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ABSTRACT

We investigate whether information technology can help physicians more efficiently acquire new knowledge in a clinical environment characterized by information overload. Our analysis makes use of data from a randomized trial as well as a theoretical model of the influence that information technology has on the acquisition of new medical knowledge. Although the theoretical framework we develop is conventionally microeconomic, the model highlights the non-market and non-pecuniary influence activities that have been emphasized in the sociological literature on technology diffusion. We report three findings. First, empirical evidence and theoretical reasoning suggests that computer based decision support will speed the diffusion of new medical knowledge when physicians are coping with information overload. Secondly, spillover effects will likely lead to "underinvestment" in this decision support technology. Third, alternative financing strategies common to new information technology, such as the use of marketing dollars to pay for the decision support systems, may lead to undesirable outcomes if physician information overload is sufficiently severe and if there is significant ambiguity in how best to respond to the clinical issues identified by the computer.

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1. Introduction

Economists who study incentives in organizations have given much attention to problems that arise when information is scarce. Indeed the premise of the vast literature on optimal incentives is that principals have incomplete knowledge about agents and their actions. It has long been recognized, however, that other important features of organizations are the result of managing a superabundance of information, but economic research on these aspects of organizations is less well developed (Brynjolfsson and Hitt, 2000). We consider economic issues that arise when agents are presented with *more* information than they can handle.

The focus of our study is information overload among physicians. In medicine, the number and variety of diseases and treatments threaten to overwhelm the information processing capacities of individual doctors. This complexity is magnified by the rapid growth of new, medically- relevant, knowledge. Failure to cope with this flood of information can cause physicians to overlook important new treatments or new findings concerning the recommended use of existing treatments. The net result is reduced care quality and slow diffusion of new medical innovations (Institute Of Medicine Committee On Quality Of Health Care In America, 2000; 2001).

We investigate how information technology (abbreviated as IT) can help physicians cope with information overload. Our analysis focuses on a particular type of computer system that has drawn considerable attention in the medical community and in public policy debates: a physician decision support tool. The system we study combines information from insurance billing records, pharmacies and labs to construct an electronic medical record for each patient. Information from this record is then passed through a sophisticated artificial intelligence program that compares treatment received with protocols drawn from the medical literature. If a discrepancy between

actual and recommended care is observed, a message is sent to the physician. This message might recommend that a certain patient is a good candidate for a specific lab or test. Alternatively the message might suggest that specific medications should be taken or stopped. The message includes citations to the medical literature, allowing the physician to read and assess the relevance of the literature to the patient's particular circumstances. By sending timely and targeted messages to physicians about evidence-based treatment protocols, the system can help doctors improve care quality and also increase the rate of diffusion of new medical knowledge.

Our analysis is both empirical and theoretical. On the empirical side we review evidence about the diffusion of medical knowledge. This review provides necessary context for understanding findings from a randomized prospective trial suggesting that computer based decision support tools can substantially enhance the diffusion of new medical knowledge among physicians. On the theory side we construct a model of physician learning that is consistent with the stylized facts about knowledge diffusion. Although the framework we develop is conventionally microeconomic, the model highlights the non-market and non-pecuniary influence activities that have been emphasized in the sociological literature on technology diffusion (Skinner and Staiger, 2005). Using this model we consider both the likely effect of IT systems on physician learning and whether private incentives are sufficient to support optimal investments in information technology. This last issue is particularly important for public policy because the Federal government is beginning large scale projects to promote the use of IT

enabled decision support tools in health care (Mullaney, 2005; President's Information Technology Advisory Committee, 2004).[1]

The remaining sections are organized as follows. In section two, we briefly review the key empirical findings concerning the diffusion of new medical knowledge. In section three, we present evidence from a randomized prospective trial suggesting that computer based decision support tools can substantially enhance the diffusion of new medical knowledge among physicians. In section four we develop a model of physician learning that is consistent with these empirical findings. We then use this model to consider whether private incentives to invest in computer based decision support technology are sufficient to assure adequate investment. We conclude by assessing the policy implications of our model and suggest future directions for research.

2. The Diffusion of Innovations in Medicine

The use of beta blocker drugs following heart attacks substantially reduces mortality rates. This fact has been established for decades yet in 2000/2001 the level of compliance with appropriate beta blocker use in the median state was just 69 percent. In some states the rate of appropriate usage was as low as fifty percent and in others as high as eighty six percent (Skinner and Staiger, 2005). This slow and variable take-up of an effective and inexpensive treatment protocol for an important illness is a specific illustration of a more general phenomenon: some

[1] Reference to the use of IT to reduce errors appeared in President Bush's *Economic Report of the President* in 2004 (President's Council of Economic Advisors, 2004) and in his State of the Union Address. "By computerizing health records, we can avoid dangerous medical mistakes, reduce costs, and improve care."(President's Information Technology Advisory Committee, 2004).

innovations appear to diffuse through the health care system much more slowly than one would expect on the basis of their cost and efficacy.[2]

Perhaps the broadest evidence supporting the slow and uneven diffusion of innovations comes from the vast medical literature on the geographic variation in practice patterns. The central finding in this literature is that the care delivered by doctors varies greatly from one geographic region to another in ways that cannot be accounted for by underlying differences in patient population, medical prices, technology or other exigencies. In the absence of other explanations, it is hard to escape the implication that these variations are due to the incomplete diffusion of the "best" medical practices to physicians.[3] These variations have substantial economic implications as well – some states spend 40-60% more per patient on heart attack treatment than others with no improvement in outcomes (Skinner and Staiger, 2005). A Rand study described in the *New York Times* finds similarly wide geographic divergence in the treatment of various cancers (Altman, 2005). Skinner, Fisher and Wennberg (2001) find that a large component of Medicare expenditures (nearly twenty percent) is the result of geographic variation in expenditures across 306 hospital referral regions. These expenditures, which are associated with the treatment of the chronically ill, appear to offer no benefits in terms of survival and the effects on quality of life are unclear. If even a portion of this variation is due to cross region productivity differences, then slow diffusion of new best-practice methods may have very substantial economic consequences. The source of geographic variations in practice

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[2] Of course not all slow diffusion of innovations is "too slow". Some new innovations may diffuse gradually because it takes time for providers to fully exploit the potential of the treatment for cost reductions and quality improvement. This appears to be the case, for example, with the use of percutaneous transluminal coronary angioplasty (PTCA), an important alternative to bypass surgery for patients with coronary artery disease (see Cutler and Huckman, 2003).

