Quantifying the Social Influence on Information Technology Adoption in Healthcare: A Hierarchical Bayesian Learning Model Analysis

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Abstract

Information technology adoption is a critical continuing challenge in healthcare. This paper presents a Bayesian learning model to quantify social learning effects on information technology adoption by physicians from a community health system. The model estimates confirm that both self-learning and social learning effects reduce the uncertainty around the perceived value of a new information technology solution, with subsequent positive impact on users' adoption of the technology. However, self-learning is not easy to influence, so this study is specifically focused on quantifying the impact of social learning effects, opinion leader effects in this community health system context, on technology adoption behavior by physicians in medical practice groups. Simulations of potential policy interventions indicate that if opinion leaders doubled their monthly technology use, their peers' technology adoption probability will increase by 4.4%, on average; however, if opinion leader effects variability decreases by 50%, i.e. opinion leaders send more consistent signals or precise information to their peers, their peers' technology adoption probability will increase by 24%, on average. More importantly, the simulated addition of opinion leaders to medical practice groups which had no opinion leaders, using the new technology 5 instances each month, shows that the adoption probability of their peer physician users will increase by a significant 44%, on average. These simulation results suggest that the more the opinion leaders use the new technology or the lower the variability of opinion leaders' signals, the higher their peers' adoption probability, and opinion leaders' consistent signals more than use frequency have stronger influence on peers' adoption behavior. Also, the addition of an opinion leader to groups that did not have one significantly impacts users' adoption probability. A Markov Chain Monte Carlo method is used for model estimation and the hierarchical Bayesian

structure of the model also shows that substantial heterogeneity exists across physicians even after controlling for demographic variables.

1. Introduction

There have been significant issues in the U.S. healthcare systems, such as low quality care, high cost, and health service delivery inefficient (Kerr et al. 2004; McGlynn, et al., 2006). So in recent years, government and consumers have put the hope of improving the patient care and decreasing the healthcare cost on system-wide implementation and utilization of healthcare information technology (HIT), and many economic incentives are now available to deploy IT via various stimulus packages, such as Health Information Technology for Economic and Clinical Health Act (HITECH), American Recovery and Reinvestment Act of 2009 (ARRA) etc. Therefore, HIT adoption and utilization has been a major topic either in the emerging health informatics field or in the traditional information systems field. In information systems, many studies have investigated the critical factors that may affect users' decision to adopt a new information technology application. Age, gender, perceived usefulness and perceived ease of use of the technology, among other factors, have been shown to have significant associations with the technology adoption decision (Yang and Folly, 2008; Venkatesh et al., 2000; Hong and Tam, 2006). However, first, from the practical perspective, those demographic factors or technology design cannot be changed or adjusted to provide managerial policy implications for promoting the existed technology adoption. Second, from the theoretical perspective, those studies have not examined adoption as a dynamic process but treat the adoption as a one-time decision, which sounds less realistic. Adopting a new technology should not be a snap decision based on a single exposure to relevant information, but a dynamic learning process about the new technology by users who are not sure how the technology would impact their work or life. In the classical book, *Diffusion of Innovations* by Rogers (2003), the author stated that innovations initially are perceived with uncertainty and risk, and most people would seek out others who have already adopted the innovation to reduce the uncertainty in order to adopt the innovation, thus the innovation will diffuse from the earlier adopters to their circle of acquaintances over time. However, Rogers did not examine the peer effects on the technology diffusion process quantitatively but surveyed many field studies and conducted case analyses. The present research examines users' adoption behavior from Rogers' perspective but using a quantitative model to describe how the social influence (or social learning) impacts the learning process by which users reduce the uncertainty associated with a new information technology, then adopt it.

The current study explicitly accounts for two specific factors affecting users' learning during the adoption process of a new mobile information technology application in healthcare: self-learning effects (personal usage) and social learning effect (in the present study, social influence is represented by opinion leader effects) on the learning process which first reduces the uncertainty about the new technology's quality then results in the adoption behavior. We are particularly interested in the opinion leader effects on the dynamic learning process of the new information technology in a social system, because opinion leader effects or social learning may be relatively easier adjustable than the self-learning effects under most deployment contexts.

