Optimal Multi-Channel Delivery of Expertise: An Economic Analysis

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Abstract

Consumers are increasingly using the Internet to minimize the uncertainties regarding important decisions relating to their health. Physicians also show interest in delivering their expertise online, despite the inability to physically inspect their patients. In this research we use a game-theoretic model to study the optimal channel strategies of capacity-constrained experts who provide consultation services via a face-to-face and an online channel. Consumers can be in two different states (good or bad) about which experts observe a number of symptoms. We show that an expert can charge a higher price online than face-to-face and still find consumers willing to use this new service. If both channels are utilized, consumers who are more certain about their states are served online. The optimal price of an online consultation increases with the time required for this type of service. We discuss the issues experts need to consider in pricing their services and why offering online consultations make economic sense. Medical experts can use the insights derived from the model to simultaneously manage face-to-face and online channels in selling their expertise.

Keywords: Online Consultation; Expert Service; Private Information Good; E-Health; Telemedicine

1. Introduction

E-health is touted as the future of health care, promising to transform the way health care entities conduct business and change the way patients relate to health care providers. E-health is growing more pervasive among physicians and patients alike. The Pew Internet & American Life Project reports that 93 million Americans have gone online for health information by December 2002 [17]. Six million Americans seek medical advice on the Internet every day. According to a Harris Interactive Report, 37 percent of adult Internet users in 2002 were willing to pay to communicate online with their physicians [34]. While consumers demand the convenience of communicating online with their doctors, the absence of physical inspection and face-to-face dialogue may create risks for medical experts by reducing their diagnosis accuracy. Still, experts offer online access to their services. A study of 1,200 physicians conducted by Deloitte and Touche and Fulcrum Analytics indicated that 23% of physicians used e-mail to communicate with their patients in 2002 [14]. Doctors expect to be reimbursed an average of $57 for an e-consultation. Recently, more than a dozen health insurers in several states have begun reimbursing doctors for online consultations with patients [35].

A recent report by the Institute of Medicine, *Crossing the Quality Chasm*, states that "patients should receive care whenever they need it and in many forms, not just face-to-face visits…access to care should be provided over the Internet, by telephone, and by other means" [11, p. 61]. Apart from the convenience, major benefits of online consultations for patients include a greater degree of control over medical records, the ability to compose questions better and save e-mails to re-read instructions, a less intimidating venue due to the "relative anonymity," which allows some level of disinhibition for patients to ask questions they may not have otherwise. Of course, emergencies and other time-sensitive issues, such as chest pain, shortness of breath, suicidality, bleeding, cannot be dealt with effectively using online consultations.

Examples of web sites that facilitate online consultations are numerous, among which perhaps the most notable is RelayHealth. By July 2005, more than 4,000 physicians have listed themselves on RelayHealth's portal (relayhealth.com) to offer e-mail consultations. The American Medical Association (AMA) also lets patients search for doctors offering online consultations both at its own web site (www.ama-assn.org) as well as at medem.com. Medem, the for-profit Internet company backed by the AMA and other medical societies, provides secure communication services that enable doctors to charge patients for online visits. Doctors in Medem's network reportedly charge $26 on average for a virtual visit [8]. Also, some of the top experts in the nation provide online second opinions for important diagnoses and treatments. The Cleveland Clinic, a well-known multi-specialty academic medical center in Cleveland, has established its online interface, the eClevelandClinic, to serve patients who need advice and possibly a major intervention but who cannot easily access the doctors in person. The electronic service is limited to life-threatening and life-altering conditions that can be safely assessed online, such as a new cancer diagnosis, cardiac procedures, joint replacements, and neurological problems. Patients provide a personal medical history and the original diagnosis as well as other relevant materials such as test results, MRI, films, x-rays, and a consent form. Three Harvard University teaching hospitals have initiated a similar service at econsults.partners.org. In addition, several leading oncologists render medical opinions at www.mdexpert.com and charge fees as high as $3,200.

In this research, we investigate the optimal channel management strategies of experts from an economic standpoint and ask the following research questions: When should highly demanded medical experts offer online consultations regarding medical conditions that can be treated online? What should be the optimal online diagnosis policy? Which types of consumers should be served face-to-face and which types online? What is the optimal pricing policy for the two channels? The answers to these questions would guide medical providers about when to adopt and how to utilize Web-based consultation services.

The above questions are broadly related to three areas of research: telemedicine, multi-channel management, and expert services. Despite the recent popularity of telemedicine, there is little research that analyzes its cost-effectiveness with respect to alternative approaches using a sound methodology. Instead, research on telemedicine is mainly conducted to answer the question "Can we do this?", leaving the important question "Should we do this?" unanswered [26]. The economic studies in this area repeatedly indicate avoidance of travel or of patient transfer as one of the most salient benefits of telemedicine, but most of these studies have methodological limitations and the generalizability of findings are rather limited [19, 20].

The literature on multi-channel management examines how firms should utilize online and traditional channels simultaneously [7, 10, 22, 23, 30, 32, 36, 38]. Focused primarily on the retail sector, the main motivation of this stream has been to understand the issues that arise due to the emergence of the Internet, including the conflict between direct and indirect sales channels, management of communications strategies and consumer segmentation, impact of network externalities and switching costs, and competition with new, pure-play competitors. Prominent studies on electronic commerce also examine the way the Internet changes the nature of competition and firms' interaction with consumers in markets with differentiated product offerings [2, 4, 21, 24, 25]. Since medical experts are also confronted with the problem of managing face-to-face and online channels simultaneously, the above studies are relevant to this study. However, consultations served by experts are substantially different from retail goods.

Consultations are essentially *private* information goods. Previous information systems research has examined *public* information goods, such as software and music, which require a significant sunk cost to produce but only a negligible cost to reproduce [3, 9, 13]. In contrast, a private information good is produced for a specific consumer only, typically with the objective of diagnosing a problem and possibly suggesting a service to eliminate the problem. The economics literature on private information markets focuses on information problems that beset the relationship between an expert and his customers in the traditional face-to-face channel. In some circumstances the customer may not observe the type of service provided, which may allow the expert to defraud the customer by misrepresenting a low-cost service as a costly one [29, 37]. In other circumstances the customer may observe the actual service provided, but not necessarily whether the more costly service was really needed [1, 5, 12, 15, 16, 33]. Also, the diagnostic effort of the expert may not be observable and the success of the service may not be verifiable [28].

