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Physician Learning and Clinical Decision Support Systems

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ABSTRACT

Despite the documented benefits of clinical decision support systems in reducing the number of adverse drug events (ADEs) and medication errors, their adoption has been very limited. In this paper, we propose a clinical learning model that incorporates the use of a Clinical Decision Support System (CDSS) to improve the decisions on the initial drug selection and ongoing dosage and application. The model allows for the analytical investigation of the effects of different CDSS functionalities on clinical learning. The analytical results suggest that using CDSS to improve drug selection decisions positively influences the importance of the patient-level information for the physician. On the other hand, absent improvements in successful drug selection, the use of CDSS may in fact negatively influence the clinical learning.

Keywords

Clinical decision support system (CDSS), clinical learning, prescription error, drug selection, dosage

INTRODUCTION

People in the U.S. younger than 65 purchased a mean of 10.8 prescription drugs, and those 65 or older purchased a mean of 26.5 prescription drugs in 2001 (Pancholi and Stagnitti 2004). Each year, physicians write four billion prescriptions, of which four percent contain an error, and 1.5 million people are injured due to preventable adverse drug effects (ADEs) and medication errors (*Wall Street Journal* 21 January 2009). According to a much-cited Institute of Medicine report, 44,000 to 98,000 of the prescription errors are fatal.[1] Physicians can prevent 28 percent of the ADEs (Bates et al. 1995).

Improving physician responsiveness, facilitating learning and clinical experience are important in preventing ADEs. As the gatekeepers to prescription medication access, physicians face significant challenges in keeping up with the developments and new findings in the market each year and in matching the best drugs to individual patients. Mirco et al. (2005) find that the most common prescription errors (in the order of importance) are deficiencies related with (i) choosing the right drug class but the wrong drug, (ii) choosing the correct dosage, and (iii) the clarity of orders. After surveying prescriptions, Seidling et al. (2007) report that many prescribed dosages tend to exceed the approved limits.

Recent empirical studies corroborate the importance of each individual physician's learning, clinical experience, and patient interaction on the actual prescription behavior. Patient-physician interaction is important due to potentially unexpected drug reactions on different patients, while clinical experience provide critical information to physicians during the prescription process. Chan and Hamilton (1996) show that even the least effective drug may still have a significant market share because of the heterogeneity of effectiveness and the side effects of drugs on patients. Coscelli and Shum (2004) find that physicians are initially reluctant to prescribe new drugs and underestimate the quality of innovations. They also find that physicians regularly update their beliefs on the efficacy of new drugs based on their clinical experience. Further, the authors observe that prices of drugs do not have much effect on physicians' prescription choices. Crawford and Shum (2005) develop a forward-looking framework to examine the learning behavior of patients who switch between different treatments. The authors find that (i) patients search for a match among different treatments for their problems, (ii) they learn fairly quickly about drug effects, and (iii) their drug efficacy perceptions vary substantially. Akçura et al. (2004) provide further evidence of learning by patients in OTC drug categories. The authors argue that marketing and communication strategies can expedite the learning behavior and contribute to the search behavior.

Clinical decision support systems (CDSS) have the potential to help physicians with their clinical learning and hence prescription accuracy. Researchers have long advocated the use of CDSS to help improve physician's prescribing choices and expand their pharmacological knowledge in order to minimize ADEs. Seidling et al. (2007) suggest that prevention of prescription dosage errors are possible but require implementation of an appropriate database and decision support tools. To

[1] See http://books.nap.edu/books/0309068371/html/.

help with physicians' learning process, Tamblyn (1997) proposes computer-based drug information networks and expert decision-making support systems as means to achieve an accurate record of drugs (and associated problems) currently being taken by patients and an expert resource in the selection of drug treatment.

CDSS may reduce physician errors by identifying the right drug for a patient. Computerized physician order entry (CPOE) plays an important role in CDSS for an improved drug – patient match. CPOE facilitates the accurate drug selection and reduces the rate of non-intercepted serious medication errors by more than half (Bates et al. 1998, Bates et al. 1999). Bochicchio et al. (2006) report that the use of web-based handheld decision support technology is highly effective in improving antibiotic decision accuracy among physicians. In a recent review of the literature, Ammenwerth et al. (2008) provide evidence that the use of CPOE leads substantial reductions in medication errors and ADEs (13 to 99 percent, as reported by 23 of the 25 studies that have been reviewed). Shamliyan et al. (2008) find that the use of CPOE was associated with a 66 percent reduction in total prescribing errors in adults.