The findings of this research will be of interest to several groups. First, organizational level management who wants to encourage the adoption or utilization of a newly deployed information technology will be more interested in leveraging the social influence or opinion leader effects for promoting the technology adoption than in working on the entire user population. Second, technology providers who want to promote a new technology or a new product's diffusion in a social system will be interested in learning about the social learning effects for the same reason.

We use a unique panel dataset with individual-level demographic information and usage data from a local community health system to investigate the opinion leader effects on a new information technology adoption. There are several advantages of this dataset for our study. First, the technology is provided at no cost to physician users by the health system and there is no mandatory use requirement either. So, physicians' usage should reflect their true preference for the technology. Second, the use of the technology is very simple and straight forward, with menu-click interface, hence easy to learn, so learning difficulty should not be a deterrent to adoption. Third, the peer group for social influence is defined by physicians' practice group and the opinion leader identity is identified exogenously by the health system administrators, which minimizes the common endogeneity problems that arise in studies related to general peer effects (detailed discussion in the following section).

Our model estimates indicate that opinion leader effects do have significant impact on users' learning process of a new technology in two ways, use frequency and signal variability, which in turn influence their peer users' adoption behavior. Along with the opinion leader effects and self-learning effects, the model also includes individual level heterogeneity and demographics within a hierarchical structure. Finally, since this technology implementation and adoption environment have no specific technology or contextual characteristics, our model is generalizable and can be applied to many other technology adoption settings.

A key contribution of this study is the introduction of a structural Bayesian learning model, drawn from marketing literature on consumer brand choices among frequently purchased goods, to the domain of healthcare IT adoption. To the best of our knowledge, this is also the first study to investigate opinion leader effects on users' information technology adoption by using the

Bayesian learning model in either healthcare or information systems. Furthermore, the extended hierarchical Bayesian learning model incorporates individual heterogeneity using demographic characteristics in the model. This Bayesian learning can facilitate experimentation with a variety of realistic scenarios that have the potential to generate useful and practical policy interventions.

2. Literature

The major literature for the current study can be classified into three streams: the Technology Acceptance Model (TAM) in the field of information systems, the Bayesian learning model from the marketing research, and the economics literature about peer effects on people's behavior.

There is extensive literature on technology adoption using the TAM (Davis 1989) which primarily uses survey methods to collect users' self-reported subjective opinions about a newly implemented information technology to analyze the motivation for adoption and the factors that influence it. One of the advantages of this method is that we can learn about users' subjective opinions about the new technology. However, the disconnect between users' perception and their actual use of a technology, or the limitations of stated-preference data from surveys compared to the revealed-preference data, such as Train (2009) has discussed, is one of the concerns of survey based research because what people say might not be what they will do. Therefore, the current study examines information technology adoption behavior based on observational data using a Bayesian learning model from a quantitative perspective.

Another stream of research on technology adoption or product choice is the use of structural Bayesian learning model to investigate consumer brand choice decision based on observational data from marketing research (Erdem and Keane, 1996), which is the basis for the model in this paper. The advantage of structural modeling is that it estimates the parameters of consumers' utility function which will not vary with the policy changes (input variables) under experimental simulation, thus simulation results provide more reliable and practical policy suggestions. Erdem and Keane (1996) introduced the structural model into marketing area to study how marketing variables affect consumers' learning process of a new brand, and thus, influence the choice decision among different brands of consumer goods. Since Erdem and Keane's paper, the Bayesian learning model has been applied to many consumer choice studies in the marketing area, such as a new durable product adoption (Song and Chintagunta, 2003), telecommunication service switching (Narayanan et al. 2007; Iyengar et al. 2007), and prescription drug adoption (Narayanan et al. 2005; Camacho et al. 2011; Ching and Ishihara 2010; Narayanan and Manchanda 2009). However, to our knowledge, there is no study yet on examining information technology adoption in the healthcare setting using a Bayesian learning model. Furthermore, a major difference between the marketing research and the current study is that marketing research have prices and purchase behavior involved in any analysis.

