the online healthcare system's diagnosis accuracy and reliability (NIA 2018). This is a legitimate concern since, in the online healthcare system, the hospital can generate more revenue by persuading online patients to have an offline visit even when they are actually in good health condition. Thus, to start with, we ask: *Are the diagnoses of the online healthcare system reliable?* We find that such diagnoses are reliable, and the online subsidiary healthcare system does not misinform healthy individuals about their health conditions. Briefly, although the opportunistic behavior of lying to online users could drive some of them to have an offline visit and generate additional revenue, it leads to fewer patients in the whole healthcare system due to the online healthcare system's bad reputation. The latter effect is shown to dominate the former one. As a result, the hospital is not incentivized to mislead patients in the online subsidiary healthcare system. This finding is interesting and timely as it provides a plausible theoretical assurance for the reliability of the emerging online subsidiary healthcare systems.

As mentioned earlier, during COVID-19, many hospitals have begun to launch their own online healthcare systems. One of the main purposes of this practice is to reduce the risk of infection by reducing the offline traffic of the hospital (Webster 2020). However, to the best of our knowledge, there is as yet no convincing evidence that the online subsidiary healthcare systems can help reduce the offline traffic of the hospitals. Thus, another important and intriguing question that naturally arises here is: *What is the impact of the online subsidiary healthcare system on the offline traffic of the hospital?* Contrary to conventional wisdom, surprisingly, we find that instead of reducing the offline traffic, the presence of an online healthcare system actually incentivizes more patients to visit the hospital offline. Our results indicate that although the online healthcare system can directly keep some patients from visiting the hospital offline by addressing their medical needs online, the dominating impact of the online healthcare system is to attract more patients to the whole healthcare system and increase the offline traffic of the hospital indirectly. This result indicates that online healthcare is not an effective tool for reducing the volume of offline hospital visits. Thus, policymakers seeking to control infectious diseases such as COVID-19, SARS and seasonal influenza by reducing offline hospital traffic should not rely solely on the use of online subsidiary healthcare systems.

Offline healthcare overtreatment (i.e., ordering excessive tests and/or treatment for patients) has long been a challenging problem in the healthcare industry (NHCAA 2018). In our paper, we investigate the role that the online subsidiary healthcare systems play in tackling the healthcare overtreatment problem. More specifically, we ask: *what is the impact of the online subsidiary healthcare system on the degree of healthcare overtreatment?* Interestingly, we find that the overtreatment problem in the offline hospital can be alleviated by adopting online subsidiary healthcare systems. A higher level of offline healthcare overtreatment (i.e., ordering more unnecessary tests or treatment) helps the hospital gain more profit from each patient visiting the hospital; however, in the meantime, it also hurts the hospital's reputation and leads to a reduced healthcare demand. Since the adoption of the online subsidiary healthcare system increases the total demand of the hospital (the sum of the online and offline demand), the latter effect of a higher level of offline healthcare overtreatment (i.e., reducing healthcare demand) becomes even more pronounced. Accordingly, the hospital will conduct less healthcare overtreatment. This result reveals a non-trivial role played by the online subsidiary healthcare system. That is, the presence of the online subsidiary healthcare system can help alleviate the excessive treatment in the hospital. Policymakers should be fully aware of such an important yet nonintuitive role played by the online subsidiary healthcare system when devising regulation policies on online healthcare system adoption.

Additionally, it is important to investigate how the online subsidiary healthcare system, an emerging information system in the healthcare industry, impacts the hospital's payoff and patients' welfare. Thus, we ask: *What are the impacts of the online healthcare system on stakeholders' payoffs*? Our results show that stakeholders will not be worse off with the launch of the online subsidiary healthcare system. Interestingly, we find that when the disease is not severe, the online healthcare system cannot benefit the hospital. Such a result suggests that small hospitals which can only tackle mild diseases should not adopt the online healthcare system; also, for large hospitals, they should provide online diagnoses only for those severe diseases.

Our research makes several theoretical and practical contributions. First, to the best of our knowledge, most of the extant literature on the economics of online healthcare systems focuses on the healthcare systems owned by third parties. Our work is among the first to model the online healthcare systems subsidiary to offline hospitals, which account for a large proportion of the healthcare market. Here, the uniqueness of the online subsidiary healthcare system lies in the fact that it serves as an additional revenue channel for the offline hospital. To design such a healthcare system, a hospital needs to balance the existing offline revenue channel and the new online revenue channel. Second, methodologically, as an attempt to connect the landmark economic theory with specific IS problems, this study is among the first analytical works adopting the Bayesian Persuasion approach in the discipline of information systems. Additionally, we contribute to the literature on Bayesian Persuasion by considering a Bayesian Persuasion framework wherein it costs the signal receivers to be persuaded and endogenizing the signal receivers' decisions on whether to be persuaded or not; moreover, we characterize the heterogeneity of receivers in the dimension of costs incurred to be persuaded in a multi-receiver Bayesian Persuasion game. Third, our analysis provides important guidelines for practitioners. Specially, our results shed light on the conditions under which consumers and hospitals can benefit from the online subsidiary healthcare system and hence could provide meaningful implications on the adopting decisions of hospitals and the regulatory decisions of policymakers.

Related Literature

Our study is mainly related to two streams of literature: (i) healthcare information technology, (ii) the economics of healthcare. Next, we provide a brief review of the literature and highlight our contribution to each of these streams.

Prior literature has studied healthcare information technology (HIT) from several aspects. For example, there is a large body of literature on the adoption of HIT (e.g., Yaraghi et al. 2015), HIT in reducing adverse drug events (e.g., Bates et al. 1998), the impact of HIT on healthcare quality (e.g., Lin et al. 2019), and the substitution effects of HIT (e.g., Lu et al. 2018). We make our contribution to this stream of literature by examining the impacts of an emerging HIT (online subsidiary healthcare systems). Additionally, most of the existing literature on HIT is conducted empirically, and our contribution also lies in the fact that we use an analytical approach to study an optimal design problem of HIT.

There is also a large body of literature on healthcare economics, especially in the discipline of operation management. For example, the existing literature has discussed the optimal healthcare payment scheme (e.g., Adida 2021), the risk-sharing contract between a drug manufacturer and a payer (e.g., Barros 2011), the optimal mechanism to improve access to rare disease treatments (e.g., Olsder 2019). More closely related to our paper, Wu et al. (2019) study the reputation and diagnostic bias in the third-party healthcare platform. We contribute to this stream of literature by studying the economics of online healthcare systems owned by offline hospitals, which, to the best of our knowledge, has not yet been studied in the literature.