[3] For a discussions of this literature from an economist's perspective see (Phelps, 1992 and 2000). For a comparison of sociological and economic perspectives in the diffusion of innovations see (Skinner and Staiger, 2005).

styles is poorly understood, but these variations suggest that physicians learn about treatments and protocols from colleagues with whom they interact on a regular basis. These interactions will play an important role in the theoretical analysis we develop in section four, below

Other evidence suggesting an imperfect diffusion of medical knowledge comes from the resources that drug companies spend promoting their products. If the results of clinical studies percolated swiftly and easily to providers, pharmaceutical companies would not need high-powered marketing campaigns and sales forces. Avorn (2004) describes how these campaigns influence the decisions of practicing physicians. He also documents a number of instances where pharmaceutical marketing appears to successfully promote the use of favored drugs even when there is good clinical evidence that these drugs were ineffective or less effective than inexpensive alternatives. In Avorn's cases it was the clinical evidence concerning the ineffectiveness of heavily marketed drugs that appears to spread too slowly.[4]

A recent econometric study of the diffusion of anti-ulcer drugs finds that equilibrium market shares are strongly determined by the resources drug companies devote to advertising (Berndt et al., 2003).[5] This study also finds some evidence for consumption externalities that enhance the diffusion of drugs towards their equilibrium market shares. Consumption externalities occur when the use of a brand of drug is enhanced by the fact that many others are using it. The authors argue that these consumption externalities are largely informational in character, i.e. physicians and consumers make inferences about the qualities of a brand by the fact that many others are using it. The existence of consumption externalities is important

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[4] A recent study of the use of anti-psychotics in Medicaid patients (Duggan, 2005) documents the heavy use of expensive new generation anti-psychotics in spite of evidence that they perform no better than older and less-expensive anti-psychotics.

[5] The authors report that the elasticity of minutes of drug detailing to equilibrium market share is around 1, suggesting that physicians are highly susceptible to this form of influence.

because they can inhibit the ability of superior new drugs and treatment modalities to enter the market.[6]

The rate of diffusion of new knowledge is of self-evident importance in an industry as technologically dynamic as health care. Given this, it is surprising that the large and growing literature on the effects of IT systems in health care pays so little attention to the issue. A recent survey of 100 published studies of computer based decision support programs (Garg et al., 2005) finds that the effects of these programs can be variable. No effort was made in the review, however, to examine whether the variation in efficacy could be linked to how "new" the recommendations were. Another survey of 257 studies of health IT systems (Chaudhry et al., 2006) finds that these systems generally increased adherence to guideline care, but the analysis did not consider potential differences between well-established guidelines and guidelines embodying relatively new clinical protocols.

One reason for this gap in the literature is that it is often difficult to distinguish protocols embodying relatively new knowledge from those that do not. Consider for example the treatment for diabetes, an important and quite costly chronic disease. Disease management programs for diabetes generally embody well understood treatment protocols (Gertler and Simcoe, 2006; Beaulieu et al., 2007) but, as we document in the next section regarding the use of ACE inhibitors, new discoveries can modify these protocols in subtle but important ways. Tracking the differential effects of similar protocols requires sophisticated electronic medical records systems and these record systems are still quite rare. Survey data collected in 2007-2008 reveals that only four percent of physicians have a fully functional electronic medical record

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[6] In the specific case of anti-ulcer drugs, the authors found that consumption externalities were not strong enough to prevent a superior late entrant, Zantac, from overcoming the initial advantage of an entrenched incumbent, Tagamet. Zantac overcame it's disadvantage due to its superior medical qualities and also due to unusually large expenditures on drug detailing (Berndt et al., 2003)

system in their office and only thirteen percent have a basic system (DesRoches et al., 2008). Similarly low rates of IT adoption are reported for electronic medical records in hospital emergency rooms and outpatient departments (Burt and Hing, 2005) and physician order entry systems in hospitals (Cutler et al., 2005). The problem of studying the effects of the diffusion of new knowledge is further limited by the fact that much of the research on IT comes from a small number of organizations that are likely to be front-runners in adopting new evidence-based protocols. Chaudry et. al.(2006), in their comprehensive review, point out that a large portion of the empirical work on health IT systems comes from the study of only four institutions: the Regenstrief Institute; Brigham and Women's Hospital/Partners Health Care ; the Department of Veterans Affairs; and LDS Hospital/ Intermountain Health Care.

3. Empirical Evidence on the Influence of Computer Generated Messages.

Physicians are highly trained and highly motivated professionals. It is reasonable to assume, therefore, that the slow and uneven distribution of new and effective therapies is not the result of simple inattention. A more likely explanation is that it is difficult for physicians to keep up with the rapidly changing state of medical knowledge and to understand what these changes mean for the treatment of specific patients. If this is the case, then we should expect that an IT based decision support system could help doctors learn about new treatments. In this section we present empirical evidence from a randomized trial indicating that IT based decision support tools might enhance the rate of diffusion of new medical treatments.

The data we use comes from a randomized controlled trial of a decision support technology.[7] In this study patients under age 65 who were members of a single HMO were randomly assigned to a study and a control group. Data from insurance billing records, laboratory feeds and pharmacies were combined to construct a virtual electronic medical record and the information in these records was passed through a sophisticated program that scanned for clinical mistakes and also deviations from evidence based, best-practice protocols.

For patients in the study group, the information was scanned in real time and, if an issue was detected, a message was sent to the physician. The message stated the name of the patient, described the potential issue, and referenced the relevant medical literature. Roughly speaking the messages sent could be divided into three categories: "start a drug", "stop a drug" or "do a test". For patients in the control group, the clinical data was saved but not analyzed. After the study was completed, the control group data was analyzed by the software and messages were generated that *would have been* sent to physicians if the control patient had been in the study group. The trial therefore allowed us to compare the rate of resolution of issues when physicians enjoyed decision support (the study group) with the rate of resolution of the same issues when no such support was available (the control group). The difference in resolution rates between the study and control group is thus a measure of the influence of the information technology on physicians.[8]

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[7] For detailed descriptions of this trial see Javitt, Reisman et. al. (2005); and Javitt, Rebitzer and Reisman (2008).

[8] Although the system we describe used cutting edge information technology, the source of the information (billing records, and data feeds from pharmacies and lab) ensured that physician's information about the patient was almost always superior to that available to the computer system. For these reasons, the messages generated by the system were communicated as recommendations that the physician should feel free to ignore. Thus it was not at all certain at the start of the study that the messages would have any influence at all.