While the above information problems are important in their own right, several studies abstract away from them in the interest of isolating a certain feature of private information markets. For example, Sarvary [31] and Ozdemir et al. [27] study the pricing of expert information in a duopoly market and show that high-quality information sellers may specialize in second opinions. Bouckaert and Degryse [6] study the pricing and quality competition in private markets while focusing only on the face-to-face channel. In a similar vein, we do not emphasize the potential of fraud in this study simply because these problems have already been discussed in the literature and the manner in which they work is relatively well understood. Although we do not explicitly consider fraud (moral hazard) in this paper, we do incorporate the costs associated with misdiagnosing consumer problems.

This study takes an economic perspective and contributes to telemedicine research by addressing the question of "When should we do it?" It also aims to connect the literature on multi-channel management and private information markets. Our main contribution to the literature is the explicit consideration of optimal diagnosis policies, pricing strategies, and profitability when consulting face-to-face and online. We derive and discuss implications for highly demanded experts about how they should manage the two channels simultaneously. In doing this we first setup a game-theoretic model and derive the value of a consultation for consumers and the expected cost of diagnosis errors for experts. Next, we obtain expressions for simultaneously determined optimal channel and diagnosis strategies and discuss the optimal pricing strategies of experts. Interestingly, we find that the optimal price for an online consultation may exceed that of a face-to-face consultation, but improvements in online consultation technology reduce the optimal price while expanding the size of patient pool and increasing optimal profits. Experts can charge a higher price online because, as long as the online visit is more convenient than a face-to-face one, there exists a segment of consumers who value the online visit more. This observation implies that, in the absence of a fixed cost for adopting the online channel, experts should always offer online consultations. We also show that the quality of communication impacts the accuracy of an expert more when diagnosing consumers whose states exhibit more uncertainty.

The rest of the paper is organized as follows: We setup the model in Section 2 and solve it in Section 3. A discussion of the results, limitations, and future work is provided in Section 4.

2. Model Formulation

To illustrate the model we use the example of experts who sell their professional opinions to a set of consumers. The consumers are uncertain about their individual states, which may be either good (g) or bad (b).[1] Experts are differentiated with respect to the demand they face; an expert with index $i \in \{1,..,N\}$ has a potential consumer base of size D^i. Consumers are differentiated with respect to the prior likelihood of being in the bad state; within each potential consumer base, the prior probability of the bad state (α) is uniformly distributed among consumers between zero and one. Consumers incur a normalized unit loss if the state is bad; no loss occurs if the state is good. In other words, if consumers knew with certainty that they were in the bad state, they would pay up to 1 in order to avoid the unit loss. Each consumer needs to decide whether to consult to an expert for a possible treatment or do nothing. An expert suggests consumers to take a treatment when he diagnoses the bad state. If the diagnosis is correct, consumers can avoid the associated unit loss by taking the suggested treatment. The cost of treatment to a consumer is less than the unit loss and is denoted by c_t $(0 < c_t < 1)$. Consumers may take the treatment only with the approval of an expert.

Experts can inspect consumers either face-to-face (f) or online (o). Consumers incur the transaction cost t_j when they visit an expert via channel $j \in \{f, o\}$. The transaction cost on the face-to-face channel (t_f) represents the cost of search and travel, the opportunity cost of time, and the implicit cost of inconvenience, while the transaction cost on the online channel (t_o) represents difficulty in gathering, storing, and sending personal information to the expert electronically. Since the latter is either negligible or has been decreasing steadily in recent years, t_o can be expected to be smaller than t_f.

[1] The bad state can be thought of as having a specific diseasse or sickness. Thus, the experts' job is to diagnose whether their customers do indeed have this specific adverse condition.

A potential disadvantage of the online channel is that experts are likely to receive less information about consumers' problems when inspecting from a distance. For example, it is very hard, if not impossible, to diagnose a patient online when a physical exam is necessary. However, there can be cases where the expert receives more information via the online channel, especially when consumers feel more comfortable in sharing personal information in the absence of the expert (e.g., in discussing sexual problems). We measure the quality of information obtained via each channel by the number of "signals." That is, the larger the number of signals experts receive on a channel, the higher is the quality of communication on that channel.[2] Denote the number of signals transmitted via channel $j \in \{f, o\}$ by n_j. One of the objectives of this research is to understand the role of the quality of communication (measured by n_j) on experts' optimal strategies.

Each signal experts receive is drawn independently from the cumulative probability distribution Φ_g if the state is good and Φ_b if the state is bad. We assume Φ_g and Φ_b are normal distributions with variance σ^2 and means μ_g and μ_b, respectively, where $\mu_g > \mu_b$. An expert aggregates all n_j signals and chooses the cutoff aggregate signal s_j such that, if this aggregate signal exceeds s_j, the expert concludes that the consumer is in the good state. Otherwise he says the consumer is in the bad state. If the null hypothesis is that the consumer is in the good state, the expert commits a Type I error when he says a consumer is in the bad state when in fact the consumer is in the good state (rejecting the null hypothesis when it is true); he commits a Type II error when he says the consumer is in the good state when the consumer is actually in the bad state (accepting the null hypothesis when it is false). Denote the cost of Type

[2] In real life, some observations about the state can potentially be more informative than others. The notion of equally informative signals used here is not restrictive because more informative observations may be considered as being equivalent to multiple equally (less) informative signals in terms of the effect they may have on the variance of the posterior probability of the bad state.

I and Type II errors by c_1 and c_2, respectively. Note that, especially in health care, the cost of a Type II error can be much higher than the cost of a Type I error. Experts aim to choose a cutoff aggregate signal s_j that minimizes the expected cost of Type I and Type II errors.

Another technology parameter of interest is "ease of use," which affects the time needed for each online consultation. Each expert can work for at most k hours. A face-to-face consultation takes a normalized one hour, while an online consultation takes τ hours. One would expect τ to be less than one given the absence of physical inspection and the ability of the expert to fit more consultations into his schedule due to the asynchronous nature of online communication. Also, easy-to-use online consultation technologies would require less time for each expert-consumer interaction. Thus, an expert can handle at most k consumers face-to-face and k/τ consumers online. We focus on experts that are in high demand (e.g., acclaimed doctors) such that the capacity constraint always binds.[3]

Taking into account the capacity constraint and the distribution of consumer states, experts select their optimal diagnosis policy and price on each channel they choose to serve. After observing the experts' channel strategies, consumers decide whether to consult to an expert in maximizing their expected utility. If their expert utilizes both channels, consumers also choose whether to visit the expert face-to-face or online. A complete list of notation is provided in the Appendix.