Modelling Framework

We build an analytical model to investigate the impacts of the online healthcare system. A mass of patients and a hospital are considered in our model. Following prior studies on healthcare economics (e.g., Adida 2021, Rajan et al. 2019), we consider that the hospital and patients maximize their respective utility. In this section, we first introduce all model parameters and variables. Subsequently, the maximization problems of the hospital and patients in the benchmark (the regime without an online healthcare system) and the main model (the regime with an online healthcare system) are introduced, respectively. A list of key notations used in this paper is provided in Table 1.

Decision Variables	
q_0	The hospital's persuasion accuracy in the offline healthcare system.
q_1	The hospital's persuasion accuracy in the online healthcare system.
p_1	The online healthcare service fee charged by the hospital.
I	Patients' decisions on seeking treatment, and I ∈ $\{I_1, I_2, I_3\}$.
Parameters	
α	Relative medical treatment cost.
β	The co-insurance rate.
v	The severity of the disease.
p_0	The outpatient fee charged by the hospital.

μ	Patients' prior belief about the probability that they are in good condition.
Other Variables	
ω	Patients' true health condition, and $\omega \in \{Good, Bad\}$.
s	Signals indicating the patients' true health condition, and $s \in \{Good, Bad\}$.
μ_0, μ_1, μ_2	Posterior belief of patients diagnosed offline (μ_0), online (μ_1), and online first and then offline (μ_2), respectively, about the probability that they are in good condition.
d_1	Number of patients directly going to the hospital.
d_2	Number of patients using the online healthcare system.
c	Patients' opportunity cost of visiting the hospital, where $c \in [0, \infty]$.

Table 1. Key Notations Table

Hospital's Persuasion Accuracy

As discussed in the introduction, hospitals and doctors typically have private information about the patients' true health conditions (i.e., ω). Thus, some hospitals and doctors may opportunistically overtreat their patients to generate a higher profit (Greenberg and Green 2014). We adopt the approach of Bayesian Persuasion (Kamenica and Gentzkow 2011) to study how the hospital would strategically transfer its private information to patients since the medical diagnosis process is a natural application context for this approach (Kamenica and Gentzkow 2011, Schweizer and Szech, 2018). Following the example provided in Kamenica and Gentzkow (2011), we consider that the hospital knows the true health conditions of each patient. In contrast, patients only hold prior beliefs about their own health condition. To transfer its private information to patients, the hospital designs conditional distribution of signals indicating the true health condition (i.e., s) conditional on the true health condition (i.e., ω), which is provided in Table 2.

	$\omega = Good$	$\omega = Bad$
$s = Good$	$P(s = Good \mid \omega = Good) = q$	$P(s = Good \mid \omega = Bad) = 1 - q'$
$s = Bad$	$P(s = Bad \mid \omega = Good) = 1 - q$	$P(s = Bad \mid \omega = Bad) = q'$

Table 2. Conditional Distribution of Signals *s*

The hospital commits to the conditional distribution provided in Table 2, which is known to patients (Kamenica and Gentzkow 2011, Drakopoulos et al. 2021). In reality, patients can know such a conditional distribution through word of mouth.

Note that it can be analytically shown that $q' = 1$ in the optimum. The hospital wants patients to believe that they are in bad condition so that the hospital can generate a higher profit from the additional treatment taken by patients. As a result, the hospital would truthfully reveal patients' true health conditions for patients in bad conditions. Hereafter, we take $q' = 1$ as given in our model and refer q to the persuasion accuracy.

In the regime without online healthcare, the hospital could only persuade patients offline. We use q_0 to denote the hospital's offline persuasion accuracy (i.e., $q = q_0$ offline). In the regime with online healthcare, the presence of an online healthcare system enables the hospital to persuade patients online, and we use q_1 to denote the hospital's online persuasion accuracy (i.e., $q = q_1$ online). Table 3 summarizes the hospital's persuasion process for different patients.

Patients Type	***Hospital's Persuasion Process***
Only go to the hospital.	Offline persuasion.
Only use the online healthcare system.	Online persuasion.
Use online healthcare system + go to the hospital.	Online persuasion + Offline persuasion
Not engaged in this healthcare system.	No persuasion.

Table 3. Hospital's Persuasion Process

Patients' Opportunity Cost of Visiting the Hospital

In reality, patients' opportunity costs of visiting the hospital offline are typically higher than those of using the online healthcare system. For example, patients visiting the hospital need to wait in long lines, risk being infected, and pay for their transportation, which would lead to relatively high opportunity costs for these patients. On the contrary, due to the convenience of online communication, the opportunity costs of using the online healthcare system are typically much lower. Thus, in our model, we consider that the opportunity costs of visiting the hospital and using the online healthcare system are 0 and c, respectively. Patients incur heterogeneous opportunity costs of visiting the hospital, and c is considered to be uniformly distributed over $[0,1]$. Note that, to focus on the key tradeoff, we consider that v is not too large to ensure that there always exist some patients not taking medical treatment.

Outpatient Fee and Online Healthcare Service Fee

As discussed earlier, hospitals and doctors typically have little control over their outpatient fees (Kliff and Lopez 2015). Instead, most of the time, it is governments and insurance companies who decide on the outpatient fee (e.g., BMCDR 2000, 2003). For example, the government of Beijing (the capital of China) has an outpatient fee and treatment fee standard for all hospitals in Beijing to follow. In other words, hospitals are price takers in terms of the outpatient fee and treatment fee. As a result, to better reflect the reality, we consider the outpatient fee p as exogenously given in our model.[3]

On the other hand, hospitals turn to be heterogeneous in their online healthcare service fee. Peking University's third hospital (rank 10th) provides the online healthcare service for free, whereas Peking Union Medical College Hospital (rank 1st) charges patients for the online healthcare service. As the hospitals are price makers in terms of online healthcare service fee p_1, we consider such a fee as one of the decision variables of the hospital.

Treatment fee and the severity of the disease

In our model, a patient would get a payoff v if the patient turns out to be in good health condition (i.e., $\omega = Good$). We normalize the patient's payoff to 0 if the patient turns out to be in bad health condition (i.e., $\omega = Bad$).[4] Therefore, v can be interpreted as the severity of the disease considered. As the severity of the disease increases, patients would have a more differentiated utility between being good and bad.

To focus on the key trade-off, we consider that patients would be in good health condition after receiving additional treatment (e.g., being hospitalized) despite their initial health conditions. Additionally, in our study, following the existing literature (e.g., Rajan et al. 2019), we consider that patients' treatment costs are independent of their opportunity costs. Typically, a higher treatment fee will be charged for more severe diseases. To capture this, we model the treatment fee as αv in our model, where $0 < \alpha < 1$ can be interpreted as the relative treatment cost. Thus, the treatment fee would increase with the severity of the disease v as well as the relative treatment fee α. For example, a relatively low treatment fee will be charged for mild diseases with relatively small value of v such as seasonal flu, whereas a relatively high treatment fee will be charged for severe diseases with relatively high value of v such as cancer. In addition to the outpatient fee introduced earlier, hospitals have little control over the treatment cost α (e.g., Kliff and Lopez 2015). We hence consider α as an exogenous parameter in our model. Note that in reality, α represents governments' policies regarding healthcare. For example, according to some governments' files,[5] Sichuan government (a province in China) sets the price for Laryngectomy for benign tumors at ¥1467, whereas Beijing government sets the price at ¥1307. Tying it back to our model, hospitals in Sichuan would have a higher α than those in Beijing.