As mentioned earlier, a critical issue in the study of peer effects or opinion leader effects is the endogeneity problem. Manski (1993) has thoroughly discussed this issue and stated that researchers cannot make inference about endogenous effects without prior information on the reference group formation. In other words, reference groups must be defined independently from the behavior being examined, otherwise the inference on endogenous effects is not possible because researchers would not know whether the group members' behavior change is due to peer influence or the endogeneity of the group formation. Data limitations have prevented many previous studies from addressing this issue successfully. For example, many pharmaceutical studies on prescribing of new drugs use physician-nominated opinion leaders in examining peer effects (Coleman et al. 1966; Van den Bulte and Lilien 2001; Iyengar et al. 2011). This raises the endogeneity problem because physicians may be choosing their opinion leaders on the basis of similar medication prescribing preferences such that the unobservables are endogenous to the behavior being studied (Nair et al. 2010). Iyengar et al. (2011) stated that self-reporting opinion leadership and socio-metric leadership are weakly correlated, and socio-metric contagion was moderated by physicians' self-perceived leadership, which is another concern for the self-nominated opinion leadership, hence unreliable. Our dataset involves physician users in peer groups based on their medical specialty, which were formed long before the introduction of the new information technology application, therefore it should be independent of the new information technology adoption behavior that we study (it would be a very rare case that a physician practice group would recruit a colleague based on their common mobile technology preference instead of their professional expertise), and so the endogeneity issue should be less of a concern for the current study. The details are discussed in the Data section.

3. Model

In this section, we develop a model that explains the Bayesian mechanism by which users learn about the new mobile information technology in the health system whereby users' uncertainty about the technology's quality is resolved via various signals in a Bayesian updating process, thus leading to the subsequent adoption/non-adoption behavior.

3.1 User's Utility Function

We assume that users are rational in this health system and they will only adopt the new technology when the utility of using this new technology is higher than not using it. The new technology's utility can be approximated by a quadratic functional form, considering that users might be risk-averse or risk-seeking. Therefore, a user i's utility function at time period t for using a new technology can be expressed as follows:

$$U_{it} = A_{it} - r_i * A_{it}^2 + \varepsilon_{it} \quad (1)$$

where A_{it} is the new technology's quality that user i experienced at time period t; r_i is the risk coefficient for user i and its sign will indicate the users are risk-averse or risk-seeking; ε_{it} is a random shock known only to the user.

The experienced quality, A_{it}, of the new technology has some variability, or randomness, because of several reasons. First, the technology itself may have hardware or software quality imperfect variability, or randomness. Second, users' use or learning of the new technology may not be exactly the same every time they use it. Therefore the experienced quality, A_{it}, is a random variable around the true quality of the new technology, α, with the noisy variance σ_{it}^2, The construction of this noisy variance is shown later. Hence, the expected utility to user i from using the new technology at time period t is

$$E[U_{it}] = E[A_{it}] - r_i * (E[A_{it}])^2 - r_i * \sigma_{it}^2 + \varepsilon_{it} \quad (2)$$

Because A_{it} is a random variable as we discussed above, the expected value of A_{it} involves its variance σ_{it}^2. If $r_i > 0$, the technology utility is concave in A_{it}, or users are risk-averse; if $r_i < 0$, then the technology utility is convex and users are risk-seeking; if $r_i = 0$, then the utility function is reduced to a linear form (which is unrealistic, usually). One of the contributions of the present study is that the risk coefficient r_i is estimated as a random effect parameter, a combination of the observable individual demographic characteristics and the unobservable individual heterogeneity across users. That is, we add a hierarchical structure to the risk coefficient of

Bayesian learning model. Because we assume that users perceive the risk-aversion differently, we introduce some user demographic characteristics into the model with a hierarchical Bayesian structure, as shown below (Rossi et al. 2006).

$$r_i = \delta_0 + \delta_1 \text{Male}_i + \delta_2 \text{Age}_i + \delta_3 \text{General Practitioner}_i + \vartheta_i \qquad (3)$$

3.2 User's Learning in A Bayesian Mechanism

A Bayesian learning model assumes that there is a true quality, α, of a new technology or product that users are unlikely to know at the beginning of its availability, so they are uncertain about the quality of the new technology. But users will learn about the true quality over time via various noisy signals in a Bayesian mechanism, thus decreasing the uncertainty. Note that this quality is unobservable to econometricians. When a user is introduced to a new technology, before using it or adopting it, he or she would have some general expectation, or an assumption, about the value or "the quality" of this new technology, which is called a prior belief. Then, as time goes, the user may learn more about the new technology via various information sources, or signals, and will update their prior belief about the technology's quality to a new level based on those signals, and the new level is called the posterior belief. This posterior will be a prior for the next time period. Thus, this learning-updating-learning cycle can be repeated again and again until, ideally, the total noisy variance will decrease to zero and the user's belief about the new technology quality converges to the true "quality value" at some time in the future.