[3] Our results may apply to physicians in general given the net shortage of doctors in the U.S. See, for example, http://www.ama-assn.org/ama/pub/category/15241.html. The qualitative results do not change when the capacity constraint does not bind.

3. Analysis

3.1. The Cost and Value of Face-to-Face and Online Consultations

Denote Φ_{gj} and Φ_{bj} as the joint cumulative probability distributions of mean of n_j signals when a consumer is in the good and bad state, respectively. Given the underlying normal distribution of each signal, Φ_{gj} and Φ_{bj} are distributed normally with variance σ^2 / n_j and means μ_g and μ_b, respectively. If the prior likelihood of the bad state is α, then the likelihood an expert says a consumer is in the bad state when in fact the consumer is in the good state is $(1-\alpha)\Phi_{gj}(s_j)$. Similarly, the likelihood the expert says the consumer is in the good state when the consumer is actually in the bad state is $\alpha(1-\Phi_{bj}(s_j))$. Hence, given the prior likelihood of the bad state α, the expected cost of Type I and Type II errors for a diagnosis provided via channel j equals

$$C(s_j, \alpha) = (1-\alpha)\Phi_{gj}(s_j)c_1 + \alpha(1-\Phi_{bj}(s_j))c_2 . \tag{1}$$

The value of a consultation depends on how much it improves a consumer's expected utility. With no consultation with an expert, consumers can maintain the unit utility only if the state is good, and therefore they expect a utility of $\Pr(\text{state} = \text{g}) = 1-\alpha$. Denote the diagnosis of the expert delivered via channel j by d_j. If the expert diagnoses the bad state, the consumer takes the treatment, incurs c_t, and maintains the unit utility. If the expert diagnoses the good state, the consumer can not take the treatment regardless of the prior likelihood of the bad state, and she maintains the unit utility with probability $\Pr(\text{state} = \text{g} \mid d_j = g)$. In other words, if the expert diagnoses the good state, the consumers loses the unit utility with the probability of the state being actually bad given the diagnosis $(1-\Pr(\text{state} = \text{g} \mid \text{d}_j = g))$. Upon obtaining the consultation via channel j (and incurring the transaction cost t_j), the consumer's expected utility $E(U \mid d_j)$ equals

$$E(U \mid d_j) = \Pr(d_j = b)(1 - c_t) + \Pr(d_j = g)\Pr(\text{state} = g \mid d_j = g) - t_j$$

$$= \Pr(d_j = b)(1 - c_t) + \Pr(\text{state} = g, d_j = g) - t_j .$$

Rearranging the terms we obtain

$$E(U \mid d_j) = \Pr(\text{state} = \text{g}) + \Pr(\text{state} = \text{b})\Pr(d_j = b \mid \text{state} = b) - \Pr(d_j = b)c_t - t_j$$

The value of a consultation equals the expected utility post consultation $(E(U \mid d_j))$ less the expected utility with no consultation with the expert $(1 - \alpha)$:

$$V_j(s_j, \alpha) = \Pr(\text{state} = \text{b})\Pr(d_j = b \mid \text{state} = b) - \Pr(d_j = b)c_t - t_j$$

$$= \alpha\Phi_{bj}(s_j)(1 - c_t) - (1 - \alpha)\Phi_{gj}(s_j)c_t - t_j \qquad (2)$$

Equation 2 indicates that the value of a consultation increases both with the prior likelihood of the bad state and the accuracy of the expert in correctly predicting the bad state. On the other hand, the value decreases with the cost of the treatment itself and with the likelihood that the expert mistakenly suggests unnecessary treatment. That is, the importance of a misdiagnosis compounds when the cost of treatment is high. Because the expert is more likely to misdiagnose a consumer's state when n_j is low, and since one would expect n_o to be less than n_f in most cases due to the absence of physical inspection, the expert is less likely to utilize online consultations when stakes are high for consumers.

Equation 2 also implies that a consumer's valuation for a consultation increases with the likelihood of the bad state (α), but more so for the channel from which the expert receives fewer signals. This is because the quality of the communication medium does not affect the value of the service much when there is little or no uncertainty about a consumer's state. Lemma 1 states this finding for $n_f > n_o$.

Lemma 1. *The values of both face-to-face and online consultations increase with the likelihood of the bad state. However, when $n_f > n_o$, the value of an online consultation increases at a higher rate than the value of a face-to-face consultation. Conversely, as the good state becomes more likely, the value of an online consultation decreases at a slower rate than the value of a face-to-face consultation.*

3.2. The Optimal Diagnosis and Channel Strategies

In order to get the highest return for labor, each expert selects the group of customers who value his service most and sets a diagnosis policy. For an expert to utilize the Internet, some of these customers should prefer to be served online. Intuitively, online consultations should be more appealing when the face-to-face transaction cost (t_f) is greater than its online counterpart (t_o). However, as we show in Proposition 1, there exists a segment of consumers that prefer an online consultation to a face-to-face one as long as $t_f > t_o$. This leads experts to always offer the online service. The proof is in the Appendix.

Proposition 1. *Given $t_f > t_o$, there exists a segment of consumers with high α who value an online consultation more than a face-to-face one.*

We can now focus on the optimal channel and diagnosis policies, which are determined simultaneously. Corollary 1 establishes that, whenever an expert offers both services, consumers with a high α prefer the online service while those with a low α prefer the face-to-face one. For example, consider the special case $\alpha = 1$ where both the consumer and the expert know with certainty that the state is bad. Since there is no room for diagnosis error in this special case, and given that the consumer can obtain the same treatment on both channels, the channel preference will be based solely on convenience, and the consumer will prefer online over face-to-face consultation. However, as the prior likelihood of the bad state decreases, the probability of a misdiagnosis increases at a faster rate online than face-to-face if the quality of communication is lower on this channel $\left(n_f > n_o\right)$, and so the consumer may prefer a face-to-face consultation below a threshold α value. The proof of Corollary 1 is also in the Appendix.

Corollary 1. *Given $t_f > t_o$, whenever an expert offers both services (which happens only when $n_f > n_o$), consumers with high (low) α values prefer the online (face-to-face) service.*

Patients with chronic health problems illustrate this point. Online consultations are reported to be especially useful for patients who have chronic conditions such as diabetes, asthma, hypertension, and heart problems [18]. Therefore, these services can be successfully offered to chronic disease populations for whom prescription refills, appointments, and laboratory tests are most frequent, rather than to healthy populations with intermittent illnesses requiring diagnostic evaluation. According to Harris Interactive, 71 percent of American adults who have Internet access prefer to get new prescriptions online for medications they already take [34]. Clearly, patients do not prefer to physically visit the doctor's office when their conditions as well as the necessary treatment are known a priori.

