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Abstract:

This research investigates the use of decision support systems while employing a classroom simulation game as a methodology. The goal of this paper is to find the unique patterns associated with the systems. Several techniques are employed to build the decision support model. The proposed model is applied in one MBA class and proved by the participants of the simulation experiments. Consequently, the model provides a feasible route to guide information technology specialists to establish effective and efficient decision support systems.

Keywords: Decision Support Systems, Simulations, Business Games.

I. INTRODUCTION

Decision support systems are widely used in today's businesses. One of the more interesting application of decision support systems is in healthcare settings. This paper explores how decision support systems are used for medical reasons and how we can influence the effectiveness of the systems.

Adults Chinese younger than 65 purchased 10.8 prescription drugs per year in the last few years. Those 65 or older purchased more than that – an average of 26.5 prescription drugs in 2001 and the number has increased since then. Each year, doctors write more than four billion prescriptions, of which four percent contain an error, and 1.5 million people are injured due to preventable adverse drug effects and medication errors. According to a much-cited Institute of Medicine report, dozens of thousands of the prescription errors are fatal. It seems that physicians can prevent 28 percent of those errors, but they need more information and better systems.

Improving physician responsiveness, facilitating learning and clinical experience are important in preventing fatal errors. 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. Some researchers 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,

Bharati and Chaudhury (2004) report that many prescribed medicine tend to exceed the limits approved by the physicians. Recent empirical studies corroborate the importance of each individual physician's learning, clinical experience, and patient interaction on the actual prescription behavior (Reinig, 2003). 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. DeLone and McLean (2003) show that even the least effective decision support system may still have effect if used properly, and therefore can yield significant benefits in healthcare because of the heterogeneity of

effectiveness and the side effects of drugs on patients. Sharda et al. (1988) explore decision support systems in various areas. They show that users of those systems are initially reluctant to use new systems 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.

Other researchers also present the ,merit of using decision support systems in this field. Srinivasan (1985) 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. Khazanchi (1991) 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 errors.

Other researchers concentrate on prevention and the use of information to assist patients. 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 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.

Furthermore, 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). The authors also 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 decision support systems 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. Our focus is DSS and the factors that affect their effectiveness. Using the proposed model, we investigate how the two CDSS features relate to the clinical learning of physicians. We follow an approach akin to that of Ein-Dor and Segev (1984) in their business game studies. 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.

II. THE MODEL

We follow the approach taken by Akcure and Ozdemir (2009) in their study of decision support systems: 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. The preferences of a certain Physician i can be represented by a set of vectors Q. Those include his past preferences and his or her present ones. Note that the prescription at hand may differ based on their prescription habits, and the subscript i captures the physician-specific carryover coefficients. A different value of 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. When considering the value of I, one needs to characterize 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.

The error term 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 the error to follow a normal distribution a certain mean and standard deviation. When a physician is not using a CDSS, the physician relies only on her own memory. This is the case where d equals to one and all the uncertainty is captured by the physician-specific variance i V . On the other hand, availability of a CDSS reduces the uncertainty. The effectiveness of the CDSS in reducing the uncertainty is captured by d. As d 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 benefits from the CDSS more than a physician with a low degree of uncertainty.

In addition, 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 preference, where the random term includes the errors related to the drug selection. This randomness follows a normal distribution also with given mean and variance. We allow the variance to vary across physicians due to differences in patient profiles. The parameter g captures another feature of the CDSS. A low value of g 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 it n new patients. Let Y denote the total number of new prescriptions in period t and follow a Poisson distribution. The probability of observing y prescriptions equals where the mean of the distribution is is proportional to an exponential one. Note that according to this data, the mean number of prescriptions for the focal drug Y depends on the total number of new patients. We see that a change alters the probability of prescribing the focal drug and may take a high value if the drug works all the time for all patients in the

therapeutic category. On the other hand, a low value reduces physicians' probability of prescribing the focal drug.