CDSS may also reduce the ongoing dosage- and drug application-related errors once the drug is prescribed. Kirk et al. (2005) assess the rate of medication errors in predominantly ambulatory pediatric patients and the effect of computer-calculated doses on medication error rates of two commonly prescribed drugs. They find a computer-calculated error rate of 12.6 percent compared with the traditional error rate of 28.2 percent, with most errors resulting from under-dosage. Berner et al. (2006) conduct a randomized, controlled experiment and find that participants with a personal digital assistant-based CDSS made fewer unsafe treatment decisions than participants without the CDSS. Mirco et al. (2005) find evidence that the use of clinical decision support systems is vital in achieving maximum medication safety and reducing medication error rates.

In this paper, we propose a clinical learning model for physicians supported by two important CDSS features. The first feature is related to the initial drug selection. The second CDSS feature provides an ongoing dosage and application support for a focal drug. The proposed framework provides an analytical model to investigate the effects of different CDSS features. Using the proposed model, we investigate how the two CDSS features relate to the clinical learning of physicians.

The analytical results suggest that the decision support on drug selection is critical. Improving the initial drug selection process raises the drug-patient match conviction and positively influences the importance of the patient-level information for the physician. On the other hand, absent improvements in successful drug selection, the use of CDSS may in fact negatively influence the clinical learning. The intuition behind this result is the following. CDSS makes physicians more certain on the expected efficacy of a drug without affecting their patient-drug match conviction. Consequently, the information gathered from individual patients is weighed relatively less compared to their efficacy expectations while prescribing a drug.

We next present a model for the clinical learning mechanism and then analyze the role of CDSS on physicians' learning behavior. We conclude the paper concludes with a summary of results and briefly outline the salient aspects of an empirical analysis that we aim to conduct in this domain.

MODEL

Consider a physician who needs to decide whether to prescribe a focal drug representing a treatment plan. Selecting the treatment requires an ongoing decision on dosage and application of the focal drug. For example, a patient may be diagnosed with bi-polar disorder. Then, the treatment plan requires an initial decision on prescribing a treatment in the therapeutic category. Once a specific treatment is prescribed, the physician observes the patient's response to the drug and collects additional information on an ongoing basis.

Prescription preferences evolve over time. Physician *i*'s preference is represented by Q_{it}. Q_{it} is a function of the past preferences $Q_{i,t-1}$, other information sources such as detailing and sampling activities by the institutions, represented by vector X_{it}, and an error term v_{it}:

$$Q_{it} = G_i Q_{i,t-1} + X'_{it}\beta_i + v_{it}. \quad (1)$$

The vector β_i in the above equation contains the parameters reflecting the i^{th} physician's responsiveness to the information sources given in X_{it}. The parameter G_i captures the persistence in preference over two successive time periods. Physicians differ based on their prescription habits, and the subscript *i* captures the physician-specific carryover coefficients. A high value of G_i implies that physicians carry over their preferences into the future periods. For example, when a physician prescribes a mature drug that has been in the market for a sufficiently long time and follows an established treatment plan, there may be limited new information during period *t*. Then, the preference towards the treatment plan would be mainly

based on past preferences. A low value of G_i characterizes the prescription behavior that is not much influenced by the previous period's preferences. When enough new information is available for a treatment plan, the prescription preference becomes a function of the most recent information $X'_{it}\beta_i$ and the error term v_{it}.