According to Corollary 1, each expert serves to consumers with high α values as long as treatment can be provided both face-to-face and online. Denote the lowest α value among the consumers served by expert i by $\underline{\alpha}^i$. In addition, assuming expert i offers consultations on both channels at optimality, denote the cutoff α value above which the expert serves online by $\overline{\alpha}^i$. Since the expert works at capacity:

$$D^i\left(1-\overline{\alpha}^i\right)\tau + D^i\left(\overline{\alpha}^i - \underline{\alpha}^i\right) = k\ . \tag{3}$$

According to Corollary 2, the consumer with $\alpha = \underline{\alpha}^i$ prefers a face-to-face consultation when both channels are used. Therefore, the highest the expert can charge to this consumer for a face-to-face consultation while working at capacity is $p_f^i = V_f\left(\underline{\alpha}^i\right)$.

Taking as given the costs of Type I and Type II errors and the distribution of prior likelihoods of the bad state, expert i decides which customers to serve online/face-to-face and which diagnosis policy to employ on each channel. This decision in turn determines the price that can be charged for the two types of services. By definition, the online and face-to-face prices of the expert make the consumer with $\alpha = \overline{\alpha}^i$ indifferent between obtaining a face-to-face and online consultation:

$$V_f\left(s_f, \overline{\alpha}^i\right) - p_f^i = V_o\left(s_o, \overline{\alpha}^i\right) - p_o^i .$$

Plugging in the value of p_f^i we have

$$p_o^i = V_o\left(s_o, \overline{\alpha}^i\right) - V_f\left(s_f, \overline{\alpha}^i\right) + V_f\left(s_f, \underline{\alpha}^i\right).$$

Given the expected per diagnosis cost of Type I and Type II errors in equation 1 and the linear relationship between $\underline{\alpha}^i$ and $\overline{\alpha}^i$ in equation 3, the problem of the expert can be stated as that of choosing the customers $\overline{\alpha}^i$ and $\underline{\alpha}^i$ and diagnosis policies s_f and s_o that maximize total net profit:

$$\underset{\overline{\alpha}^i,\underline{\alpha}^i,s_f,s_o}{\text{Max}}\ \Pi^i = D^i\left[\left(1-\overline{\alpha}^i\right)p_o^i + \left(\overline{\alpha}^i - \underline{\alpha}^i\right)p_f^i - \int_{\underline{\alpha}^i}^{\overline{\alpha}^i} C\left(s_f,\alpha\right)\mathrm{d}\alpha - \int_{\overline{\alpha}^i}^{1} C\left(s_o,\alpha\right)\mathrm{d}\alpha\right]$$

$$\text{s.t.}\quad D^i\left(1-\overline{\alpha}^i\right)\tau + D^i\left(\overline{\alpha}^i - \underline{\alpha}^i\right) = k$$

Since the optimal $\overline{\alpha}^i$ determines the optimal $\underline{\alpha}^i$, we only need to maximize with respect to $\overline{\alpha}^i$. We obtain the following equality from the first-order condition for $\overline{\alpha}^{i*}$:

$$\left(1-\overline{\alpha}^{i*}\right)\left(\frac{\partial V_o}{\partial \overline{\alpha}^i} - \frac{\partial V_f}{\partial \overline{\alpha}^i}\right) + \left(1-\underline{\alpha}^{i*}\right)\frac{\partial V_f}{\partial \overline{\alpha}^i}(1-\tau) = V_o\left(s_o^*,\overline{\alpha}^{i*}\right) - V_f\left(s_f^*,\overline{\alpha}^{i*}\right) + (1-\tau)V_f\left(s_f^*,\underline{\alpha}^{i*}\right)$$

$$-C\left(s_o^*,\overline{\alpha}^{i*}\right) + C\left(s_f^*,\overline{\alpha}^{i*}\right) - (1-\tau)C\left(s_f^*,\underline{\alpha}^{i*}\right). \tag{4}$$

Similarly, the expert sets the optimal cutoff policies s_f^* and s_o^* according to the following equalities obtained from the first-order conditions for s_f^* and s_o^*, respectively:

$$D^i\left(1-\overline{\alpha}^{i*}\right)\left[-\frac{\partial V_f\left(s_f^*,\overline{\alpha}^{i*}\right)}{\partial s_f} + \frac{\partial V_f\left(s_f^*,\underline{\alpha}^{i*}\right)}{\partial s_f}\right] + D^i\left(\overline{\alpha}^{i*} - \underline{\alpha}^{i*}\right)\frac{\partial V_f\left(s_f^*,\underline{\alpha}^{i*}\right)}{\partial s_f} = \frac{\partial C\left(s_f^*,\underline{\alpha}^{i*}\right)}{\partial s_f} \tag{5}$$

$$D^i\left(1-\overline{\alpha}^{i*}\right)\frac{\partial V_o\left(s_o^*,\overline{\alpha}^{i*}\right)}{\partial s_o} = \frac{\partial C\left(s_o^*,\overline{\alpha}^{i*}\right)}{\partial s_o} \tag{6}$$

Equation (4) states that, at the interior optimum, the marginal benefit and the marginal cost of raising $\overline{\alpha}^i$ are equal. A unit increase in $\overline{\alpha}^i$ leads to a unit decrease in the number of online consultations and a τ increase in the number of face-to-face consultations. Thus, the total number of consultations served by expert i decreases by $1-\tau$. Catering to a smaller consumer segment allows the expert to serve to those who have a higher value for his services. Consequently, the expert can charge $\frac{\partial V_f\left(\underline{\alpha}^{i*}\right)}{\partial \overline{\alpha}^{i*}}(1-\tau)$ more to all of his $D^i\left(1-\underline{\alpha}^{i*}\right)$ customers. Further, he can charge $\frac{\partial V_o\left(\overline{\alpha}^{i*}\right)}{\partial \overline{\alpha}^i} - \frac{\partial V_f\left(\overline{\alpha}^{i*}\right)}{\partial \overline{\alpha}^i}$ more to $D^i\left(1-\overline{\alpha}^{i*}\right)$ online customers. On the other hand, the expert loses $D^i\left[V_o\left(\overline{\alpha}^{i*}\right)-V_f\left(\overline{\alpha}^{i*}\right)+V_f\left(\underline{\alpha}^{i*}\right)\right]$ at the margin due to raising $\overline{\alpha}^{i*}$ and selling fewer online consultations and can only make up $D^i\tau V_f\left(\underline{\alpha}^{i*}\right)$ by selling additional face-to-face consultatios. Because of serving fewer consultations, the total cost of diagnosis errors committed reduces by $D^i\left[C\left(s_o^*,\overline{\alpha}^{i*}\right)-C\left(s_f^*,\overline{\alpha}^{i*}\right)+(1-\tau)C\left(s_f^*,\underline{\alpha}^{i*}\right)\right]$.