For our purposes, we would like to know if the messages from the decision support tool increased the rate of adoption of new medical evidence. We therefore focused our attention on messages concerning the class of medications known as ACE-inhibitors. ACE-inhibitors were first approved by the FDA in 1981 for treatment of severe hypertension. Shortly before the randomized trial began in 2001, several major clinical trials established the beneficial effect of ACE-inhibitors for patients with mild and moderate hypertension, heart failure, past heart attacks, chronic renal disease, certain subgroups of diabetics and patients at high risk for cardiovascular events. Taken together, these trials greatly expanded the number of patients for whom an ACE-inhibitor was indicated. One particularly important trial was the Heart Outcomes Prevention Evaluation or HOPE trial. The computer system was set up to include recommendations from the HOPE trial among the messages it sent to physicians. By comparing the resolution rates for patients in the study group who triggering the HOPE trial based recommendations with control group patients who would have triggered those recommendations, we can directly assess the influence of computer generated messages on newly discovered medical protocols.

The sample of participants in column one of Table 1 consists of those who would have qualified for an ACE-inhibitor on the basis of the HOPE trial criteria, but who were not receiving the drug. The dependent variable is a dummy variable equal to 1 if the issue of ACE-inhibitor use is successfully resolved, i.e. if records indicate that the patient received ACE-inhibitors within 270 days of the message being sent to the physician. The coefficient on the variable *Study* captures the differences in success rates between the study and the control group. Patients in the study group whose physician received computer generated messages regarding ACE-inhibitors, were thirteen percentage points more likely to take up the ACE-inhibitor than those in the control

group. To put this result in context, the resolution rate in the control group whose physicians received no messages was about 0.14. Thus the decision support tool nearly doubled resolution rates.

In column two of Table 1, we run analogous probit regressions for participants who received "add a drug" recommendations other than those relating to HOPE trial recommendations. We observe that the rate of resolution of these "add a drug" recommendations was 0.258 in the control group. The effect of being in the study group was to increase the resolution rate by 0.035. This difference is statistically insignificant and behaviorally not very important.

Comparing columns 1 and 2 it is clear that the decision support system had a more substantial effect on the relatively new ACE-inhibitor recommendation than on all other recommendations that suggested adding a drug. At the time of our study, the new clinical evidence regarding ACE-inhibitors was widely promoted in the conventional manner, i.e. via disease management programs and journal articles. We suspect, on the basis of informal conversations with providers, that the computer generated messages had extra influence because they were reliable, timely, and focused physician attention on a specific issue concerning a specific patient. Put differently what the IT support tool did that other conventional communication channels did not, was link a useful general recommendation to a specific patient's situation.

The results in Table 1 are consistent with the possibility that IT based decision support can enhance the diffusion of new medical knowledge, but it is important to observe that they do not constitute a definitive proof of that claim. Non-ACE "add a drug" messages are a mix of many different recommendations. If these messages have heterogeneous effects, pooling the

drugs together may create the impression that the entire set of non-ACE, "add a drug" messages are ineffective when some of them were in fact quite effective. Pursing this alternative interpretation of the data would require a larger study that would allow us to better analyze specific sub-sets of the non-ACE "add a drug" recommendations.

4. Influence and Physician Learning: A Simple Analytical Framework

In this section we develop a model of physician learning in an environment characterized by information overload. The evidence in the preceding discussions suggests that a reasonable model of physician learning must account for three empirical relationships. Firstly, new clinical knowledge does diffuse through the health care system, but the rate of diffusion is often slow. Secondly, as the geographic variations in practice patterns suggest, physicians learn about new medical treatments from other physicians with whom they interact on a daily basis. Thirdly, IT based decision support technology can influence physician behavior and this influence is greatest for newly discovered treatment protocols.

We introduce slow diffusion of new knowledge into our model by assuming that physicians are hampered by two cognitive limitations: the flow of new medical knowledge exceeds the fixed information processing capacities of individual physicians; and it is difficult for physicians to link the new medical knowledge they acquire to the clinical needs of specific patients.

To capture the role of informal interactions in the process of knowledge diffusion we assume that physicians compensate for their cognitive limitations by relying on the recommendations of colleagues with whom they interact on a day-to-day basis. Colleague recommendations are helpful because they can link specific treatments to the clinical needs of particular patients under a physician's care, but these recommendations are not sufficient to

resolve the problem of information overload. After all, physicians making recommendations have limits on their own cognitive abilities and these limits will generally make it hard for them to keep abreast of all the newest procedures. For this reason, physicians will also have to devote time to independent reading in medical journals. Reading journal articles may expose the physician to the newest innovations, but journal articles do not identify for the physician the specific patients for which the innovation applies. The influence of IT enabled decision support follows naturally in this set-up. In comparison to traditional learning modalities (colleagues' recommendations and independent reading of medical journals) the computer based decision support tools are more likely to suggest treatments that are both new *and* relevant to the care of a specific patient.[9] As a result, the new information technology will have greater influence on physicians and will, under plausible conditions, enhance the rate of diffusion of new knowledge.

Model Set-up

In every period medical research generates s new treatments that are relevant to the care of a physician's patients. A physicians' objective when reading about new medical treatments is to maximize the sum of medical benefits from treatment adoption across his patients. We introduce limitations in physician information processing capabilities in the simplest possible way by assuming that in each period physicians can read n articles with $n < s$.[10] Physicians are also limited in their ability to apply information about new treatments to specific patients. We capture this aspect of limited cognition by stipulating that when reading about a new treatment in

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[9] One might argue that specialists are at least as good as computer data bases in keeping up with new developments in their discipline. This may be so, but computer based decision support systems have the advantage of giving primary providers access to the relevant knowledge of specialists in many disciplines.

[10] We could easily endogenize n by including doctor's effort cost of reading about treatments. This would complicate the analysis, but not add any additional insight.

a medical journal, the likelihood that a physician identifies the treatment as relevant to their patients is r, where $r < 1$. The value of r is determined by the relevance of the new treatment to his or her patient population and by the probability that the physician will recognize the relevance of the treatment. Because physicians cannot read about all new treatments produced in each period and sometimes fail to see the relevance of a treatment, there will always be a stock of potentially relevant treatments that the physician will have missed in the period in which they were introduced.