The error term v_{it} captures the errors associated with the drug efficacy which depend on the use, application and dosage. For example, depending on the specific condition of the patient, the optimal prescription dosage, frequency of use and overall application may change. We let v_{it} follow a normal distribution with $N(0, \delta V_i)$ where, $0 < \delta < 1$, $0 < V_i$. When a physician is not using a CDSS, the physician relies only on her own memory. This is the case where δ equals to one and all the uncertainty is captured by the physician-specific variance V_i. On the other hand, availability of a CDSS reduces the uncertainty. The effectiveness of the CDSS in reducing the uncertainty is captured by δ. As δ decreases towards zero, the CDSS becomes more effective and essential in identifying and minimizing dosage related errors. Note that, according to the model, although CDSS provides a useful tool in reducing uncertainties, physicians still differ given their own work environments and skills, and a physician experiencing a high degree of uncertainty (V_h) benefits from the CDSS more than a physician with a low degree of uncertainty (V_l) since $(1-\delta)(V_h - V_l) > 0$.

Patient life styles vary and may influence the initial decision to follow a specific treatment. Some patients working under strenuous conditions or suffering from other pains may not follow certain types of treatments or take drugs that may interfere with their conditions. The number of new prescriptions is a function of

$$Q_{it} + \omega_{it}, \tag{2}$$

where the random term ω_{it} includes the errors related to the drug selection. ω_{it} follows a normal distribution with mean 0 and variance γW_i, where $0 < \gamma < 1$, $0 < W_i$. We allow the variance W_i to vary across physicians due to differences in patient profiles. The parameter γ captures another feature of the CDSS. A low value of γ indicates that the CDSS is effective in identifying and reducing the potential drug interaction with patient profile match related errors.

Suppose during period *t* physician i handles n_{it} new patients. Let Y_{it} denote the total number of new prescriptions in period *t* and follow a Poisson distribution. The probability of observing y_{it} prescriptions equals

$$\mathrm{p}(Y_{it} = y_{it}) = \frac{\mu^{y_{it}} e^{-y_{it}}}{y_{it}!}, \tag{3}$$

where the mean of the distribution μ_{it} is proportional to

$$n_{it} \exp(Q_{it} + \omega_{it}). \tag{4}$$

According to Equations (3) and (4), the mean number of prescriptions for the focal drug Y_{it} depends on the total number of new patients n_{it}. We see in Equation (4) that a change in Q_{it} alters the probability of prescribing the focal drug (μ_{it}/n_{it}) and accounts for n_{it}. Q_{it} takes a high value if the drug works all the time for all patients in the therapeutic category. On the other hand, a low value of Q_{it} reduces physicians' probability of prescribing the focal drug.

Clinical Experience

So far, the process discussed above captures a prescription behavior independent of the *clinical* learning that occurs via the treatment plans followed by patients. Whereas in reality, each physician likely develops an intrinsic preference about a treatment plan based on the clinical experience with the patients. In general, physicians follow their patients while searching for the best treatment plans, the right drugs and applications in order to better serve their patients. A search behavior leads to changes in choices when sufficient new information is acquired (Kohn and Shavell 1974) and learning occurs as inferences about the quality of available alternatives are made (Meyer 1982). For example, if a physician discovers after an initial prescription that the focal drug being used for the treatment is leading to certain adverse side effects on patients, she may revise her intrinsic preference. Alternatively, a repeated positive experience with a focal drug may lead a physician to prescribe the drug more frequently.

Physicians start each period with a prior preference based on the perception of a drug's efficacy. Physicians' clinical experience in a period allows them to update their perception of the drug's efficacy at the end of the period to form a

posterior perception, a process that is repeated every period. Let physician *i*'s prior preference at time *t* be denoted by $Q_{i,t|t-1}$. The index *t*|*t*-1 represents the fact that the updating process involves the clinical information gathered until the end of period *t*-1, but it does not include the clinical information obtained in period *t*. $Q_{i,t|t-1}$ is a function of the physician's posterior preferences at the end of period *t*-1, $Q_{i,t-1|t-1}$.