[3] In this study, we focus on the hospital in the regions with strict regulations on healthcare payments.

[4] An equivalent model way is a patient would get payoff v if the patient turns out to be in good health condition, whereas get payoff 0 if the patient turns out to be in bad health condition.

[5] See https://www.sc.gov.cn/ and https://www.pkufh.com/.

Co-insurance Rate

For offline healthcare (i.e., outpatient fee p and treatment fee αv), patients typically are covered by insurance (Rajan et al. 2019, Adida 2021). As a result, we consider that patients only need to pay a certain proportion β of the offline healthcare fee, where $0 < \beta < 1$ and β is the co-insurance rate. The practice of whether to cover patients' online healthcare fees is ambiguous. In China, only online healthcare services in a few pilot hospitals are covered by insurance (CNR 2020). In the United States, insurance coverage for online healthcare depends hugely on federal and state laws as well as insurance company policies (CHIRON 2020). Besides, even for those insurance with online healthcare coverage, only limited kinds of such online services are covered (e.g., Medicare 2020). Given the majority of online healthcare service is not covered by insurance, we consider the patients need to pay the online healthcare service fee p_1 themselves.

Patients' Prior and Posterior Beliefs

Patients initially believe that they are in good condition with probability μ, where $0 < \mu < 1$ and μ is referred to as a prior belief. Prior belief μ could be interpreted as the symptom severity of the disease. For example, if a patient fractures his elbow, then she would definitely know that she is in bad health condition (i.e., $\mu = 0$). In contrast, a patient in an early stage of cancer probably believes she is good (i.e., $\mu = 1$) since cancer is typically asymptomatic at the beginning (Lieberman 2009). In our model, we consider that μ is not too high (i.e., $\mu < \bar{\mu}$); otherwise, individuals would be too confident about their health condition and never engage in the healthcare system, so our model would be irrelevant.

Patients would have different posteriors regarding their health conditions since the way they engage in the healthcare system is different. Conducting Bayesian updating with the conditional distribution provided in Table 2, we derive the patients' posteriors depending on the signals they receive. In particular,

(a) for patients diagnosed offline, their posterior on being good is μ_0, where

$$\mu_0|(s = Good) = \frac{\mu q_0}{\mu q_0 + (1-\mu)0} = 1,$$

$$\mu_0|(s = Bad) = \frac{(1-\mu)}{\mu(1-q_0) + (1-\mu)} = \frac{1-\mu}{1-\mu q_0}.$$

(b) for patients diagnosed online, their posterior on being good is μ_1, where

$$\mu_1|(s = Good) = \frac{\mu q_1}{\mu q_1 + (1-\mu)0} = 1,$$

$$\mu_1|(s = Bad) = \frac{(1-\mu)}{\mu(1-q_1) + (1-\mu)} = \frac{1-\mu}{1-\mu q_1}.$$

(c) for patients diagnosed online first and then offline, their posterior on being good is μ_2, where

$$\mu_2|(s = Good) = \frac{\mu_0 q_1}{\mu_0 q_1 + (1-\mu_0)0} = 1,$$

$$\mu_1|(s = Bad) = \frac{(1-\mu_0)}{\mu_0(1-q_1) + (1-\mu_0)} = \frac{1-\mu_0}{1-\mu_0 q_1}.$$

Maximization Problems of Hospitals and Patients

We divide this subsection into two parts. The first part illustrates the players' maximization problems in benchmark, which is a regime without an online healthcare system, and the second part illustrates the maximization problems in the main model where the online healthcare system is present. Our solution concept is subgame perfect Nash equilibrium (Kamenica and Gentzkow 2011).

Benchmark

In the benchmark, the hospital first designs the offline persuasion by deciding q_0 to maximize its own profit and patients then decide whether to go to the hospital and take treatment. We denote patients' decisions on seeking treatment by I, where $I = I_1$ indicates that a patient decides to go to the hospital offline (hereafter, such patients are referred to as offline patients) and $I = I_3$ indicates that a patient decides to stay at home (hereafter, such patients are referred to as no-service patients). Note that to focus on the key trade-off, we consider patients are risk-neutral when making their decisions. Figure 1 below depicts the decision process of patients.

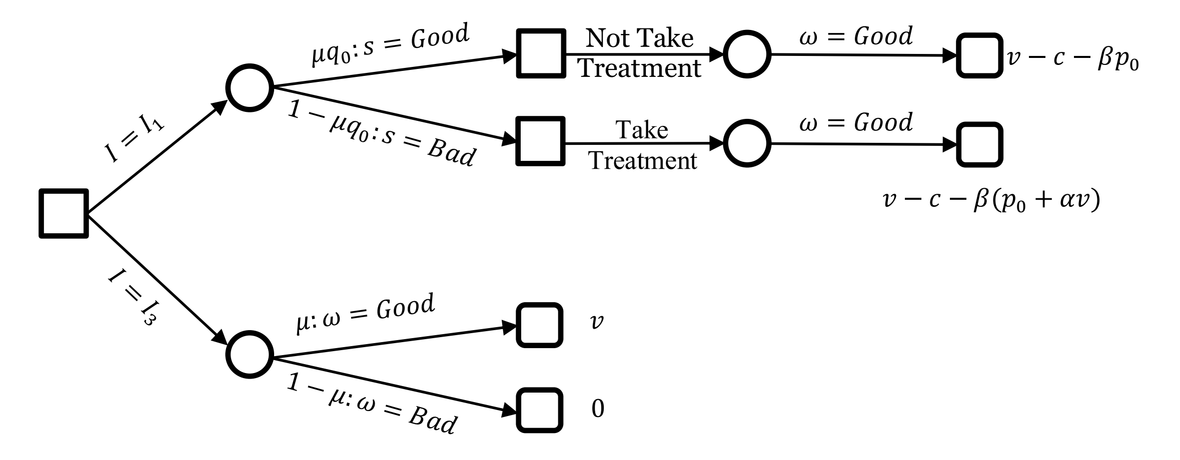

Figure 1. Patients' Decision Process in Benchmark

For offline patients, they would receive signal G (i.e., $s = Good$) with probability μq_0 and receive signal B (i.e., $s = Bad$) with probability $1 - \mu q_0$. If an offline patient receives signal G, she will not take the treatment since she is in good condition for sure and does not need additional treatment, and her payoff would be $v - c - \beta p_0$. If a patient receives signal B, she will follow the hospital's recommendation to take treatment and turns good (otherwise, she would be better off by staying at home, which can be analytically shown), and her payoff would be $v - c - \beta(p_0 + \alpha v)$. For no service patients, they gamble on being in a good situation. Patients compare their expected utility and choose a preferred action.