In fields as technologically dynamic as medicine, the value of innovations tends to depreciate over time. We capture this depreciation through the assumption that patients experience benefits B when the physician adopts a relevant treatment in the same period it was discovered, a benefit Bq, where $q<1$, when the physician adopts a relevant treatment in the period after discovery, and benefit 0 from treatments that are more than two periods old. Because treatments older than two periods are clinically irrelevant, we can unambiguously refer to established treatments as treatments whose discovery occurred in the prior period.

Physicians can learn about the relevance of established treatments from interactions with other doctors. The advantage of learning from other physicians is that colleagues identify treatments that are relevant to specific patients. The disadvantage is that colleagues are also overloaded by new information and therefore cannot keep abreast of the newest procedures. We represent this feature by assuming that colleagues recommend only relevant established treatments – never new ones. Thus, the expected marginal benefit of reading a journal article about a treatment recommended by colleagues is qB. We model the heightened relevance of treatments recommended by colleagues by assuming that $q > r$. In this way, information flows have a local flavor because the physician always prefers reading about the highly relevant

treatments recommended by informal interactions with colleagues than independent reading about new treatments in journals.

We focus on an equilibrium in which the behavior of all doctors in a region can be captured by a single representative physician. Let x_t and y_t respectively denote the number of established and new treatments the physician chooses to read about in period *t*. Let z_t denote the number of recommendations a doctor receives from her colleagues. We endogenize z_t by assuming that the recommendations a doctor gives come from the new treatments that he has adopted for his own patients in the previous period. Formally we capture this by assuming that $z_t = \alpha r y_{t-1}$, where α is a parameter and ry_{t-1} simply denotes the average number of new treatments that physicians adopted in the previous period. Since the physicians always prefer reading about treatments recommended by colleagues to reading about new treatments in journals, this implies that physicians learn about the following number of treatments from colleagues

(1) $x_t = \alpha r y_{t-1}$,

so that information on the remaining treatments comes from reading medical journals. Thus

(2) $y_t = n - x_t$.

We focus on the steady state equilibrium in which a physician does not change her learning choices from one period to the other, i.e. $x_t = x$ and $y_t = y$ for all t. This, together with equations (1) and (2) implies that in equilibrium physicians read about $y = \frac{n}{1+\alpha r}$ new treatments and $x = \frac{\alpha r n}{1+\alpha r}$ established treatments. The flow of new knowledge in our model is depicted graphically in Figure One.

Introducing Computer-based Decision Support

We now introduce computer based decision support systems. As described above, these systems compare a patient's treatment with best practice protocols drawn from the medical literature. If the system finds a discrepancy, a message is sent to the physician. New treatments are written into the computer's software in each period and we assume that the technology only sends messages concerning new treatments that are clinically relevant for a physician's patients.[11, 12] The physician can expect to receive θm messages from the decision support technology each period, where m is the number of new treatments entering the data base in each period and θ is the fraction of treatments relevant to the physician's patients. From the physician's perspective, the benefit of reading about a treatment recommended in a computer generated message is given by B (it is always new and relevant), whereas the benefit of reading about a treatment recommended by a colleague is qB, where q is the discount factor reflecting the delay in learning about new treatments from colleagues. Thus a doctor will always prefer reading about a computer generated recommendation over a colleague's recommendation.

It is costly to incorporate new innovations into the decision support software, so it is unlikely that the decision support software will ever be sufficiently comprehensive to serve as the sole source of recommendations for physician learning. Rather than modeling these costs explicitly, we assume that $\theta m < n$, implying that a doctor who has access to the technology will read about all the treatments recommended in the computer generated messages and still have enough mental "shelf space" to continue learning about established treatments recommended by

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[11] Relaxing this assumption by allowing the technology to send messages about both new and established treatments would complicate the analysis considerably, but not affect the results.

[12] Assuming instead that the technology also sent out some erroneous messages would not change the results of our analysis as long as the likelihood that a message is useful is larger than q.

other sources. Put differently, the heightened timeliness and specificity of computer generated recommendations displaces, but doesn't eliminate, the use of other learning modalities.

In the US health care system, clinical data about patients rarely sits in a common electronic data base. The IT revolution has been slow coming to hospitals and only in recent years have large expenditures in electronic medical record systems begun. Physicians' offices are typically paper based and, where they have moved to electronic records, these systems often do not interface neatly with hospital systems (DesRoches et al., 2008).[13] Common standards for electronic medical records systems are only now being put in place.

Efficient decision support software requires that patient information reside in a single data base or a set of interconnected data bases, and this sort of integration is precluded by the Balkanized system of medical records maintained by providers. Insurance companies, in contrast, are well positioned to act as aggregators of medical information because most clinical transactions involving their members appear coded into their data bases for billing purposes. This is why the decision support technology we discussed in section three was designed to use insurers' data and perhaps this also explains why the informatics company that developed the decision support technology was eventually purchased by a large health insurer.

Insurers' data systems are also fragmented in that they are confined to individuals who are current policy holders. For this reason, computer based decision will have both a direct and

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[13] "…to be effective, CDSS [clinical decision support systems] diagnostic systems require detailed, patient-specific clinical information (history, physical results, medications, laboratory test results), which in most health care settings resides in a variety of paper and automated datasets that cannot easily be integrated. Past efforts to develop automated medical record systems have not been very successful because of the lack of common standards for coding data, the absence of a data network connecting the many health care organizations and clinicians involved in patient care, and a number of other factors." Institute Of Medicine Committee On Quality Of Health Care In America, 2001, p. 154.

an indirect effect on physician learning. The direct effect is captured by the θm computer generated messages a physician receives. The indirect effect results from the way that knowledge acquired from the computer system spills over to other physicians who have no access to the computer system. To capture these spillovers we stipulate that a share β of physicians have access to a particular decision support technology and a share $(1-\beta)$ does not have access to the technology. Both groups of physicians interact with each other so that information that flows directly to physicians with access to the technology can flow via recommendations to other physicians not included in the system.[14]

Let the subscript $i \in \{1,2\}$ reflect whether the physician has technology access ($i = 1$), or does not have technology access ($i = 2$). As in the previous section let z denote the number of recommendations a doctor of type i receives from colleagues, where $z = \alpha$ (the average number of new treatments that physicians adopted in the previous period.). Because a physician will always read about all the care messages generated by the decision support technology and $\theta m < n$, we have

$$(3) \qquad z = \alpha\left(\beta\left(\theta m + ry_1\right) + \left(1-\beta\right) ry_2\right)$$

As in the previous section, the expected benefit from reading about a treatment generated by a colleague's recommendation is greater than the expected benefit from reading independently selected newly published articles ($q>r$). Thus all physicians will read all colleagues' recommended treatments before reading independently selected journal articles. We focus our analysis on the equilibrium in which all read about some new treatments, i.e.