First, consider the end of period *t*-1 when the physician incorporates all the information and establishes the posterior perception $Q_{i,t-1|t-1}$. Let $Q_{i,t-1|t-1}$ follow a normal distribution with $N(M_{i,t-1|t-1}, R_{i,t-1|t-1})$. Then, the mean and variance of physician *i*'s prior perception at the start of period t, $Q_{i,t|t-1}$, are given by:

$$M_{i,t|t-1} = G_i M_{i,t-1|t-1} + X'_{it}\beta_i, \tag{5}$$

$$R_{i,t|t-1} = G_i^2 R_{i,t-1|t-1} + \delta V_i. \tag{6}$$

We observe in Equation (5) that the mean of the prior perception $M_{i,t|t-1}$ depends on the mean of posterior perception, $M_{i,t-1|t-1}$, as well as information signals from the most recent information in X_{it}. The uncertainty associated with the prior perception is reflected in the expression for $R_{i,t|t-1}$ in Equation (6).

$Q_{i,t|t}$ denotes the posterior updated *after* the observation of the clinical experience by the physician during period *t*. Let φ_{it} represent the observed mean efficacy of the treatment plan at the end of this period. Then, the distribution of the posterior is given by $Q_{i,t|t} \sim N(M_{i,t|t}, R_{i,t|t})$, where

$$M_{i,t|t} = M_{i,t|t-1} + K_{it}(\varphi_{it} - M_{i,t|t-1}), \tag{7}$$

$$R_{i,t|t} = R_{i,t|t-1} - K_{it} R_{i,t|t-1}, \tag{8}$$

$$K_{it} = \frac{R_{i,t|t-1}}{R_{i,t|t-1} + \gamma W_i}. \tag{9}$$

Equations (7), (8) and (9) are obtained by a technique called Kalman filtering, which requires marginalizing a joint normal distribution, is a common technique used in the learning literature (Akçura , Gönül and Petrova 2004, Coscelli and Shum 2004). See Appendix for a sketch of the proof. In our case, Equations (1) and (2) are jointly normal, and Equations (7) to (9) are derived by marginalizing the joint distribution given the information obtained from the prescription observation φ_{it}.

Analysis of the Clinical Learning Model

Equations (7), (8) and (9) jointly represent the clinical learning mechanism. Next, we review these equations and analyze the clinical learning behavior. Following this analysis, we investigate the impact of the CDSS on the clinical learning behavior.

First, consider Equation (7). The term $(\varphi_{it} - M_{i,t|t-1})$ in Equation (7) represents the information discrepancy between the observed efficacy at the end of period *t* and the physician expectation at the start of period *t*. The change in posterior mean $M_{i,t|t}$ in Equation (7) depends on the sign of this discrepancy. For example, a physician may realize that certain dosages should not have been prescribed and the treatment plans may have more adverse effects. This results in a lower-than-expected observed efficacy and a negative $(\varphi_{it} - M_{i,t|t-1})$. Then, such a clinical observation reduces the posterior mean $M_{i,t|t}$.

Equation (8) shows that the posterior variance decreases as new information is acquired. Over time, physicians gain clinical experience and reduce their uncertainties on the drug's performance and its fit to their patients. The posterior uncertainty ($R_{i,t|t}$) decreases in proportion to the prior uncertainty ($R_{i,t|t-1}$) in Equation (8). The information obtained initially under a high level of uncertainty reduces the uncertainty relatively more compared to the information obtained later when the degree of uncertainty is lower .

We also observe in Equations (7) and (8) that the extent to which a physician relies on new clinical experience in updating the efficacy perception is determined by the value of the coefficient K_{it}. K_{it} represents the weight attached by physician *i* to the information signals received through clinical experience. The magnitude of K_{it} ranges between 0 and 1 depending on the uncertainty levels ($R_{i,t|t-1}$ and γW_i) as specified by Equation (9).

If a physician faces a high level of treatment uncertainty, learning through clinical experience will be significant. A high δV_i in Equation (6) results in a high value of $R_{i,rlr-1}$, which in turn increases K_{it} through Equation (9) and allows significant updating through clinical observations (see Equations 7 and 8). On the other hand, a physician who is relatively more confident about the drug efficacy and the treatment plan (i.e., low δV_i) will update her preference in a much limited manner since low values of δV_i and $R_{i,rlr-1}$ result in a small K_{it} value (close to zero). This restricts the value of new information and limits the updating process through clinical experience.