Figures 1 and 2 illustrate the intuitions behind equation 4.[4] Figure 1(a) shows that the utilization of the online channel increases with n_o. However, a relatively high demand increases the time benefit of the online consultation and thereby the utilization of the Internet. Figure 1(b) shows that an expert should handle more consumers online as τ decreases. Here again the time benefit of online consultations becomes an important factor when the expert has a relatively high demand. The expert may start serving less online below a certain τ value since a low τ substantially increases the expert's capacity and limits his ability to charge a high price in the absence of price discrimination.

[Figure 1 is approximately here.]

When $\tau < 1$, the increased utilization of the online channel due to a high n_o also increases the number of consumers served and thereby puts a downward pressure on prices (see Figure 2(a)). If the demand and n_o is sufficiently large, the expert can operate entirely via the online channel. In this case a further increase in n_o does not increase the number of consumers served, and the expert raises his online price to take advantage of further improvements in

[4] Figures 1 and 2 are drawn using the following parameter values: $\mu_b = 0$, $\mu_g = 10$, $\sigma = 10$, $c_1 = 1$, $c_2 = 5$, $c_t = 0.05$, $t_f = 0.005$, $t_o = 0$, $n_f = 100$, $k = 12$ (hours), $D^i_{\text{small}} = 30$ and $D^i_{\text{large}} = 40$. Also, Figures 1(a), 2(a), and 2(c) are drawn assuming that an online consultation takes less time than a face-to-face one $(\tau = 0.75 < 1)$, wheras Figures 1(b), 2(b), and 2(d) are drawn assuming that an online consultation provides less information than a face-to-face one $(n_o = 40 < n_f = 100)$.

technology. Figure 2(b) shows that the optimal online price is higher than the face-to-face one when the two types of consultations take about the same time. As τ decreases, experts find the online channel more attractive and reduce their online prices to serve more consumers via the Internet. Figures 2(c) and 2(d) both indicate that profits increase with improvements in online consultation technology, both in terms of quality of communication (n_0) and ease of use (τ). However, since profits increase at a higher rate when capacity is more limited relative to the demand, we conjecture that medical experts that are most pressed for time will benefit more from online consultations and should seriously consider adoption as technology improves.

[Figure 2 is approximately here.]

Proposition 2. *While an expert may expect a higher return from his online service, his optimal online price decreases as the online consultation technology gets easier to use. Also, the higher the demand relative to capacity, the more an expert benefits from improvements in quality of communication and ease of use.*

Equations (5) and (6) state that the marginal benefit and the marginal cost of raising s_f and s_o are equal, respectively. By incrementally increasing s_f, an expert can charge $-\frac{\partial V_f\left(\overline{\alpha}^i\right)}{\partial s_f}+\frac{\partial V_f\left(\underline{\alpha}^i\right)}{\partial s_f}$ more for his online service to $D^i\left(1-\overline{\alpha}^{i*}\right)$ customers. Similarly, he can charge $\frac{\partial V_f\left(\underline{\alpha}^i\right)}{\partial s_f}$ more for his face-to-face service to $D^i\left(\overline{\alpha}^{i*}-\underline{\alpha}^{i*}\right)$ customers. The change in the expected cost of Type I and Type II errors in this case is $\frac{\partial C\left(s_f^*,\underline{\alpha}^{i*}\right)}{\partial s_f}$, which should be equal to the expected gain of incrementally increasing s_f. A change in s_o does not affect the expert's face-to-face price, which is only a function of s_f. By incrementally increasing s_o, the expert can charge $\frac{\partial V_o\left(\overline{\alpha}^i\right)}{\partial s_o}$ more for his online service to $D^i\left(1-\overline{\alpha}^{i*}\right)$ customers. Such a change affects the expected cost of Type I and Type II errors by $\frac{\partial C\left(s_0^*, \underline{\alpha}^{i*}\right)}{\partial s_o}$.

Figure 3 illustrates the intuitions behind equations 5 and 6.[5] First, the optimal cutoff aggregate signal increases with the relative costs of Type II versus Type I errors. Since misdiagnosing a customer with the good state is costlier than misdiagnosing her with the bad state when $c_1 < c_2$ and vice versa, customers are more likely to be diagnosed with the bad state when $c_1 < c_2$ than otherwise. Partially due to malpractice suits filed against doctors, this behavioral pattern is prevalent in the U.S. health care sector and is also known as physician-induced demand in health care economics. Second, as the prior likelihood of the bad state increases, experts rely more on this likelihood than the observed signals about the state, and thus they increase their cutoff aggregate signals and diagnose the bad state more frequently. In other words, the same aggregate signal may lead an expert to diagnose different states depending on the prior probability of the bad state. And third, when $c_1 < c_2$, less information (smaller n_j) leads experts to diagnose the bad state more often as they try to be on the safe side, but at the expense of diagnosis accuracy. An implication of this observation is that, by restricting the flow of information between experts and the consumers, the online environment can exacerbate the problem of unnecessary prescription of treatments.

[5] Figures 3(a) and 3(b) are drawn using the following parameter values: $\mu_b = 0$, $\mu_g = 10$, $\sigma = 10$, $c_t = 0.05$, $t_f = 0.005$, $t_o = 0$, $\tau = 0.75$, $k = 12$ (hours), and $D^i = 40$. $c_1 < c_2$ implies $c_1 = 1$ and $c_2 = 5$, and conversely. Small (large) n_j implies $n_j = 40$ $\left(n_j = 40\right)$ for $j \in \{f, o\}$.

[Figure 3 is approximately here.]

4. Discussion and Conclusions

Past research on telemedicine mainly addresses the question “Can we do this?”, leaving the important question “Should we do this?” unanswered [26]. We believe that this important question should be tackled from the perspective of providers while taking into account their physical operations. Therefore, the study of optimal channel management strategies of experts provided here, while significant in its own right, is uniquely positioned at the interface of the literatures on telemedicine, multi-channel management, and expert services.