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[14] Our analysis would not change if we assume that share *(1-β)* of physicians had access to a different computer based system.

$\theta n + z < n$. In this case $x_1 = x_2 = z$ and the number of independently selected journal articles a doctor chooses to read about is given by

(4) $y_1 = n - \theta m - z$

(5) $y_2 = n - z$

Equations (3) - (5) determine steady state equilibrium y_1^*, y_2^* and $x_1^* = x_2^* = z^*$. The steady state disposition of new knowledge with computer support software is depicted in Figure Two. From this set-up it is easy to prove the following lemma.

Lemma 1: The Effects of Computer Support Systems on Physician Learning: If $n > \theta m\left(1 + \alpha r + \alpha\beta\left(1 - r\right)\right)$, then there exist a steady state equilibrium in which the doctors with access to the technology will read about all treatments recommended by the technology and by colleagues, and some treatments from independently selected journals. Doctors without the technology will read about all treatments recommended by colleagues and some treatments from independently selected journal articles. Doctors with the technology access will read fewer independently selected journal articles than doctors without technology access.

Proof: see appendix

We are interested in understanding how the decision support technology affects knowledge diffusion. For this purpose, we define knowledge diffusion among *doctors* of type *i* as:

(6) $\eta_1\left(m\right) = ry_1^* + \theta m + qx_1^*$

(7) $\eta_2\left(m\right) = ry_2^* + qx_2^*$

where η_i simply denotes the total number of relevant treatments that a doctor of type *i* will learn about and adopt in each period. As before, established treatments are discounted by *q*. We define the diffusion of knowledge about a treatment included in the technology and a treatment *not* included in the technology respectively as:

(8) $\mu_t\left(m\right) = \beta\left(\theta + \frac{ry_1^*}{s}\right) + \left(1 - \beta\right)\frac{ry_2^*}{s} + q\left(\beta\left(\theta + \frac{ry_1^*}{s}\right) + \left(1 - \beta\right)\frac{ry_2^*}{s}\right)$

$$(9) \qquad \mu_{nt}(m) = \beta\left(\frac{ry_1^*}{s}\right) + (1-\beta)\frac{ry_2^*}{s} + q\left(\beta\left(\frac{ry_1^*}{s}\right) + (1-\beta)\frac{ry_2^*}{s}\right)$$

In (8) and (9), the first term denotes the likelihood that doctors using the decision support technology adopt the treatment in the first period. The second term denotes the likelihood that doctors without the technology adopt the treatment in the first period. The last term denotes the likelihood that any doctor adopts the treatment in the second period as a result of recommendations from colleagues. Comparing (8) and (9) we can see that adding a new treatment protocol to the decision support data base increases the likelihood of adoption by θ in the first period and by $q\theta$ in the second period. Let ω denote total adoption of new knowledge among all doctors. Note that equations (6) and (7), and equations (8) and (9) are necessarily related as follows:

$$(10) \qquad \begin{aligned} \omega &= (s-m)\mu_{nt} + m\mu_t \\ &= \beta\eta_1 + (1-\beta)\eta_2 \end{aligned}$$

By differentiating (6)-(10) with respect to *m* we establish the following proposition:

Proposition 1: Expanding Computer Based Decision Support Enhances The Rate of Knowledge Diffusion: Increasing the number of treatments in the technology *increases* overall knowledge diffusion among all doctors, even among those who do not have access to the technology. This holds even though the rate of diffusion of treatments not in the computer database will decline.

Proof: see appendix

An important implication of the analysis so far is that the spread of IT-based decision support is likely to reduce geographic variation in practice patterns. To see this assume that: underlying patient clinical needs are the same across regions; and that the medical informatics company offers the same decision support technology in all the regions in which it operates. What differs across regions then are: (i) the degree to which the technology has penetrated a

region (captured by β) and (ii) the degree to which physicians in a region rely upon their idiosyncratic reading of articles in medical journals. We have shown in Lemma 1 that the presence of information technology displaces reading that is not stimulated by recommendations from colleagues or the IT system. Inspection of the proof of Lemma 1 shows that as m increases, both steady state y_1 and y_2 decrease. Thus in a steady state as m increases, the idiosyncratic reading of journals (the sort of reading that leads to variation across regions) becomes less important for all physicians. The same proof also shows that as m increases, steady state recommendations from colleagues (z) increases. By the logic of our model, the only reason that z would increase with m is that as m increases, the IT system identifies more relevant protocols in the first period that they are released. This source of new information is, however, common across regions. Thus, as m increases, cross-regional variation in observed practice patterns should decline.

Private Incentives to Invest in Decision Support System

Given the central role that health insurers currently play as information aggregators in our health care system, we begin by analyzing their incentives to invest in physician decision support systems. We simplify our analysis by assuming that the insurer is a Health Maintenance Organization (HMO) that must attract physicians to sign on to its network of providers (Cooper and Rebitzer, 2006). Maintaining our assumption that providers derive a direct benefit from offering their patients better care, the HMO will be able to attract physicians to the network at lower cost by investing in a decision support technology that improves care quality.[15]

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[15] Alternatively we could assume that the purchasers of health insurance would pay more for insurance if the insurer supplied decision support technology to physicians that improved care outcomes. Because physicians in our setup experience the same utility from improved outcomes as patients do, the results under these assumptions would be unchanged.

The flow of new knowledge with decision support is depicted in Figure Two. It is clear from this Figure that doctors who do not have access to the decision support technology still benefit in period two from the learning induced by the computer technology in period one. This learning spillover leads to Corollary 3. To establish this, let *p* be the cost of adopting a new treatment. Then, the net private benefits of an insurer with technology access is given by $\eta_1(B-p)$, whereas the total net benefit to providers is given by $(\eta_1+\eta_2)(B-p)$. Thus, the Corollary follows from the fact that both η_1 and η_2 are increasing in *m*, which was established in Proposition 1.

Corollary 1: Insurers will Under-invest in Computer Based Decision Support.

The underinvestment in the new technology is the result of knowledge spillovers from one set of providers to another. The conventional economic response to positive externalities is to internalize them with subsidies financed by lump sum taxes. This approach is, however, famously difficult to implement. In this case, however, an alternative approach might be feasible because what appears as externalities to health care providers and insurers are actually sources of revenue to other market actors. The pharmaceutical and device manufacturers profit from the informal spread of new information about their products and may therefore have more powerful incentives than providers and insurers to promote the spread of computer based decision support tools.