If a physician experiences significant drug selection uncertainty and patient-drug match is in doubt (high γW_i), the effect of new clinical experience on the preference updating process will be limited. Note that K_{it} decreases with γW_i (see Equation 9). Drug interactions and different patient lifestyles may generate idiosyncratic differences that prevent a physician from obtaining all the necessary information and, in turn, limit the updating of the efficacy perception (low K_{it}). In the presence of a significant patient-drug match uncertainty, a physician will not be able to make inferences about the quality of the treatment. Consequently, clinical learning as well as the level of change in future prescription behavior will be limited.

The dynamic structure behind the clinical learning mechanism and K_{it} allows the information obtained at the beginning of the process to have more impact on clinical learning compared to the information obtained later in the process. Note that, as discussed before, $R_{i,rlr-1}$ decreases as physicians obtain more information and become more certain on a treatment's efficacy (see Equation 8). Decreasing uncertainty ($R_{i,rlr-1}$) also results in a lower K_{it} value as physicians reduce their uncertainty with more experience (see Equation 9). Consequently, the role of new information in the updating process is limited.

We provide a graphical illustration of the model in Figure 1. Figure 1a represents the case with no impact of clinical experience. In the figure, the horizontal axis represents the time period while the vertical axis represents the likelihood physicians prescribing the focal drug (μ_{it} / n_{it}). The solid line in the figure provides the clinical efficacy on the patients. As an example, take the case where the focal treatment should be prescribed to the majority of the patients in the category. In this example, the physician prescribes the treatment at a strictly lower rate, which is represented by the dotted curve entitled Physician Prescription Preference in Figure 1a. Although the drug has a superior efficacy than what is actually perceived by the physician (and perhaps despite the patients' overwhelmingly positive response to the drug), she does not incorporate these observations in her prescription behavior. Consequently, over the periods, the actual physician preference represented by the dotted curve remains well below the correct prescription rate. The difference between the actual prescription preference and the clinical efficacy-based correct prescription is represented by the long dashed curve in Figure 1a, which does not trend lower since the physician does not incorporate the information gained from the clinical experience. In Figure 1b, we present a similar graph for the evolution of the prescriptions, but this time with an active learning mechanism. Contrary to the case with no clinical learning, the gap between the actual preference and the efficacy eventually disappears, and the long dashed curve approaches zero over time.

If a physician effectively uses new information and updates her intrinsic preference, the overall error in Figure 1b should be quickly minimized and the observed prescription rate should closely follow the correct prescription rate. This is the case where K_{it} coefficient in Equation (9) is high, suggesting a significant level of updating through Equation (7) and the long dashed curve's quick approach to zero in Figure 1b. Recall that K_{it} is subject to the values of the physician-level uncertainties δV and γW (see Equation 9) and CDSS adoption plays a role on K_{it}.

In the special case where $\delta = 1$ and $\gamma = 1$, the CDSS has no impact on physicians' prescribing behavior. The long dashed curve in Figure 2 is the equivalent of the long dashed curve in Figure 1b. This curve represents the base case with no CDSS. Next, consider the case where the CDSS supports correct dosage successfully (lowers δ) but with no significant impact on the correct drug selection decision. The dotted curve in Figure 2 represents this case ($\delta < 1$ and $\gamma = 1$). Although the curve trends towards zero, the trend is slower than that in the baseline case with no CDSS (see the dotted curve versus the long dashed curve in Figure 2). Hence, the difference between physician prescription rates and the prescription rates based on the actual clinical efficacy is higher compared to the base case. In other words, lowering δ without first lowering γ through the use of CDSS may not be effective since physicians discount most of the clinical observations. This represents the case where CDSS usage makes physicians more certain on the expected effects of the focal drug without improving their patient-drug match conviction. This may be because significant drug interactions and uncertain observations confound physicians and limit their clinical learning ability.