We use d_1 to denote the number of offline patients. Then, the hospitals' maximization problem is maximizing its own profit by choosing q_0. Specifically,

$$\max_{q_0} d_1[p_0 + (1 - \mu q_0)\alpha v]$$

For patients going to the hospital, as mentioned above, they do not take treatment and the hospital just earns p_0 at possibility μq_0, whereas they take treatment and the hospital earns $p_0 + \alpha v$ at possibility $1 - \mu q_0$. Thus, on average, the marginal profit of each patient deciding to go to the hospital is $d_1[p_0 + (1 - \mu q_0)\alpha v]$.

Main Model

In our main model, in addition to offline persuasion accuracy q_0, the hospital can also decide on online persuasion accuracy q_1 and online healthcare fee p_1. Patients can then additionally choose to use online healthcare first, and then decide whether to have an offline visit according to the signal given by the online healthcare system. We use $I = I_2$ to represent the decision to use the online healthcare system, and patients with $I = I_2$ are referred to as online patients hereafter. Figure 2 below depicts the decision process of patients in the main model.

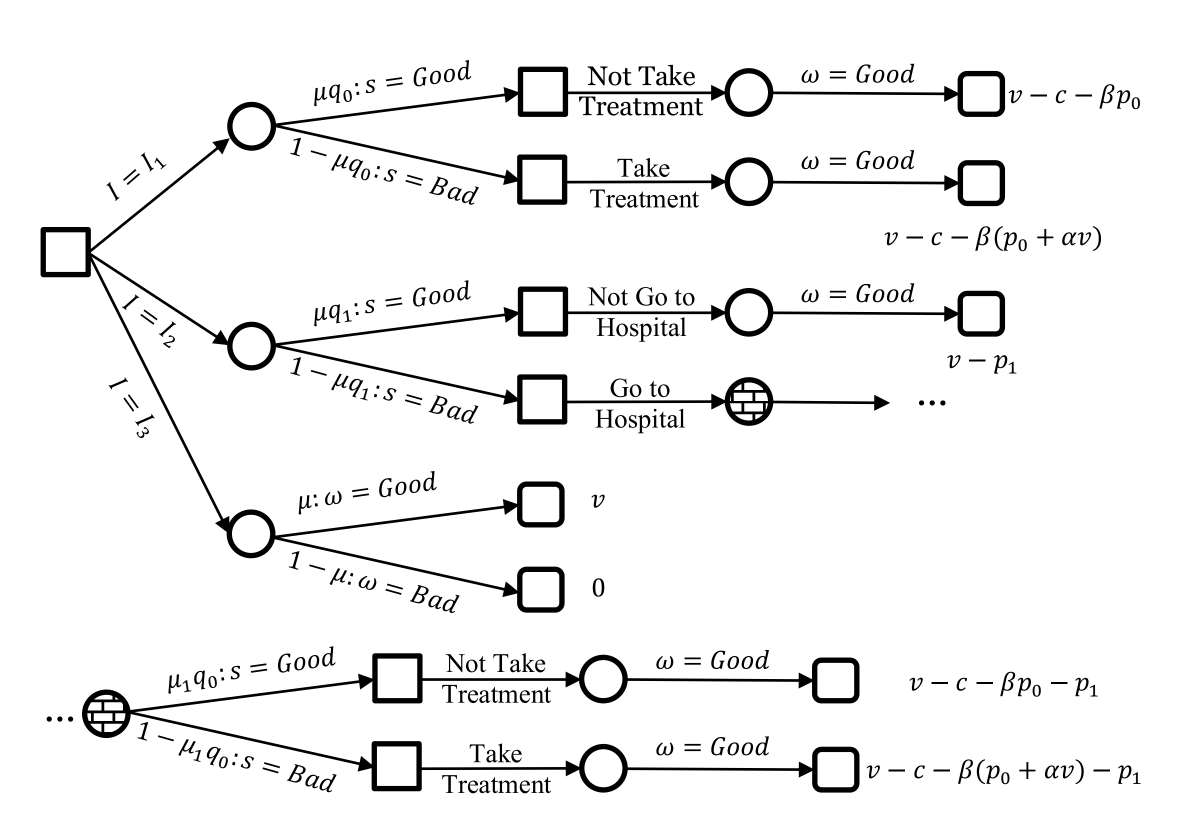

Figure 2. Patients' Decision Process in the Main Model

First, note that in Figure 2, for simplification, we use μ_1 to represent $\mu_1|(s = Bad)$, which is the patients' belief on the probability that they are healthy conditional on their receiving signal B. For a similar reason, online patients will follow the online suggestions to decide whether to go to the hospital (which can also be analytically shown); otherwise, they can be better off not using the online healthcare system. Here, the subsequent nodes of the shaded circular node take a similar structure as the subsequent nodes behind $I = I_1$. However, please note that patients' belief before receiving the offline signal is μ_1 instead of μ, since those patients have already updated their beliefs through the online signal.

In addition to d_1, we use d_2 to denote the number of online patients. Then, the hospitals' maximization problem would be maximizing its own profit by choosing q_0, q_1 and p_1. Specifically,

$$\max_{q_0,q_1,p_1} d_1[p_0 + (1 - \mu q_0)\alpha v] + d_2[p_1 + (1 - \mu q_1)(p_0 + (1 - \mu_1 q_0)\alpha v)]$$

For online patients, the hospital can earn them an online healthcare service fee p_1 for sure. However, those patients would come to the hospital only when they receive signal B from the online healthcare system, the probability of which is $1 - \mu q_1$. Likewise, each patient going to the hospital after using an online healthcare system would generate an expected profit $p_0 + (1 - \mu_1 q_0)\alpha v$ for the hospital.

In the presence of online healthcare, besides the revenue from patients directly visiting the hospital (i.e., offline patients) as in the benchmark, the hospital could also generate revenue from patients who first ask for the help of the online healthcare system (i.e., online patients).

Time Sequence

To describe the game structure more clearly, based on those model descriptions listed above, we summarize the time sequence of the benchmark and the main model, respectively, as follows

Benchmark: In stage 1, the hospital decides the persuasion accuracy of the offline healthcare system q_0; in stage 2, patients decide whether to go to the hospital; in stage 3, all randomization and payoffs realize.

Main Model: In stage 1, the hospital decides the persuasion accuracy of the offline healthcare system q_0, the persuasion accuracy and price of the online healthcare system q_1 and p_1; in stage 2, patients decide whether to go to the hospital, use online healthcare, or stay at home; in stage 3, all randomization and payoffs realize.