A pharmaceutical or device manufacturer's increased profit from including a treatment in the decision support system is given by

$$\Delta\pi = \left(\mu_t(m+1) - \mu_{nt}(m)\right)p$$

The next proposition shows that for a sufficiently large price of treatment, p, the seller of the treatment is willing to pay more for the inclusion of a new treatment than would a provider or an insurer.

Proposition 2: Pharmaceutical and Drug Makers Can Have More Powerful Incentives to Invest in Computer Based Decision Support than Insurers: There exists a $p_1 < B$, s.t. if $p > p_1$ then the seller of a new treatment is always willing to pay more than the HMO for including this treatment into the technology.

Proof: see appendix

Proposition 2 has potentially important public policy implications. It suggests that one might create appropriate incentives to invest in computer support technology by allowing pharmaceutical firms and device manufacturers to invest in decision support technology. For concreteness imagine that this investment takes the form of paying the IT company who runs the decision support system to include their new products into the computer system's database. This sort of investment might avoid cumbersome government bureaucracy while ensuring that the health care system has a sufficiently comprehensive decision support technology.

This strategy raises, however, a concern when one considers the cognitive limitations under which physicians operate. Paying for the inclusion of one or another company's products in the computer support technology displaces other forms of learning that might lead physicians to adopt different treatments. This crowding out of learning about other products creates negative externalities and therefore creates incentives to over-invest in the decision support technology- a point made in the following proposition:

Proposition 3: Pharmaceuticals and Device Makers May Have Incentives to Over-invest in Computer Based Decision Support Technology. There exists a $p_2 < B$, s.t. if $p > p_2$ then the seller of a new treatment is willing to pay more than the social marginal benefit for including this treatment in the technology. Other pharmaceuticals will bear the full cost of this overinvestment. Health care providers and insurers will benefit from the overinvestment.

Proof: see appendix

If one overlooks the effects of wasted resources resulting from over investment by pharmaceutical and device makers, Proposition 3 seems to suggest that private financing of decision support systems may be a sensible way to offset the investment shortfall resulting from knowledge spillovers. Just as Google finances enhanced information flow on the internet through the use of marketing dollars, so might the marketing efforts of pharmaceutical and device makers be used to support enhanced information flows about treatment protocols in the health care system. As we demonstrate in the next section, however, this conclusion rests on unrealistically strong assumptions about the unambiguous nature of new knowledge.

Ambiguity, Influence and Marketing

We have so far considered messages whose information content is unambiguously correct. In many settings, however, the right drug or treatment is less clear. Suppose, for example, that a pharmaceutical company has a patent for an anti-ulcer medication, a class of drugs for which there exist a number of competing brands (Berndt et al., 2003). Assume that all of these anti-ulcer drugs are effective, but no single drug dominates the others. Rather each drug works better for a subset of the ulcer population, but it is hard to identify ex-ante which patient would benefit most from which drug. In this setting the pharmaceutical company might profitably subsidize a message that suggests this drug to all physicians with ulcer patients because the message may prove relevant to some subset of physicians. We will refer to this sort of message as a marketing message because its expected relevance to the treatment of a specific ulcer patient is low.

As before, assume that the technology sends each physician θm targeted messages. In addition the technology sends marketing messages for k treatments. For each patient, there is some probability, $\delta > 0$, that the marketing message will prove relevant to some of his patients,

but the relevance of the marketing message is less than other messages included sent by the system so that $\delta < \theta$. Doctors know that the decision support software includes both marketing and non-marketing messages, but cannot identify any individual message as the result of marketing. Thus doctors respond to each message by consulting the cited literature and deciding whether the recommended drug is appropriate for their patient. The likelihood that the message is suggesting a new relevant treatment is given by

$$\lambda = \frac{\delta k + \theta m}{k + \theta m}$$

Proposition 4 states that marketing messages can have a negative impact on the rate of diffusion of new knowledge and overall welfare. The intuition is very simple: As long as $\lambda > r$, the expected relevance of messages sent by the decision support tool exceeds that available through other channels. Thus a doctor will prefer reading about a treatment recommended by the decision support tool to any other learning modality, despite his knowledge that the messages include *k* marketing messages. Getting doctors to read the *k* marketing messages is profitable for the drug company because some of these drugs will actually prove relevant to a patient and therefore generate sales. Offsetting this private benefit, however, is the opportunity cost of inducing physicians to read about relatively low value suggestions contained in marketing messages. Such reading displaces physicians' reading about treatments from independently selected journal articles. This displacement has a negative impact on knowledge diffusion if $\delta < r$, i.e. the expected relevance of a marketing message is lower than expected relevance of independent reading in journal articles. This reasoning leads directly to the following proposition:

Proposition 4: Marketing Messages: If $\delta < r$, then the inclusion of marketing messages has a negative impact on the rate of diffusion of new knowledge and overall welfare, even though the firm will benefit from such a message.

Proof: see appendix

This result suggests that although it might be privately profitable to use decision support software as a sophisticated cybernetic drug detailer, doing so could undermine the social benefits produced by the technology.

5. Conclusion

Physicians are overwhelmed by the task of managing vast amounts of information relating to patient conditions and new treatment protocols. This information overload acts as a drag on the diffusion of new knowledge. IT enabled decision support tools have attracted the attention of health care providers and policy makers because they offer a way to alleviate this drag and hence to improve care quality. Increasing the rate of diffusion of new knowledge might also have the effect of increasing returns to innovative activity and therefore stimulate more rapid innovation. Just as small increases in productivity growth rates accumulate over time to transform living standards; so enhanced innovation rates resulting from the faster diffusion of new knowledge could yield transformations in the quality of health care.

Because of the fragmented state of the IT infra-structure in the health care system, insurance companies currently play a central role as information aggregators and are therefore in a good position to finance investments in decision support. Our model suggests, however, that insurers' incentives to invest will generally be inadequate. The problem is the result of knowledge spillovers: doctors who learn about a new treatment protocol from the IT system will likely transmit that information to other physicians through informal interactions. These spillovers improve care quality, but the benefits do not accrue to the insurers financing the decision support software. Our analysis of limited mental "shelf space" and clinical ambiguity suggests that alternative approaches, such as financing investment in improved information flows

with marketing dollars, may undermine the social value generated by decision support technology.