Figure 1: An Illustration of Prescription Behavior Model

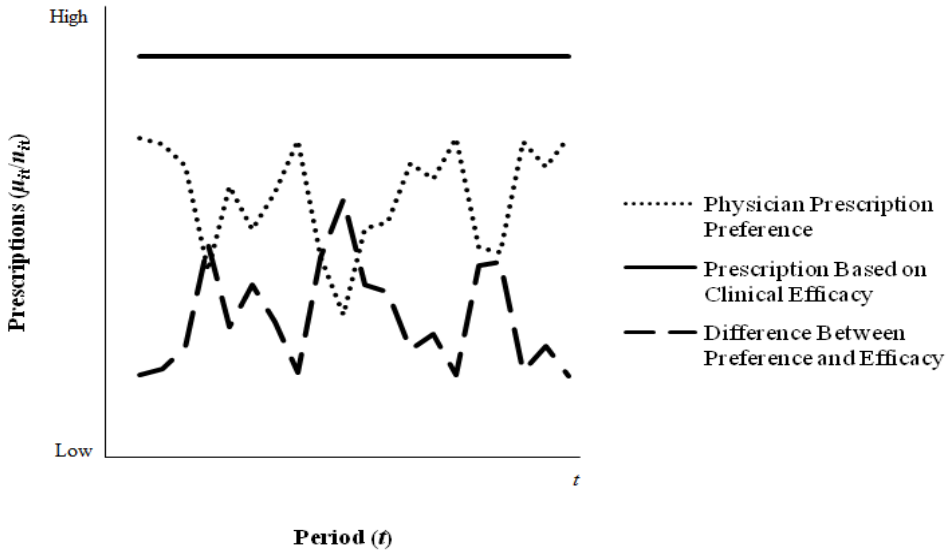

Figure 1a: Prescribing the focal drug - No impact of clinical experience

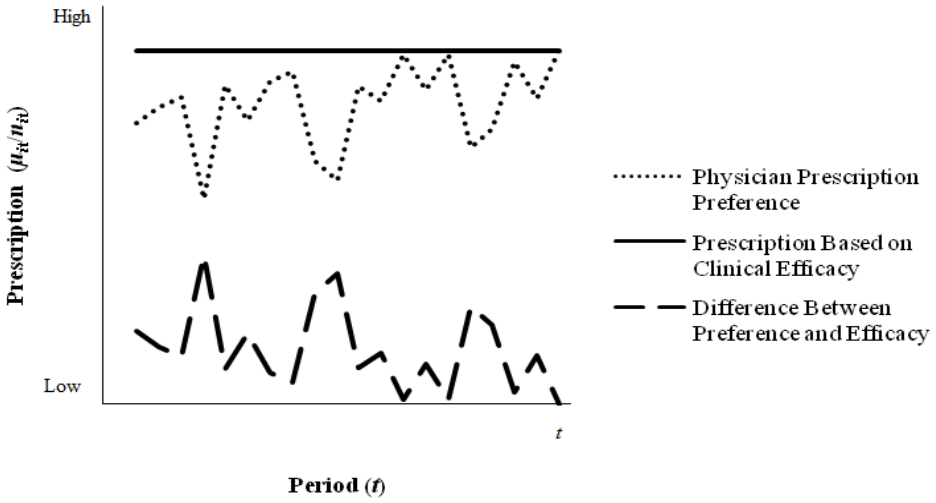

Figure 1b: Prescribing the focal drug - With clinical learning

According to Figure 2, lowering the selection uncertainty ($\gamma < 1$) provides the most effective learning environment for physicians, one that allows them to extract the observation-specific efficacy information and integrate the clinical observations efficiently with their overall treatment efficacy perceptions. This, in turn, results in the quick elimination of the difference between preference and clinical efficacy. The minimum error is achieved when the CDSS supports both features. The solid line in the Figure represents the most consistent level of prescriptions with minimum errors.

CONCLUSION

Business value of information technology (Menon et al. 2000, Devaraj and Kohli 2000) and its adoption within the health care sector (Hu et al. 1999, Braa et al. 2004, Khoumbati et al. 2006, Bhattacherjee and Hikmet 2007, Braa et al. 2007, Menachemi et al. 2007, Miscione 2007, Hikmet et al. 2008) have been the focus of the past IS research on health care. We contribute to this literature by investigating how clinical decision support systems (CDSS) support physician learning and

their prescription behavior. We investigate the conditions under which adoption of CDSS improves clinical learning and contributes to the reduction of drug-related errors. Improved patient-drug match facilitates a more responsive physician behavior and, therefore, positively contributes to the improvements in the prescription behavior.