We have modeled the diagnosis problem of experts as that of selecting the state of a consumer under uncertainty, where the diagnosis accuracy depends critically on the quality of communication in a consultation. Experts face different levels of demand, are capacity-constrained, and can consult both face-to-face and online. Consumers maximize expected surplus while experts maximize profit. The insights we obtain from this model offer several practical implications that can help experts in setting the extent of their online offerings and deciding who to serve online within their specialty given their patient portfolio. For example, according to a recent Harris Interactive survey, most physicians have serious reservations about consulting online because of concerns about reimbursement, among others [34]. This research shows that experts can always find consumers who would be willing to pay more for an online service than a face-to-face one. Interestingly, physicians may still have to charge a lower price online at optimality in order to serve a larger patient pool. As the online consultation technology improves, physicians may have to charge even less online but would earn more, especially if they are facing a high demand and therefore are pressed for time. Also, medical experts should target their online services to consumers with more certain health conditions because the potentially negative effect of communication quality would be more pronounced when inspecting patients with more uncertain state expectations.

Of course, the stylized model considered here applies only to certain situations. For example, we have only considered the case where the process of getting an online consultation is more convenient than getting a face-to-face one $(t_f > t_o)$, disregarding in the process the medical conditions that render obtaining and sending personal information prohibitively costly for patients. Still, our analysis covers many situations because of the recent advances in telemedicine technologies that ease the collection and transfer of patient information. Today's technologies enable doctors to monitor their patients' every heartbeat as they go about their daily activities. Even in the most remote locations, sensors connected to patients can beam images and signals to medical experts at distant centers for real-time consultations, diagnoses and monitoring. Second, we have assumed the fixed cost of adopting online consultations to be zero because physicians only need basic Internet connection to offer these services (e.g., using Medem's secure messaging suite of tools), and the cost of an Internet connection is negligible compared to many other cost items in health care. Of course, certain types of consultations may require special technical equipment. In psychiatry, for example, videoconferencing equipment may be necessary to get a good sense of patients' problems. In such circumstances the optimal investment in online consultation technology would become another important decision, which could be investigated in future research by extending the current model in a way that would associate the amount of investment in the technology to the quality of communication.

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References

1. Alger, I. and Salanié, F. A theory of fraud and overtreatment in expert markets. *Journal of Economics & Management Strategy*, 15, 4, (December 2006) 853-881.

2. Bakos, J.Y. Reducing buyer bearch costs: Implications for electronic marketplaces. *Management Science*, 43, 12 (December 1997) 1676-1692.

3. Bakos, J.Y. and Brynjolfsson, E. Bundling information goods: Pricing, profits, and efficiency. *Management Science*, 45, 12 (December 1999), 1613-1630.

4. Balasubramanian, S. Mail versus mall: A strategic analysis of competition between direct marketers and conventional retailers. *Marketing Science*, 17, 3 (1998) 181-195.

5. Bartels, R., Fiebig, D. and Soest, A. Consumers and experts: An econometric analysis of the demand for water heaters. *Empirical Economics*, 31, 2, (May 2006), 369-391.

6. Bouckaert, J. and Degryse, H. Price competition between an expert and a non-expert. *International Journal of Industrial Organization*, 18, 6, (August 2000) 901-923.

7. Byers, R.E. and Lederer, P.J. Retail bank services strategy: A model of traditional, electronic, and mixed distribution choices. *Journal of Management Information Systems*, 18**,** 2 (Fall 2001), 133-156.

8. Carrns, A. Medem to enable physicians to charge for online visits. *Wall Street Journal*, 25 February 2003, B8.

9. Chen Y. and Png. I. Information goods pricing and copyright enforcement: Welfare analysis. *Information Systems Research*, 14**,** 1 (March 2003), 107-123.

10. Chiang, W.K., Chhajed, D. and Hess, J.D. Direct marketing, indirect profits: A strategic analysis of dual-channel supply-chain design. *Management Science*, 49, 1 (January 2003), 1-20.

11. Committee on the Quality of Health Care in America, Institute of Medicine. *Crossing the quality chasm: A new health system for the 21st century*. Washington, DC: National Academy Press; 2001.

12. Darby, M. and Karni, E. Free Competition and the optimal amount of fraud. *Journal of Law and Economic*s, 16, 1 (April 1973) 67-88.

13. Dewan, R., Freimer, M., and Seidmann, A. Organizing distribution channels for information goods on the Internet. *Management Science*, 46, 4 (April 2000), 483-495.

14. Edlin, M. Joint ventures and coalitions drive the e-prescribing bandwagon. *Managed Healthcare Executive*, 12, 12 (December 2002), 30-31.

15. Emons, W. Credence goods and fraudulent experts. *RAND Journal of Economics*, 28, 1 (Spring 1997), 107-119.

16. Emons, W. Credence goods monopolists. *International Journal of Industrial Organization*, 19, ¾ (March 2001), 375-389.

17. Fox, S. and Fallows, D. *Internet Health Resources*. (http://www.pewinternet.org/pdfs/PIP_Health_Report_July_2003.pdf). Last accessed on November 2, 2006.

18. Freudenheim, M. Digital Rx: Take two aspirins and e-mail me in the morning. *The New York Times*, 2, March 2005, A1.

19. Hailey, D., Roine, R., and Ohinmaa, A. Systematic review of evidence for the benefits of telemedicine. *Journal of Telemedicine and Telecare*, 8 (Supplement 1, 2002), 1-7.

20. Hailey, D., Roine, R., and Ohinmaa, A. Study quality and evidence of benefit in recent assessments of telemedicine. *Journal of Telemedicine and Telecare*, 10, 6 (December, 2004) 318-324.

21. Hann, I. and Terwiesch, C. Measuring the frictional costs of online transactions: The case of a name-your-own-price channel. *Management Science*, 49, 11 (November 2003) 1563-1579.

22. Hitt, L.M. and Frei, F.X. Do better customers utilize electronic distribution channels? The case of PC banking. *Management Science*, 48, 6 (June 2002), 732-748.

23. King, R.C., Sen, R. and Xia, M. Impact of web-based e-commerce on channel strategy in retailing. *International Journal of Electronic Commerce*, 8, 3 (Spring 2004) 103-130.

24. Lal, R. and Sarvary, M. When and how is the Internet likely to decrease price competition? *Marketing Science*, 18, 4 (1999) 485-503.