Modeling Solution

In this section, we solve the benchmark and the main model provided in the previous section.

Benchmark Solution

Following the convention of backward induction, we first analyze the patients' medical treatment choice at Stage 2, which is followed by the analysis of the hospital's decision in Stage 1.

Patients Medical Treatment Choice

Given the hospital's decision on offline persuasion accuracy, Lemma 1 summarizes the patients' medical treatment choices.

Lemma 1 (Patients Medical Treatment Choice in Benchmark)

In the benchmark where the online healthcare system is not available, given the hospital's decision on the offline persuasion accuracy q_0, the patients with low opportunity cost (i.e., $c \leq \tilde{c}_0$) become offline patients, whereas the patients with high opportunity cost (i.e., $c > \tilde{c}_0$) become no-service patients.

Based on Lemma 1, only patients with lower opportunity costs will choose to visit the hospital in person, and patients with higher opportunity costs (e.g., patients in a remote area, patients busy with their business) will choose to stay at home. Accordingly, we can compute the hospital's demand in the benchmark. Specifically, in the benchmark,

$$d_1 = \tilde{c}_0 = v\big(1 - \mu - \alpha\beta(1 - q_0\mu)\big) - p_0\beta.$$

Comparative statistics show that such a demand increases with the severity of disease v but decreases with the outpatient fee p_0, which is consistent with intuition. More importantly, the offline persuasion accuracy q_0 positively impacts the hospital's demand. This is because a higher q_0 indicates less excessive medical treatment, which leads to a higher expected utility of patients and incentivizes patients to visit the hospital.

Hospital's Offline Persuasion Accuracy Decision

Next, in Lemma 2, we derive the hospital's decision on the offline persuasion accuracy q_0.

Lemma 2 (Optimal Offline Persuasion Accuracy in Benchmark)

In the benchmark where the online healthcare system is not available, the optimal offline persuasion accuracy is $q_0^{b^*} = 1$ if the outpatient fee is relatively high (i.e., $p \geq \frac{v(1-2\alpha\beta)(1-\mu)}{2\beta}$); otherwise, $q_0^{b^*} = \frac{2p\beta - v(1-2\alpha\beta-\mu)}{2v\alpha\beta\mu}$.

When deciding the optimal persuasion accuracy in the benchmark, the hospital needs to tradeoff between the offline demand and the profit per patient visiting the hospital offline. Specifically, the profit per patient visiting the hospital is $p_0 + (1 - \mu q_0)\alpha v$, which consists of the outpatient fee p_0 and the expected treatment fee $(1 - \mu q_0)\alpha v$ (i.e., the probability of taking treatment times the treatment fee). Recall that among patients visiting the hospital, only those receiving signal B (i.e., $s = Bad$) would choose to take treatment, and increasing offline persuasion accuracy q_0 would reduce the probability of patients receiving signal B $1 - \mu q_0$. Thus, a higher offline persuasion accuracy q_0 leads to fewer patients (who visit the hospital) taking treatment; accordingly, the expected treatment fee decreases, and the profit per patient visiting the hospital decreases. However, in the meanwhile, a higher offline persuasion accuracy q_0 would also increase the patients' expected utility of visiting the hospital and hence bring the hospital more offline demand. The hospital needs to strike a delicate balance between the offline demand and the profit per patient visiting the hospital.

Main Model Solution

Similarly, in this subsection, we first analyze the patients' medical treatment choices in Stage 2, which is followed by the analysis of the hospital's decision in Stage 1.

Patients' Medical Treatment Choices

Given the hospital's decisions at Stage 1, Lemma 3 summarizes the patients' medical treatment choices in Stage 2 in the main model.

Lemma 3 (Patients' Medical Treatment Choices in the Main Model)

In the main model where the online healthcare system is available, given the hospital's decisions on the offline persuasion accuracy q_0, online persuasion accuracy q_1 and the online healthcare service fee p_1,

1. *when $vq_0\alpha\beta\mu(1-q_1) < p_1 < vq_0(1-q_1\alpha\beta)(1-\mu)\mu$ and $p_1 > p_0q_1\beta\mu + (1-q_0)q_1\beta\mu v\alpha$, the patients with low opportunity cost (i.e., $c \le \tilde{c}_1$) become offline patients, the patients with medium opportunity cost (i.e., $\tilde{c}_1 < c \le \tilde{c}_2$) becomes online patients, and the patients with high opportunity costs (i.e., $c > \tilde{c}_2$) become no-service patients;*
2. *when $vq_0\alpha\beta\mu(1-q_1) < p_1 < vq_0(1-q_1\alpha\beta)(1-\mu)\mu$ and $p_1 \le p_0q_1\beta\mu + (1-q_0)q_1\beta\mu v\alpha$, or when $p_1 \le vq_0\alpha\beta\mu(1-q_1)$, patients with low/medium opportunity cost (i.e., $c \le \tilde{c}_2$) become online patients, and the patients with high opportunity costs (i.e., $c > \tilde{c}_2$) become no service patients;*
3. *when $p_1 \ge vq_0(1-q_1\alpha\beta)(1-\mu)\mu$, patients' decisions are identical to the benchmark; specifically, patients with opportunity cost $c \le \tilde{c}_0$ become offline patients, whereas patients with opportunity cost $c > \tilde{c}_0$ become no service patients.*

Depending on the hospital's decisions in Stage 1, patients can have different medical treatment choices. When the online healthcare fee p_1 is relatively high (i.e., case (3) in Lemma 3), none of the patients would use the online healthcare system due to the high online service fee, and hence the patients' medical treatment decisions remain the same as those in the benchmark. When p_1 is medium (i.e., case (1) in Lemma 3), the patients with low opportunity cost remain offline patients, whereas the patients with medium opportunity cost become online patients who could save their opportunity cost and outpatient fee by visiting the online healthcare system, and the patients with high opportunity cost are still out of the healthcare system. When p_1 is relatively low (i.e., case (2) in Lemma 3), none of the patients is offline patients since it benefits the patients by firstly taking an online treatment under a relatively low online healthcare fee; at this case, patients with low/medium opportunity cost become online patients and the rest of patients are no-service patients. Notably, comparing the benchmark and the main model, we have $\tilde{c}_2 \ge \tilde{c}_0$, which indicates that fewer patients are no-service patients and more patients get involved in the healthcare system in the presence of online healthcare.

From Lemma 3, we can derive the demand of the hospital in the main model. For case (1) in Lemma 3, the number of offline patients is $d_1 = \tilde{c}_1$ and the number of online patients is $d_2 = \tilde{c}_2 - \tilde{c}_1$; for case (2) in Lemma 3, the number of offline patients is $d_1 = 0$, and the number of online patients is $d_2 = \tilde{c}_2$. For case (3) in Lemma 3, the number of offline patients is $d_1 = \tilde{c}_0$ and the number of online patients is $d_2 = 0$.