One effective way to measure those changes is by using a simulation. A simulation is by definition a highly complex man-made environment. Its objective is to offer participants the opportunity to learn by doing and to engage them in a simulated experience of the real world (e.g., Ben-Zvi, 2006; Garris et al., 2002; Martin, 2000). This makes it possible to come up with conclusions that can later be generalized to reality as the behavior of participants changes along the simulation (e.g., Lainema and Makkonen, 2003).

When looking at the literature, many studies looked at simulations or used simulations as a research tool. For example, Ben-Zvi and Carton, 2007; Courtney and Paradice, 1993; Dickson et al., 1977; Faria, 1987, 1998. However, researchers that explored simulations and decision support systems did not find one tool that may become handy in measuring the effectiveness of systems. See Affisco and Chanin 1989, Goslar et al. 1986, Kasper 1985.

The game we use in this study represents a tool that is successfully implemented in our classes and then can be used for other purposes. We use it in the healthcare setting we have created. The simulation develops several skills that we regard as important to explore, definitely in the field of medicine.

III. METHODOLOGY

The need for curricula to be up-to-date with the knowledge of current practices, business models and applications is well recognized in the current dynamic environment. Responding to the challenge of meeting the ever moving target of 'being current' and 'relevant', academic institutions are involved in an on-going curriculum development effort. Developing and teaching a current and relevant curriculum is challenging and stimulating because of the topic's rapid evolution and its interfacing effect on every aspect of business. The dot com crash in 2001 undermined some of the foundational premises on which technology is taught in business schools. For example, the electronic marketplaces and application service providers (ASPs) that were predicted to create multi-billion dollar markets by 2004, rapidly faded out as several firms went out of business. Also, in China, the number of electronic marketplaces has declined significantly from around 150 in 2001 to less than three in 2006.

It is challenging to keep up-to-date and be on top of the changing nature of technology applications, teaching materials and the introduction and occasional disappearance of some new and interesting business models, software applications and environmental conditions. Because of the ever-changing nature of course content and case studies, it is very hard to develop a course that is stable on some theory and applications, and has some longevity. It is possible that a certain course which was considered successful in 2005 may be viewed as a significant failure by 2010. For example, an established brick-and-mortar retailer in Australia has acquired its strong online competitor, a successful online retailer of green groceries and simply merged it with its existing fledgling online retailing unit. With these dynamic changes occurring regularly, it is difficult to maintain a set of local case studies and examples and present them for analysis in the class. Taking into consideration these dynamic changes, simulation courses may simply consist of some interesting overseas case studies of successes and failures, and an explanation of current applications. Such courses simply lack the sufficient depth in content and process, and do not equip students with the conceptual frameworks and critical skills necessary to deal with the changing technology and business models in the workplace.

Rapid changes in the field make course development and maintenance extremely resource intensive. In addition to keeping abreast of the evolving and changing content, academic staff teaching these courses must also continuously learn constantly evolving software applications, hardware and networks. To be effective across the broader curriculum, teaching simulations requires bringing together a wide variety of skills from a number of academic disciplines. Because of its multi-disciplinary nature, simulations also include some traditional content from

other disciplines such as finance, accounting and logistics. This requirement creates a need to integrate the offerings and content across different courses taught in the business schools.

The difficulties of delivering an effective and relevant course may be exacerbated if the classes are small. With increasing number of electives to choose from, this is often the case in many business schools. This together with the recent down turn of the demand for information technology/system based courses in general in many universities; the class sizes have typically become smaller. While small classes facilitate critical analysis of case studies and critical appraisal of the latest frameworks and technology, and learning by sharing and interacting, lecture-based teaching typical in large classes is considered inappropriate for such a subject.

The following table (Table 1) presents some data about our two test groups.