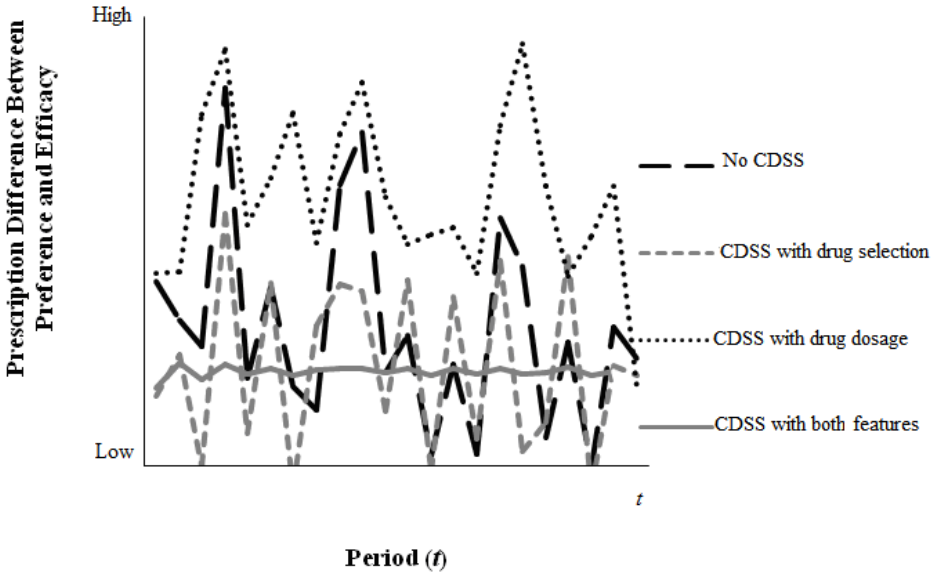

Figure 2: Difference between Preference and Efficacy for different CDSS functionalities

Our next step is to conduct an empirical analysis that incorporates some of the physician-level characteristics that may affect clinical behavior and CDSS use. We have obtained a dataset from a large pharmaceutical company in the United States that includes individual physician prescription records in a therapeutic category. We have the number of new prescriptions written by each physician in the sample during each month between 2001 and 2003. The data also include the number of details (visits by sales representatives) and the number of samples received by each physician per month for the drug. We also have data on each physician's specialty and location by zip code. We will augment the data made available by the pharmaceutical firm with secondary data about per capita income and urbanicity index of each zip code in which the physicians in our sample are located. We are planning to use this data to estimate physicians' response to detailing (by physician type and location) and the persistence in their preferences toward the drug's efficacy over time. We will also analyze the estimation results by the type (general practice vs. specialty) and location (high vs. low income zip code) of the physicians. Such an analysis would provide insights on which types of decision support offer more potential for which categories of physicians, and correspondingly, which CDSS implementations are more likely to fail. We expect to obtain the empirical results by AMCIS 2009.

While we focus on the clinical learning in this study, we acknowledge that physicians have access to and benefit from other information sources such as training and detailing by pharmaceutical companies. A CDSS may be used for training activities as well. While our model can incorporate such additional information sources, the relative importance of these sources (e.g., detailing) diminishes once physicians start prescribing a focal drug. Therefore, we maintain that physicians rely most extensively on their clinical prescription experience.

APPENDIX

At the beginning of period *t*, Equations (1) and (2) follow the joint normal distribution:

$$\begin{matrix} Q_{i,t|t-1} \\ \Phi_{i,t|t-1} \end{matrix} \sim N\begin{bmatrix} M_{i,t|t-1} & R_{i,t|t-1} & R_{i,t|t-1} \\ M_{i,t|t-1} & R_{i,t|t-1} & R_{i,t|t-1}+\delta W_i \end{bmatrix}$$

At the end of period *t*, the information set includes the information obtained from the prescription observation $\varphi_{i,t}$. Note that $\varphi_{i,t}$ is an observation from the distribution of $\Phi_{i,t|}$. We filter $Q_{i,t|t}$ given this observation at the end of the period by marginalizing the joint normal distribution to obtain $Q_{i,t|t}$, see Greene (1997) p.90.

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