Hospital's Healthcare System Design Decisions

Lemma 4 below summarizes the hospital's healthcare system design decisions at Stage 1. Specifically, the decisions on online healthcare fee p_1, offline persuasion accuracy q_0, and online persuasion accuracy q_1.

Lemma 4 (Optimal Hospital's Healthcare System Design Decisions)

The hospital tells patients the truth online (i.e., $q_1^* = 1$) in equilibrium, whereas its decisions on online healthcare fee p_1 and offline persuasion accuracy q_0 depend on several market conditions. Specifically,

1. *when the outpatient fee $p_0 \le \tilde{p}_0^1$, the hospital sets $p_1^* = \frac{2\beta(p_0(1+\beta)-v(1-\alpha-\alpha\beta))(1-\mu)\mu}{(1+\beta)^2\mu-(1-\beta)^2}$ and sets $q_0^* = \frac{4p_0\beta-v(1-\mu+\beta(1-4\alpha-\mu))}{v\alpha((1+\beta)^2\mu-(1-\beta)^2)}$ such that there exist both online patients and offline patients;*

(2) *when the outpatient fee* $\tilde{p}_0^1 < p_0 \le \tilde{p}_0^2$*, the hospital sets* $p_1^* = \frac{1}{2}v(1-\alpha-\alpha\beta)(1-\mu)\mu$ *and sets* $q_0^* = 1$ *such that there exist both online patients and offline patients;*
(3) *when the outpatient fee* $\tilde{p}_0^2 < p_0 \le \tilde{p}_0^3$*, the hospital sets* $p_1^* = \frac{1}{2}(p_0(1+\beta) - v(1-\alpha-\alpha\beta))(1-\mu)$ *and sets* $q_0^* > \frac{(p_0+v\alpha)\beta\mu - p_1}{v\alpha\beta\mu}$ *such that no patients are offline patients;*
(4) *when the outpatient fee* $p_0 > \tilde{p}_0^3$*, the online healthcare system is irrelevant regardless of the hospital's decision.*

When designing the online healthcare system, the hospital faces several interesting tradeoffs. To understand such tradeoffs, in Table 4, we summarize how the design of the healthcare system impacts the online demand, offline demand as well as total demand.

	Online Healthcare Fee p_1 ↗	Offline Persuasion Accuracy q_0 ↗	Online Persuasion Accuracy q_1 ↗
Offline Demand ($\tilde{c}_1$)	↗	↗	↘
Online Demand ($\tilde{c}_2 - \tilde{c}_1$)	↘	↘	↗
Total Demand ($\tilde{c}_2$)	↘	↗	↗

Table 4. Impact of Healthcare System Design on Demands

The optimal online healthcare fee p_1 depends on a traditional tradeoff between price and demand. More specifically, the hospital can benefit more from each online patient by charging a higher online healthcare fee p_1; however, at the same time, a higher online healthcare fee p_1 would incentivize fewer patients to use the online healthcare system, potentially hurting the hospital's revenue. Notably, although the decrease in online healthcare fee p_1 can bring the hospital more online demand, it would also cannibalize the hospital's offline demand. As a result, if the offline demand is more profitable, the hospital should be more cautious when seeking to increase online demand by decreasing the online healthcare fee. For example, according to Lemma 4, the optimal online healthcare fee p_1 increases with the outpatient fee p_0, since a higher outpatient fee makes the offline demand more profitable, and the hospital is expected to generate more offline demand by increasing p_1.

When deciding the offline persuasion accuracy q_0, the hospital faces a similar tradeoff between the total demand and the profit per patient visiting the hospital, as illustrated in the discussion following Lemma 2. Meanwhile, although an increase in offline persuasion accuracy q_0 could increase the offline demand, it would also cannibalize the online demand. Thus, as shown in Lemma 4, when the offline demand is less profitable (e.g., the outpatient fee p_0 is lower), the hospital will set a lower offline persuasion accuracy to generate more online demand.

The online persuasion accuracy q_1 impacts the hospital's profitability in three ways. First, an increase in q_1 lead to a lower offline demand since a higher online persuasion accuracy make the offline treatment less attractive. Second, a higher online persuasion accuracy q_1 lead to a higher online demand, which is intuitive to understand. Third, a higher online persuasion accuracy makes online patients more likely to receive signal G from the online healthcare system, and accordingly, online patients are less likely to visit the hospital; thus, the profit per online patient (i.e., $p_1 + (1-\mu q_1)(p_0 + (1-\mu_1 q_0)\alpha v)$) decreases with online persuasion accuracy q_1. The hospital needs to tradeoff between those three impacts mentioned above to solve the optimization problem over q_1.

Equilibrium Analysis

In this section, we analyze the equilibrium results solved in the previous section. As mentioned earlier, there are several concerns over the diagnosis accuracy of online healthcare systems. Proposition 1 highlights the hospital's decision on such diagnosis accuracy decisions (i.e., online persuasion accuracy).

Proposition 1 (Optimal Online Persuasion Accuracy)

In equilibrium, the hospital sets the online persuasion accuracy to the maximum value (i.e., $q_1^* = 1$*). That is, the hospital provides the most accurate diagnosis online.*

Intuitively, one may expect that the hospital can lie to patients in the online healthcare system since by doing so, more patients can receive signal B from the online healthcare system; accordingly, more online patients can be transferred to visit the hospital offline and benefit the hospital. However, our results show that it is not the case, and the hospital actually would not lie to online patients (more specifically, the hospital would not lie to healthy online patients by telling them they are sick).

Although a lower online persuasion accuracy (i.e., lying to patients) could drive more online patients to have an offline visit and bring the hospital additional value, it makes fewer patients engaged in the overall healthcare system. Such a loss in the overall demand could not be compensated by the additional profit driven by the additional traffic from the healthy online patients who are persuaded to visit the hospital offline. In other words, it is not worthy for the hospital to lie to patients to attract their offline visits since the total number of patients engaged in the healthcare system would be reduced then. Note that although the hospital tells the truth online, the hospital's profit still depends on the offline persuasion accuracy q_0 since it is critical to the hospital's offline demand.

The result of Proposition 1 generates important managerial implications for the practice. First, the hospital should truthfully reveal the health condition of patients who visit the online healthcare system. Second, the patients should be fully aware that online healthcare is reliable since the hospital does not have economic incentives to lie to patients.

As discussed earlier, in reality, there has been criticism that hospital is ordering excessive medical treatment for patients. In Proposition 2, we show how the online healthcare system impacts the hospital's behavior regarding excessive medical treatment. More explicitly, we compare the offline persuasion accuracy of the hospital under the benchmark and the main model. A higher offline persuasion accuracy means that the hospital persuades fewer healthy patients to take medical treatment and hence stands for less excessive treatment.