We develop the Bayesian learning model as follows. At the beginning of time period 1, we assume that all users start with a prior belief about the quality of the new technology, A_0, which is assumed to be normally distributed with mean α_0 and variance σ_0^2.

Prior: $A_0 \sim N(\alpha_0, \sigma_0^2)$ (4)

Over subsequent time periods t, t = 1, 2,…n, if user i receives one or more signals, these signals will assist the user to learn about the true quality of the technology. More specifically, we assume that there are two types of signals, an intrinsic signal 1 (self-learning effects) , S_{it1}, and an extrinsic signal 2 (opinion leader effects), S_{it2}, for user i at time period t, and both of them provide some noisy information around the true quality, α, with random errors, Q_{it1} and Q_{it2}, respectively (as modeled in (5) and (5)'). To simplify the Bayesian updating mechanism, we also assume that both of the noises follow normal distributions with mean zero and variances$\sigma_{\varsigma 1}^2$ and $\sigma_{\varsigma 2}^2$, which reflect the probabilities that the noisy signals and product quality a user experienced are not precise. Hence, users' perceived quality distributions mixed with the signals around the true quality value, α, are denoted as shown in (6) and (6)'.

Noise 1 distribution: $Q_{it1} \sim N(0, \sigma_{\varsigma 1}^2)$ (5)

Signal 1 distribution: $S_{it1} = \alpha + Q_{it1},\ S_{it1} \sim N(\alpha, \sigma_{\varsigma 1}^2)$ (6)

Noise 2 distribution: $Q_{it2} \sim N(0, \sigma_{\varsigma 2}^2)$ (5)'

Signal 2 distribution: $S_{it2} = \alpha + Q_{it2}\ ,\ S_{it2} \sim N(\alpha, \sigma_{\varsigma 2}^2)$ (6)'

Since both the prior (4) and the perceived quality mixed with signals ((6) and (6)') follow normal distributions, the posterior belief of the quality of this new technology at the end of time period t, A_{it} , is also normally distributed with a mean α_{it} and variance σ_{i1}^2 (DeGroot 1970) as shown in (7), (8) and (9).

$A_{it} \sim N(\alpha_{it}, \sigma_{i1}^2)$ (7)

$$\alpha_{it} = \alpha_{t-1} + D_{it1} * \beta_{it1}(S_{it1} - \alpha_{t-1}) + D_{it2} * \beta_{it2}(S_{it2} - \alpha_{t-1})$$

$$\text{with } \beta_{it1} = \frac{\sigma_{it}^2}{\sigma_{it}^2 + \sigma_{\varsigma 1}^2} \quad \text{and} \quad \beta_{it2} = \frac{\sigma_{it}^2}{\sigma_{it}^2 + \sigma_{\varsigma 2}^2} \tag{8}$$

$$\sigma_{it}^2 = \frac{1}{\frac{1}{\sigma_0^2} + \frac{\sum_{\tau=1}^{t} D_{i\tau 1}}{\sigma_{\varsigma 1}^2} + \frac{\sum_{\tau=1}^{t} D_{i\tau 2}}{\sigma_{\varsigma 2}^2}} \tag{9}$$

Note that D_{it1} here is the observable indicator of how many signals a user received. If user i received n signal 1's at time period t, then D_{it1} will be n (n = 1, 2, ...). Otherwise, D_{it1} will be 0 and the prior will not be updated. The same logic applies to D_{it2}.

The posterior information for time period t, as (7) – (9) show, is also the prior information for time period (t + 1). The same Bayesian mechanism can be iterated repeatedly. If a user receives more than two types of signals in one time period, equations (7) to (9) can be naturally expanded with similar structural terms.

In addition, for estimation simplicity, the random shock, ε_{it}, in model (2) is stochastic and assumed to follow i.i.d. Gumbel. Thus, the choice probability for adopting the new technology for user i at time t is a typical logit of the form,

$$P_{it} = \frac{e^{E[U_{it}]}}{1 + e^{E[U_{it}]}} \tag{10}$$

Based on Equation (10), we use a hierarchical Bayes approach to estimate this Bayesian learning model with a demographic heterogeneous risk coefficient.