Given the current surge in investments in health care IT and the positive and negative externalities inherent in these investments, the role of public policy in guiding these investments should be an important area of future research.

Appendix

Proof of Lemma 1: Solving equations (3)-(5) for y_1, y_2 and z implies:

$$y_1 = \frac{n - \alpha\beta\theta m(1-r)}{1+\alpha r} - \theta m$$
$$y_2 = \frac{n - \alpha\beta\theta m(1-r)}{1+\alpha r}$$
$$z = \frac{\alpha r n + \alpha\beta\theta m(1-r)}{1+\alpha r}$$

This denotes an equilibrium if q_1, q_2 and $z > 0$. Thus, we must have $n > \theta m\left(1+\alpha r + \alpha\beta(1-r)\right)$.

Proof of Proposition 1: Differentiating equations (6)-(10) with respect to *m* yields:

$$\frac{\partial \eta_1}{\partial m} = \theta(1-r)\frac{1+\alpha r(1-\beta)+q\alpha\beta}{1+\alpha r} > 0$$
$$\frac{\partial \eta_2}{\partial m} = \alpha\beta\theta(1-r)\frac{q-r}{1+\alpha r} > 0$$
$$\frac{\partial \mu_t}{\partial m} = -\beta r\theta(1+\alpha)\frac{1+q\alpha}{s(1+\alpha r)} < 0$$
$$\frac{\partial \mu_{nt}}{\partial m} = -\beta r\theta(1+\alpha)\frac{1+q\alpha}{s(1+\alpha r)} < 0$$
$$\frac{\partial \omega}{\partial m} = \beta\theta(1-r)\frac{q\alpha+1}{1+\alpha r} > 0$$

Proof of Proposition 2: First note that

$$\Delta\pi = \left(\mu_t(m+1) - \mu_{nt}(m)\right)p$$
$$= \beta\theta(q\alpha+1)\frac{s+s\alpha r-r-\alpha r}{s(1-\alpha r)} > 0$$

The pharmaceuticals' willingness to pay for including the treatment is $\Delta\pi \cdot p$, whereas an HMO's willingness to pay is $\eta_1(B-p)$. Thus, the pharmaceutical is willing to pay more than the

HMO if $p > \frac{\eta_1}{\Delta\pi + \eta_1} B$. Since $\Delta\pi > 0$ this implies that there exist a $p_1 < B$, s.t. if $p > p_1$ then the seller of a new treatment is always willing to pay more than the HMO for including this treatment into the technology.

Proof of Proposition 3: The net benefits of the HMOs are given by $\omega(B-p)$. The net benefits of the pharmaceuticals are ωp. Thus, the social marginal net benefit is $\frac{\partial \omega}{\partial m} B$. Using the calculations from the proof of Propositions 1 and 2, the pharmaceutical's marginal net benefit is larger than the social marginal net benefit if

$$\beta\theta(q\alpha+1)\frac{s+s\alpha r-r-\alpha r}{s(1-\alpha r)} p > \beta\theta(1-r)\frac{1+\alpha q}{1+\alpha r} B$$

This implies $p > \frac{(1-r)s}{s+\alpha sr-r-\alpha r} B$, where $\frac{(1-r)s}{s+\alpha sr-r-\alpha r} < 1$ since $s > 1$. Thus, there exists a $p_2 < B$, s.t. if $p > p_2$ then the seller of a new treatment is willing to pay more than the social marginal benefit for including this treatment in the technology.

Proof of Proposition 4: Now we need to distinguish between diffusion of three different types of treatments: treatments in the technology that are marketed, treatments in the technology that are not marketed, and treatments that are not in the technology. Diffusion of a treatment in the technology that is marketed is given by:

$$\hat{\mu}_t(m) = \beta\left(\delta + \frac{ry_1^*}{s}\right) + (1-\beta)\frac{ry_2^*}{s} + q\left(\beta\left(\delta + \frac{ry_1^*}{s}\right) + (1-\beta)\frac{ry_2^*}{s}\right))$$

Thus, total adoption is given by

$$\omega = (s-m-k)\mu_{nt} + m\mu_t + k\hat{\mu}_t$$
$$= \left(\beta\theta m(1-r) + nr + \beta k(\delta - r)\right)\frac{1+\alpha q}{1+\alpha r}$$

We can see that $\frac{\partial \omega}{\partial k} < 0$ if $\delta < r$. Thus, if $\delta < r$, then the inclusion of marketing messages has a negative impact on the rate of diffusion of new knowledge.

By comparing $\hat{\mu}_t(m)$ to $\mu_{nt}(m)$ we can see that adding a new treatment protocol to the decision support data base increases the likelihood of adoption by $\beta\delta$ in the first period and by $q\beta\delta$ in the second period. Thus, the pharmaceuticals have positive willingness to pay for inclusion of marketing messages.

Table 1

	(1) Probit	(2) Probit
	Successful Resolution "Add Ace Inhibitor for Hope Qualifier Drug" Message	*Successful Resoltion for Any Other "Add a Drug" Message*
	[0.141]	[0.258]
Study	0.130	0.035
	(2.82)*	(0.69)
Number of patients	311	290
Number of patients in study group	155	166
Log pseudo-likelihood	-154.018	-158.877

In column 1, the sample consists of participants who would have qualified for an Ace inhibitor on the basis of the HOPE trial criteria, but who were not receiving the drug according to computer records.
In column 2 the sample consists of participants who received an "add a drug" message other than that in column 1.

The message is successfully resolved if there is evidence in the data base that the patient started the relevant drug within 270 days after the message was sent.

Robust z statistics in parentheses. [ ] is mean of dep. var. in the control group in 2001
* significant at 5%; ** significant at 1%

Coefficients are expressed as "derivatives". Thus in column 1 members in the study group were 13 percentage points more likely to have resolved the issue successfully than those in the control group.