Proposition 2 (Impacts of Online Healthcare System on Offline Persuasion Accuracy)

Compared to the regime without an online healthcare system, under the regime with an online healthcare system, the hospital sets a higher offline persuasion accuracy (i.e., $q_0^* \geq {q_0^b}^*$*).*

Interestingly, according to Proposition 2, the presence of an online healthcare system could incentivize the hospital to set a higher offline persuasion accuracy. In other words, the online healthcare system can alleviate the excessive treatment problem in the offline hospital.

To understand this counterintuitive result, we first revisit the tradeoff that the hospital faces when optimizing the offline persuasion accuracy q_0 in the benchmark, as discussed following Lemma 2. In the benchmark, the hospital's profit is formulated as

$$d_1[p_0 + (1 - \mu q_0)\alpha v].$$

A higher offline persuasion accuracy q_0 brings a higher offline demand d_1(see Lemma 1), but hurts the profit per patient visiting the hospital offline (i.e., $p_0 + (1 - \mu q_0)\alpha v$). Correspondingly, the hospital's profit in the main model is formulated as

$$d_1[p_0 + (1 - \mu q_0)\alpha v] + d_2[p_1 + (1 - \mu q_1)(p_0 + (1 - \mu_1 q_0)\alpha v)].$$

In the main model, the negative impact of a higher offline persuasion accuracy remains the same as that in the benchmark (i.e., it hurts the profit per patient visiting the hospital). However, in the presence of an online healthcare system, not only the offline patients (the amount is d_1) but also part of online patients who receive signal B from the online healthcare (the amount is $d_2(1 - \mu q_1)$) contribute to the total offline hospital visiting. In addition, the total offline hospital visiting $d_1 + d_2(1 - \mu q_1)$ is increasing in offline persuasion accuracy q_0, and the increasing speed is higher than that in benchmark due to the additional part of online patients contributing to the offline hospital visiting. Accordingly, the positive impact of a higher persuasion accuracy (attracting more patients to have an offline visit to the hospital) is higher than the benchmark. Subsequently, as the negative impact remains unchanged, facing a higher positive impact of increasing offline persuasion accuracy q_0, the hospital sets a higher offline persuasion accuracy.

Such a result indicates a nonintuitive role played by the online healthcare system. That is, the online healthcare system could help alleviate the excessive treatment of hospitals. Hence, according to this result, policymakers should focus more on those hospitals without online healthcare systems when they regulate the excessive treatment problem.

One of the purposes of online healthcare is to reduce the patients' offline hospital visiting. As mentioned in the introduction, during the global pandemic COVID-19, many hospitals have started to build their own online healthcare system, aiming to reduce the offline hospital traffic to avoid spreading infection. In Proposition 3, we formally investigate whether the online healthcare system is really helpful in reducing offline hospital traffic.

Proposition 3 (Impacts of Online Healthcare System on Offline Hospital Traffic)

Compared to the regime without an online healthcare system, under the regime with an online healthcare system, the offline traffic of the hospital increases.

Contrary to the common wisdom, surprisingly, we find that far from reducing the offline hospital traffic, the presence of an online healthcare system actually incentivizes more patients to visit the hospital offline. More specifically, the offline traffic in the benchmark (i.e., $\tilde{c}_0$) is lower than that in the main model (i.e., $\tilde{c}_1 + (1 - \mu q_1)(\tilde{c}_2 - \tilde{c}_1)$). We use Figure 3 to illustrate the rationale behind this interesting finding.

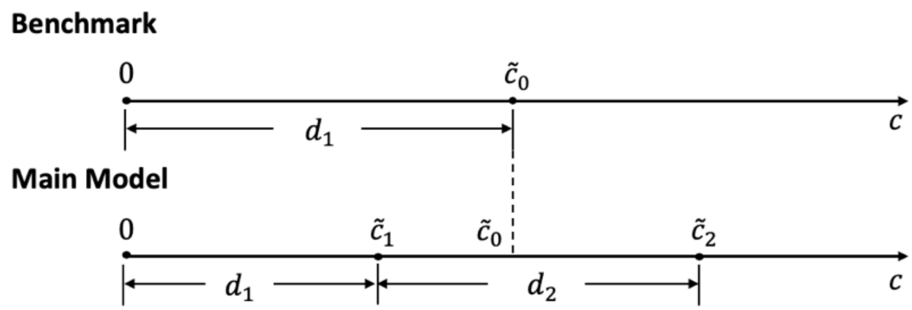

Figure 3. Offline Traffic of Hospital

In the benchmark without an online healthcare system, there are $d_1 = \tilde{c}_0$ offline patients who visit the offline hospital directly and the offline hospital traffic is $\tilde{c}_0$. In the presence of online healthcare, the patients with $c \in [\tilde{c}_1, \tilde{c}_0]$ are converted to the online channel, who could potentially get their problem solved in the online healthcare system and not visit the hospital offline. Thus, the offline visit from patients with $c \in [0, \tilde{c}_0]$ decreases due to the benefit of online healthcare on saving opportunity cost, which is consistent with the intuition. However, the other important impact of online healthcare is to attract more patients to be involved in the overall healthcare system and increase the offline traffic indirectly. In particular, patients with $c \in [\tilde{c}_0, \tilde{c}_2]$ will not engage in the overall healthcare system in the benchmark due to the high opportunity cost; however, in the presence of the online healthcare system, this part of patients become online patients, who would visit the hospital offline conditional on receiving signal B from the online healthcare system. To summarize, although the online healthcare system could directly keep some patients from visiting the hospital, the more dominating impact of the online healthcare system is attracting more patients to engage in the overall healthcare system and indirectly increase the offline hospital traffic. This finding is consistent with that of several empirical research. For example, it is in line with the finding of Bavafa et al. (2018) that "*Using a panel data set from a large healthcare system in the United States, we find that e-visits trigger about 6% more office visits*", and is also consistent with the finding of Ayabakan et al. (2020) that "*Non-chronic patients experience a 45% increase in their inpatient admissions, within 30 days after a telehealth visit, suggesting a gateway effect in inpatient settings*."

Proposition 3 generates important managerial implications for policymakers. According to our results, online healthcare is not an effective way to reduce offline hospital traffic; on the contrary, it would increase individuals' offline hospital visiting. As a result, policymakers aiming to control infectious diseases such as COVID-19, SARS, and seasonal influenza by reducing offline hospital traffic should not rely on the online healthcare system.

In the following, we examine the impacts of the online healthcare system on the payoffs of stakeholders in our model and summarize the results in Proposition 4.

Proposition 4 (Impacts of Online Healthcare System on Stakeholders' Payoffs)

Compared to the regime without an online healthcare system, under the regime with an online healthcare system,

(1) when $0 < v < \tilde{v}$, stakeholders' payoffs remain the same as those in the benchmark without an online healthcare system;
(2) otherwise, both the hospital's profit and the patients' surplus increase.