25. Lynch, J. and Ariely, D. Wine online: Search costs affect competition on price, quality, and distribution. *Marketing Science*, 19, 1 (Winter 2000) 83-103.

26. Mair, F.S., Haycox, A., May, C., and Williams, T. A review of telemedicine cost-effectiveness studies. *Journal of Telemedicine and Telecare*, 6 (Supplement 1, 2000) 38-40.

27. Ozdemir, Z.D., Akcura, M.T. and Altinkemer, K. Second opinions and online consultations. *Decision Support Systems*, 42, 3 (December 2006) 1747-1758.

28. Pesendorfer, W. and Wolinsky, A. Second opinions and price competition: Inefficiency in the market for expert advice. *Review of Economic Studies*, 70, 243 (April 2003) 417-437.

29. Pitchik, C. and Schotter, A. Honesty in a model of strategic information transmission. *American Economic Review*, 77, 5 (December 1987) 1032-1036.

30. Riggins, F.J. A Multichannel model of separating equilibrium in the face of the digital divide. *Journal of Management Information Systems*, 21, 2 (Fall 2004) 161-179.

31. Sarvary, M. Temporal differentiation and the market for second opinions. *Journal of Marketing Research*, 39, 1 (February 2002) 129-136.

32. Steinfield, C., Bouwman, H., and Adelaar, T. The dynamics of click-and-mortar electronic commerce: Opportunities and management strategies. *International Journal of Electronic Commerce*, **7**, 1 (Fall 2002) 93-119.

33. Taylor, C.R. The economics of breakdowns, checkups and cures. *Journal of Political Economy*, 103, 1 (February 1995) 53-74.

34. Taylor, H. and Leitman, R. eds. *Health Care News*. (http://www.harrisinteractive.com/news/newsletters/healthnews/HI_HealthCareNews2002Vol2_Iss08.pdf). Last accessed on November 2, 2006.

35. Terry, K. Online “visits” insurers pay. *Medical Economics*, 83, 17 (September 1, 2006), 30-34.

36. Viswanathan, S. Competing across technology-differentiated channels: The impact of network externalities and switching costs. *Management Science*, 51, 3 (March 2005) 483-496.

37. Wolinsky, A. Competition in a market for informed experts’ services. *RAND Journal of Economics*, 24, 3 (Fall 1993) 380-398.

38. Zettelmeyer, F. Expanding to the Internet: Pricing and communications strategies when firms compete on multiple channels. *Journal of Marketing Research*, 37. 3 (August 2000) 292-308.

Appendix

Proof of Proposition 1. We only need to show $V_o(\alpha) > V_f(\alpha)$ for some $\alpha \in [0,1]$, given $t_f > t_o$. Consider the consumer who is certain of the bad state $(\alpha = 1)$. For this consumer $V_o(1) > V_f(1)$ when $t_f - t_o > (1 - c_t)[\Phi_{bf}(s_f) - \Phi_{bo}(s_o)]$. But since the state is certain when $\alpha = 1$, the expert always correctly diagnoses on both channels $(\text{i.e.}, \Phi_{bf}(s_f) = \Phi_{bo}(s_o) = 1)$. Thus, as long as $t_f > t_o$, consumers who are very likely to be in the bad state derive more value from online consultations.

Proof of Corollary 1. The proof follows from Lemma 1 and Proposition 1. For $n_o > n_f$, $V_o(\alpha) > V_f(\alpha)$ for all $\alpha \in [0,1]$. In this case the expert offers only the online service. By Proposition 1, consumers with a very high α prefer the online service. By Lemma 1, when $n_f > n_o$, the online consultation loses its value faster than the face-to-face consultation as α decreases from one. Consequently, consumers with lower α may prefer the face-to-face consultation if $t_f - t_o$ is sufficiently small, which should be the case for the expert to offer the face-to-face service.

Table A: List of Notation

s	Consumer state. $s \in \{g, b\}$; $g \equiv$ good, $b \equiv$ bad
i	Expert index
D^i	The size of consumer base for expert i
α	Prior probability of the bad state
c_t	The cost of treatment
j	Channel. $j \in \{f, o\}$; $f \equiv$ face-to-face, $o \equiv$ online
t_j	Transaction cost on channel j
n_j	The number of signals transmitted via channel j
Φ_s	The cumulative probability distribution for state s (normal with variance σ^2 and mean μ_s)
Φ_{sj}	The joint cumulative probability distribution of mean of n_j signals for state s
s_j	Cutoff aggregate signal used when serving via channel j
c_1, c_2	The cost of Type I and Type II errors, respectively.
k	Time constraint for experts
τ	The length of time required for an online consultation
$E(U \mid d_j)$	Expected consumer surplus (U) given the diagnosis delivered via channel j (d_j)
$V_j(\alpha)$	The value of a consultation of type j as a function of α
$\underline{\alpha}^i$	The lowest α value among the consumers served by expert i
$\overline{\alpha}^i$	The cutoff α value above which expert i serves online
p_j^i	The price of expert i at channel j

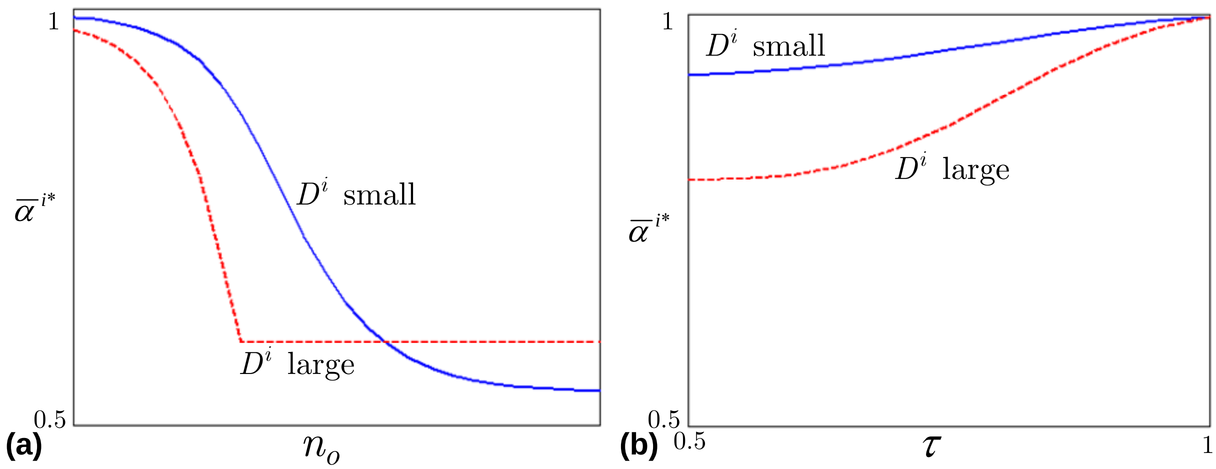

Figure 1. Optimal channel mix as a function of market demand and the online channel's quality of communication (n_o) and ease of use (τ)