4. Data and Variables

The data for this study was obtained from a community health system with more than 400 associated physicians, about 4,000 employees, and over 500 beds across two hospital campuses and many satellite clinics across the community. In June 2006, the health system deployed a Mobile Clinical Access Portal (MCAP), a secure wireless PDA-based client-server solution accessible anywhere via a Wi-Fi connection, as a supplement to the health system's desktop Electronic Medical Record system. Physicians access MCAP using a handheld Personal Digital Assistant (PDA) to use 266 menu-click medical applications, such as accessing patient medical histories, electronic prescribing, placing lab orders, checking lab results and so on. Within a year after deployment, the total number of medical applications had narrowed down to 24, most of them being search or lab related features. This PDA-enabled technology was provided free-of-charge with no requirements or incentives for using it. Therefore, its usage over time should primarily reflect users' preferences based purely on the utility of the technology.

Three data sources provided relevant data for modeling and analysis. The first dataset is a list of 250 physicians with their demographic variables, including gender, age, specialty area, and whether they are opinion leaders-- the set of vocal and influential physicians who encouraged and promoted this PDA-enabled access to MCAP in the health system. The second dataset includes the practice group information, with practice groups formed according to specialty areas such as internal medicine or orthopedics, and the size of practice groups depends on the market demand. Because most practice groups were spread out across the community, we assume that physicians have more interactions within the same practice group than across groups. The third dataset includes approximately 363 thousand physician use records, each record representing use of a given medical mobile application at a given time by a given physician from June 2006 to

March 2008. After merging all the datasets and dropping the records with missing values (validated with t-tests that dropping the records has no significant impact on the results) and solo practitioners, the final dataset includes148 physicians, including 18 opinion leaders randomly distributed across various practice groups. Although we have individual level daily usage data, we estimate the Bayesian learning model at a monthly time interval because usage is very sparse at weekly or daily level.

Several key concepts need to be clarified. First is how to define adoption and we argue that adoption should be defined case by case. In most marketing, information systems or pharmaceutical literature, adoption has traditionally been defined as a one-time purchase or one-time prescribing of a product/drug or one-time use of a technology. In marketing situations, where consumers have to pay a price to buy a consumable product or a service, the adoption decision is likely the result of careful consideration, and once the product is purchased, it is appropriate to consider it 'adopted'. However, for some information technologies, usage over a time period may be a more important indication of adoption than one-time use because the single use may be when the user initially tried the technology, perhaps as a free trial, and never used it again later. Therefore, we define adoption of this PDA system as a dynamic decision over time whereby a user has to use the PDA 30 times or more in some month in order to be defined as an adopter. More specifically, in the first time period in which a user meets this threshold, s/he is defined as having adopted the technology. This threshold was arrived at after multiple explorations of the usage data. Additionally, before reaching this adoption threshold, a user's previous month's usage is assumed to be a proxy for their self-learning, indicating how many signals that the user receives. That is, if a user tries the PDA a few times in a previous time period, then s/he learns about the PDA via their own experiences and would develop a better idea about the new technology. If a physician is in a practice group with an opinion leader/s, then the total opinion leaders' usage (some groups may have more than one opinion leader) in that month will be a proxy for opinion leader effect, indicating how many opinion leader signals the user receives.

How to define opinion leaders (OPL) is another key concept. In our study, the opinion leaders were selected by the hospital administration based on dynamic observations over a long period of time and a deep understanding of their own social system (informant's ratings method as discussed by Rogers (2003)). In addition, the opinion leaders are not only influential physicians in this health system, but also have strong interests in the new PDA-enabled MCAP technology. All the physicians who are opinion leaders adopted the mobile technology after receiving the PDA in the first two months of deployment, which is also consistent with previous literature that early users are more likely to be adopters (Iyengar et al. 2011). Table 1 shows the distribution of opinion leaders (OPL) across practice groups. We also did correlation analysis on the OPL group assignment and it does not show statistical significance for OPL distribution across groups.

Table 1 Physician Practice Groups

Group Size	The # of Groups	The # of Groups with OPL
1*	54	3
2	22	3
3	11	3
4	8	3
5	3	2
6	2	1
9	1	0
12	1	1

Note: * solo physician users are not included in the analysis of this study.