According to Proposition 4, when the severity of the disease is relatively low, the stakeholders' payoffs remain the same as those in the benchmark. To understand this, we first illustrate why compared with the offline hospital, the attractiveness of the online healthcare system increases with the severity of disease v. Compared to directly visiting the hospital offline, using the online healthcare system make healthy patients less likely to face the hospital's excessive treatment since the patients using the online healthcare receive two signals from the overall healthcare system, and the patients directly visiting the hospital online just receive one signal, and two signals are accurate than one signal. Accordingly, using online healthcare system helps patients reduce the risk of facing excessive treatment. In addition, the cost of being performed excessive treatment (i.e., αv) increases with v. Hence, using online healthcare would benefit the patients more when the severity of disease v is relatively high. As a result, when v is relatively low (i.e., $0 < v < \tilde{v}$), the attractiveness of offline hospitals is higher than that of the online healthcare system, and in such a case, no patients would visit the online healthcare system despite the hospital's decision (which corresponds to case (4) in Lemma 4). Hence, the stakeholders' payoffs remain the same as those in the benchmark.

When $v \geq \tilde{v}$, equilibrium results show that at least part of patients become online patients. At that time, the offline persuasion accuracy is higher compared to the benchmark (see Proposition 2), and hence, each patient could have a higher surplus than the benchmark since they face a hospital with a higher offline persuasion accuracy and has an additional choice of using the online healthcare system. Accordingly, the patients' total surplus increases. As for the hospital, compared to the benchmark, it cannot be worse off by setting a relatively high online healthcare fee to price patients out of the online healthcare system; however, in equilibrium, the hospital makes its decisions such that some patients become online patients, which indicates that under the regime with the online healthcare system, the hospital generates a higher profit than the benchmark.

Proposition 4 provides a guideline for hospitals on whether to adopt the online healthcare system. We find that online subsidiary healthcare systems can only benefit the hospital when the severity of the disease is relatively high. Such a result suggests that small hospitals which could only tackle mild diseases should not adopt the online healthcare system; also, for large hospitals, they should only provide online diagnoses for those severe diseases.

Concluding Remarks

During the era of COVID-19, many hospitals have begun to launch their own online healthcare systems. Yet, there is little information in the literature about how and to what extent the online subsidiary healthcare system impacts the existing healthcare ecosystem. To fill this critical gap in the literature, we build a theoretical model to study the economics of such online healthcare systems. More specifically, we analyze how the hospital should set the persuasion accuracy of the online healthcare system; in addition, we investigate the impact of the online subsidiary healthcare system on offline hospital traffic; moreover, we study the impact of the online healthcare system on the degree of offline healthcare overtreatment; also, we investigate the impact of online healthcare on the hospital's profitability and patients' surplus.

Our study generates several intriguing findings. We find that, interestingly, the hospital will set the online persuasion accuracy to the maximum value to generate more healthcare demand. Second, counterintuitively, we find that the presence of an online healthcare system actually increases patients' offline visits to the hospital, since some of the online patients acquired by the online healthcare system could be converted into offline hospital traffic. Third, we find that the online healthcare system is an effective tool to alleviate the hospital's offline healthcare overtreatment since it amplifies the negative consequence of committing healthcare overtreatment. Finally, our results indicate that the online healthcare may not necessarily benefit the hospital and the patients; sometimes, the payoffs of those stakeholders in our model may not be affected by the presence of an online healthcare system.

Our paper contributes to the literature in two aspects. First, we contribute to the literature on health information technology by examining the impacts of an emerging HIT (i.e., online subsidiary healthcare systems). Additionally, given that most existing literature focuses on the impact and the adoption of HIT, our contribution also lies in the fact that we study an optimal design problem of HIT. Moreover, given that most prior studies on HIT are conducted empirically, we make our contribution by analytically analyzing an important and timely problem surrounding HIT. Second, we contribute to the literature on healthcare economics by studying the hospital's design of the online subsidiary healthcare system. Different from a third-party online healthcare platform, to design its own online healthcare system, a hospital needs to strike a delicate balance between the existing offline revenue source and the new online revenue source; hence, the impact of such a healthcare system can be intricate. Despite the large market share of online subsidiary healthcare system, to the best of our knowledge, the existing literature has not examined the economic impact of an online healthcare system subsidiary to an offline hospital and the optimal design of such a healthcare system. We aim to fill this research gap.

Our results provide valuable managerial insights that can guide hospitals to better manage the online subsidiary healthcare system and help policymakers devise proper regulation policies. For example, according to our results, the hospital should truthfully reveal patients' health condition who visit the online healthcare system since such a truth-revealing policy attracts more patients to participate in the overall healthcare system; accordingly, the patients should not be concerned about the healthcare overtreatment problem in the online healthcare system since the hospital will provide online patients with the most accurate diagnosis. Additionally, according to our results, online healthcare is not an effective way to reduce the offline hospital traffic; on the contrary, it would increase individuals' offline hospital visiting. The reason is that although the online healthcare system can keep some patients from directly visiting the hospital, the more dominating impact of the online healthcare system is to attract more patients to the whole healthcare system and increase the offline throughput of the hospital indirectly. As a result, policymakers seeking to control infectious diseases such as COVID-19, SARS, and seasonal influenza by reducing offline hospital traffic should not rely on the online healthcare system. Our results also reveal a nonintuitive role the online healthcare system plays in reducing offline healthcare overtreatment, and the policymakers should be fully aware of such an advantage of the online healthcare system. Moreover, we find that online healthcare can only benefit the hospital when the severity of the disease is relatively high. The reason is that, for the patients with mild diseases, the attractiveness of offline hospitals is always higher than that of the online healthcare system. Such a result suggests that small hospitals that can only tackle mild diseases should not adopt the online healthcare system; also, for large hospitals, they should only provide online diagnoses for those severe diseases.

This paper has several limitations that suggest directions for future research. For example, we consider that the hospital knows all the patients' true health conditions, and future works could relax this assumption and examine the scenario where the hospital does not have accurate information about the true health conditions of all the patients. Moreover, we only focus on the theoretical analysis of the online healthcare system, and future research can conduct empirical analyses to validate the results and derive additional insights. Besides, in this paper, we only focus on the hospital in the regions with strict regulations on the healthcare payments and consider exogenous outpatient fee; however, private hospitals in certain regions of the world are not necessarily restricted by such regulations and often compete with other hospital chains by charging lower fees. Thus, future research can endogenize the outpatient fee to derive additional insights. Additionally, in this research, we consider that patients' treatment costs are independent of their opportunity costs. However, in certain scenarios, serving higher opportunity cost patients (e.g., minority groups such as the elderly) may require higher treatment costs. As a result, future research can relax this assumption and further explore the impact of online healthcare system.

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