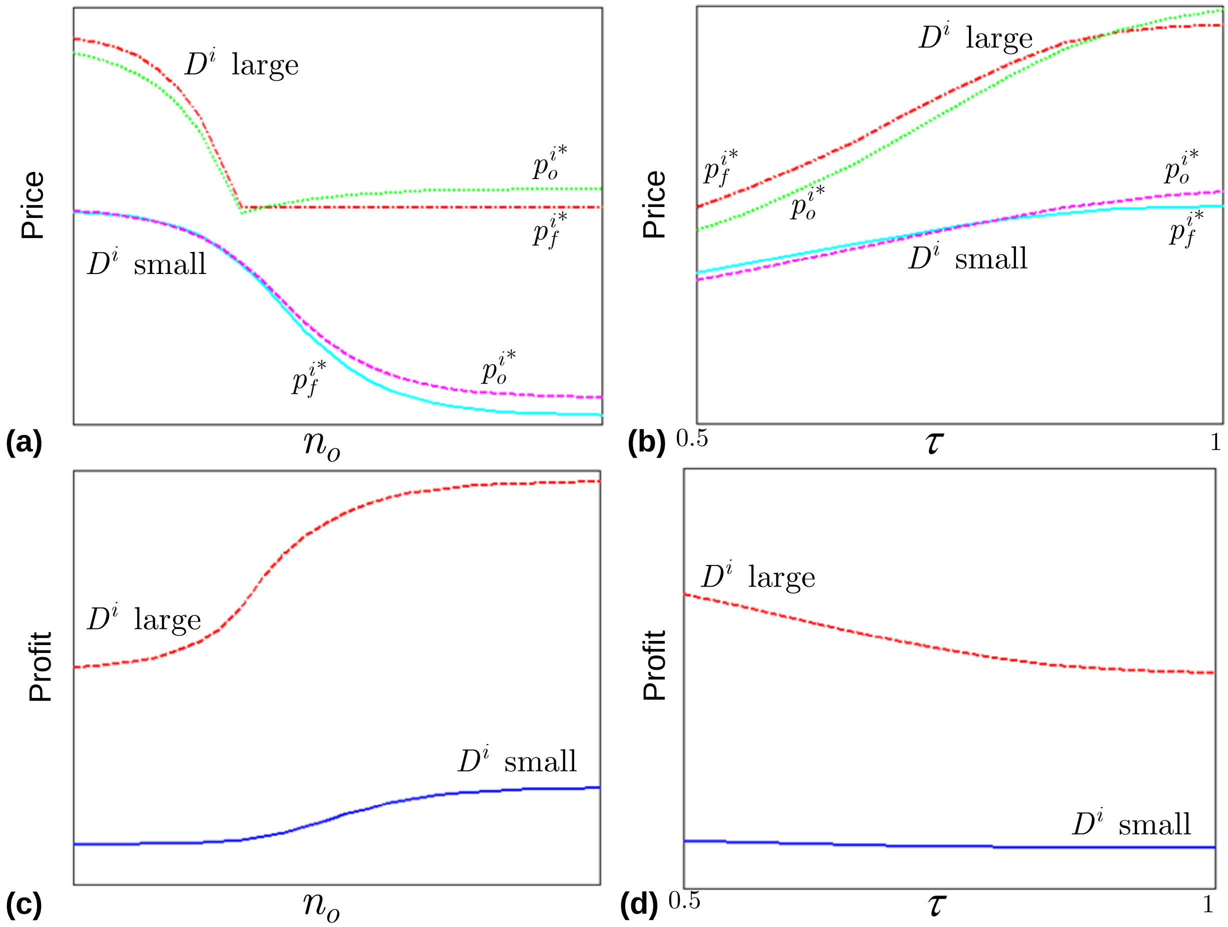

Figure 2. Optimal prices and profits as a function of market demand, the online channel's quality of communication (n_o) and ease of use (τ)

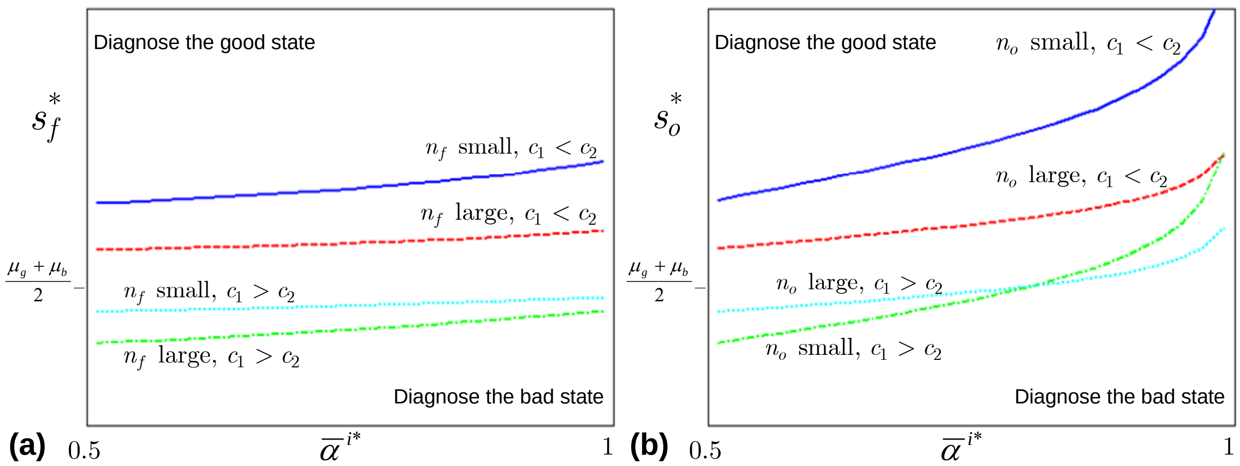

Figure 3. Diagnosis policies as a function of $\bar{\alpha}^{i*}$, n_j, and c_1/c_2 : (a) face-to-face and (b) online

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