Figure 1: The Steady State Disposition of New Knowledge

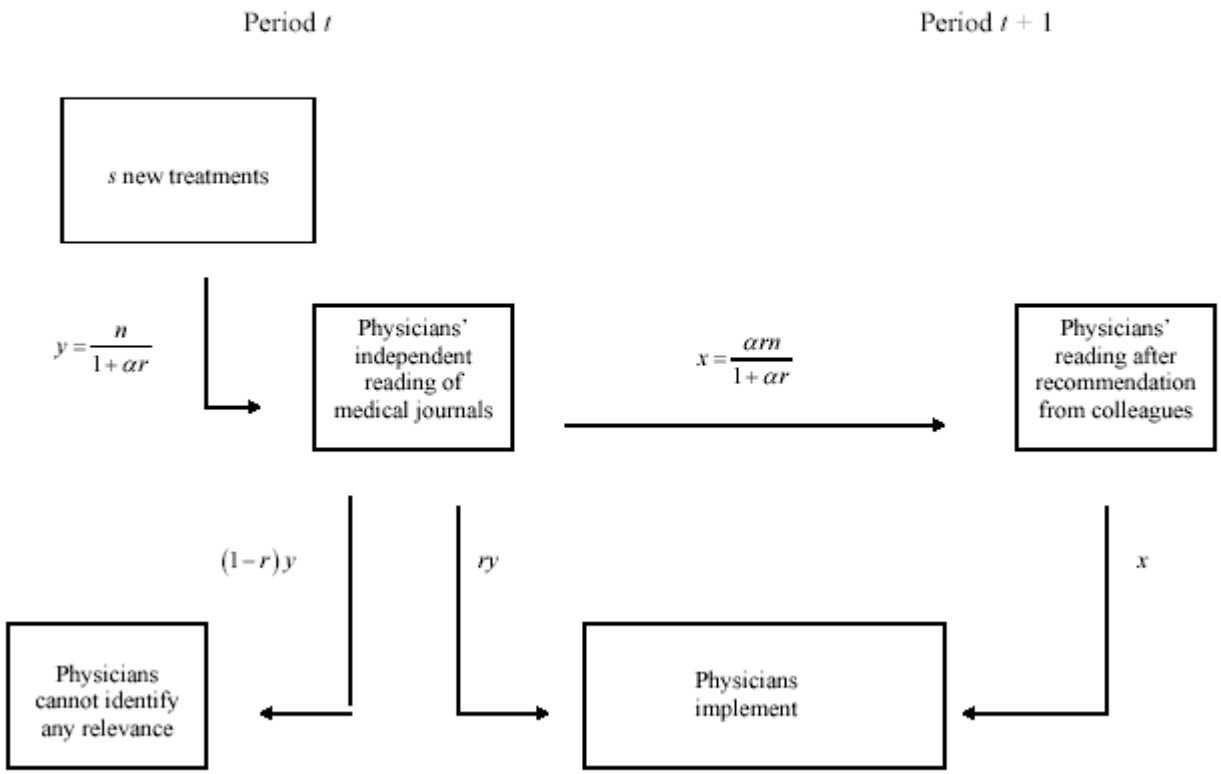
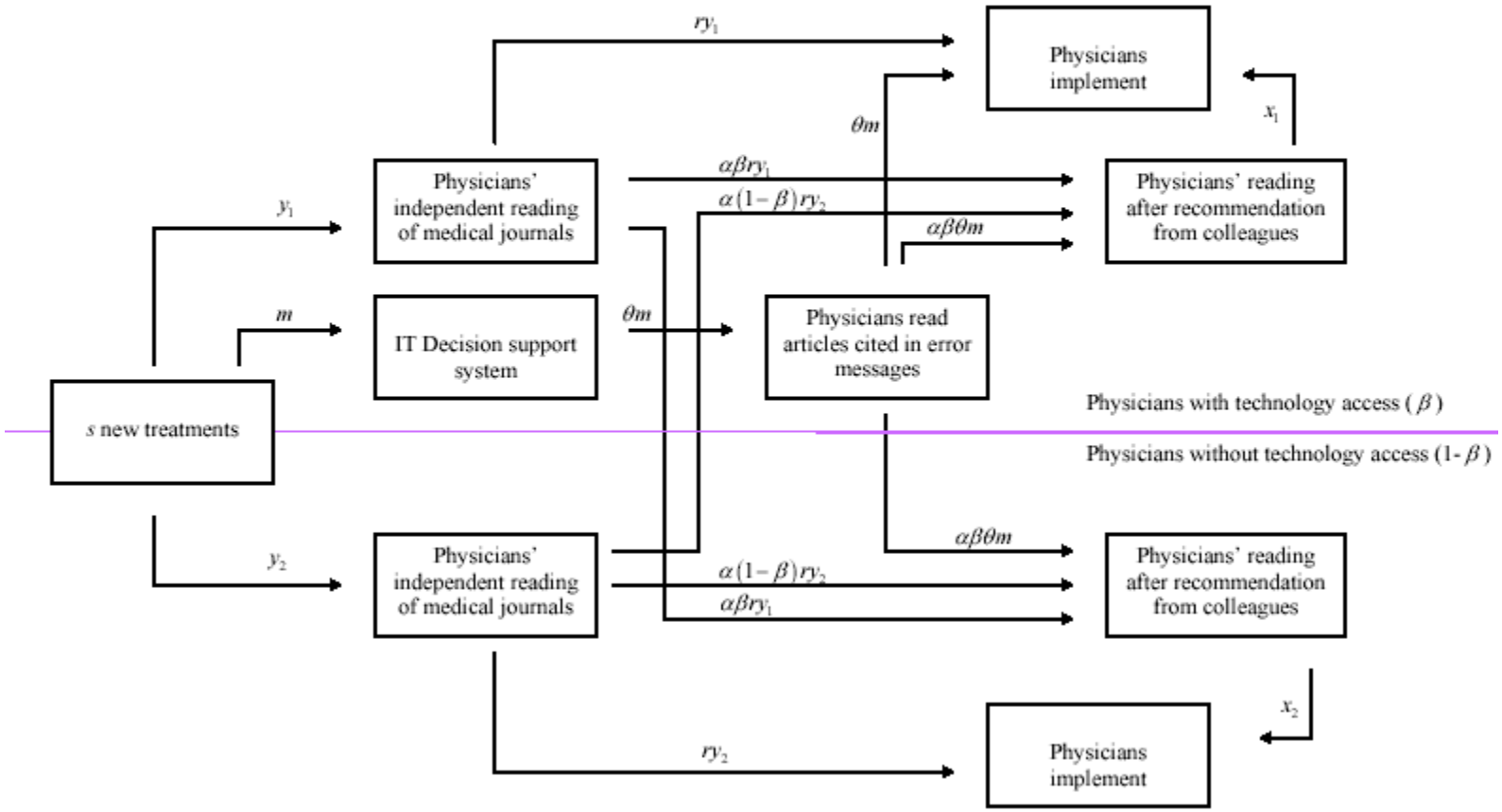


Figure 2: The Steady State Disposition of New Knowledge with Computer Based Decision Support



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