Table 1. Demographic Statistics for the Two Investigated Groups

Variable	Test Group 1	Test Group 2
Male	358	725
Female	293	525
% of Female	45	42

IV. HYPOTHESIS TESTS RESULTS

When measured the levels of effectiveness of the created decision support systems, we used 4 indexes: use, design, satisfaction and contribution. We asked the participants what was their level of use; whether the design of the system was a burden, what was the level of satisfaction and whether the system contributed to making the right decisions. Those questions represent the different measures of effectiveness of the systems. We present the main results in Table 2. Performing statistical tests, our findings show that the levels of satisfaction were the highest, although the contribution was lower than expected.

Table 2. Means, Standard Deviations (S.D.), Z values and p-values of System Effectiveness

Variable	Group 1		Group 2		Z	p-value
	Mean	S.D.	Mean	S.D.		
Use	5.25	0.59	5.16	0.51	1.36	0.1854
Design	5.04	0.41	4.96	0.46	1.64	0.1168
Satisfaction	4.92	0.82	4.98	0.86	1.84	0.0791
Contribution	5.13	0.74	5.01	0.69	1.13	0.2335

Next, we examined how the participants felt when using the simulation: whether they had greater control over the experience. We ran tests in both groups. Our findings show that although the participants experienced moral dilemmas, the two test groups did not show a higher level of dilemmas than other studies in the past. Therefore, we could not confirm that decision support system helps resolve moral dilemmas. However, on average, the participants came to realize that when making ethical decisions using a system, one should pay attention to his or her conscience. Also, they understood that solutions to ethical problems are usually not easily definable. Therefore, when examining the use of decision support systems, one should pay close attention

to other issue than effectiveness. The results from both groups along with the statistical tests are presented in Table 3.

Table 3. Means and Standard Deviations (S.D.), Z values and p-values of Responses for the two Test Groups.

Variable	Group 1		Group 2		Z	p-value
	Mean	S.D.	Mean	S.D.		
Greater Control	5.55	0.68	5.62	0.62	0.76	0.4421
Moral Dilemmas	4.53	0.64	4.61	0.67	0.81	0.3843
Awareness of one's conscience	5.08	0.59	5.01	0.51	0.89	0.3713
Ethical problems are not easily definable	5.93	0.52	5.86	0.46	1.01	0.3106
Experiencing problems	5.86	0.58	4.59	0.42	17.49	<0.001

Our final investigation dealt with the degree the additional technical burden placed on the participants, due to the fact that they had to interface via the internet and the system is not just a static system that they operate. We also studied how technical factors affect their behavior and what is the nature of communications conducted between players and the administrators. Based on the information presented in Table 3, it can be concluded that timeliness was not achieved and internet-use problems, rather than learning coaching, dominated participant communications for both groups. The results, however, present a significant difference between the two groups.

V. DISCUSSION AND CONCLUSIONS

Business value of information technology in general, and decision support systems in particular are a major concern to any company today. The adoption of information technology with its variety of components, such as information systems, expert systems and decision support within the health care sector is extremely important as data is being accumulated in a faster pace than ever. Implementing information technology in healthcare settings has been the focus of many information system researchers in the last few years.

Our modest contribution to this literature is by investigating how clinical decision support systems may support physician practice, learning and their prescription behavior over time. We investigate the conditions under which adoption of these types of systems 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. Our results show that the participants came to realize that when making ethical decisions using a system, one should pay attention to his or her conscience. Also, they understood that solutions to ethical problems are usually not easily definable. Therefore, when

examining the use of decision support systems, one should pay close attention to other issue than effectiveness.

Our next step would be to conduct an empirical analysis that incorporates some of the physician-level characteristics that may affect clinical behavior and decision support systems 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 in the past 7 years. 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 other demographic indexes 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 decision support systems implementations are more likely to fail. We expect to obtain the empirical results in the near future.

While in this paper our main focus is on the clinical learning aspect of decision support systems, we acknowledge that physicians in general have access to and can benefit from other information sources as well. Those sources can very well be training and detailing by pharmaceutical companies and others. A decision support system may be used for training activities as well. Those activities can serve as tools for medical students, still obtaining their degree. In addition, 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 over time, rather than relying on the system they actually use.

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