We aggregate physicians' specialty areas into two larger categories: General Practitioner, which includes family practice, internal medicine, and pediatrics; and Specialist, which includes all the remaining 30 specialty areas because many specialties only include a few physicians and it is difficult to categorize them. Since technology adoption decision is generally not linearly related to physicians' age, we group the 130physicians into three age groups of similar size: less than 45 years old (no physician is younger than 31 years old), between 46 to 55 years old, and above 56 years old. Tables 2 and 3 summarize the descriptive statistics about the 18opinion leaders and the 130 non-opinion leader physicians in our dataset.

Table 2Descriptive statistics of opinion leaders excluding solo users (18 obs.)

Variable	Mean (Total Number)	Std. Dev.	Min	Max
Adopted	100%(18)	N/A	-	-
Male	89% (16)	N/A	-	-
Age	49.5	6.69	39	60
Age less than 45	33%(6)	N/A	-	-
Age between 46 and 55	50%(9)	N/A	-	-
Age above 56	16%(3)	N/A	-	-
Group Size	4.11	2.25	2	12
General Practitioner	78% (14)	N/A	-	-
Total Usage	8,101	14,020	150	58,768
Month to adopt	1.6	0.5	1	2
Average monthly usage	378	667	7	2,798

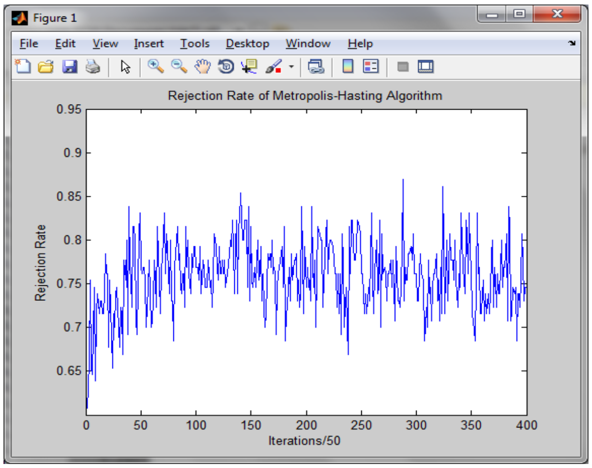
Table 3 Descriptive statistics of non-opinion leader group users (130 obs.)

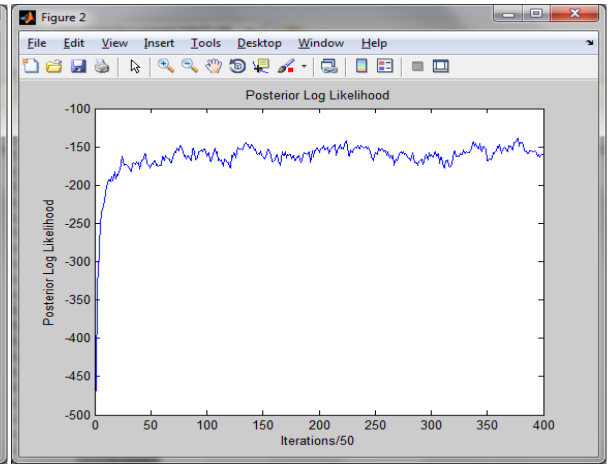
Variable	Mean (Total Number)	Std. Dev.	Min	Max
Adopters w/ OPL vs. w/o OPL	88% vs. 63%	N/A	-	-
Male	77% (100)	N/A	-	-
Age	49	9.5	30	78
Age less than 45	34% (44)	N/A	-	-
Age between 46 and 55	42% (54)	N/A	-	-
Age above 56	22% (28)	N/A	-	-
In OPL Group	26% (34)	N/A	-	-
Group Size	4.5	3	2	12
General Practitioner	47% (61)	N/A	-	-
Total usage	954	2,047	2	13,438

Months to Adopt	6.8	6.6	3	22
Average monthly usage	51	105	0	704

5. Identification and Estimation

Identification issues in the evolution of learning parameters in a Bayesian learning model have been discussed in many papers (Erdem and Keane, 1996; Mehta et al. 2003; Narayanan et al. 2005), therefore, we will not repeat it. From a pure Bayesian conjugate family of distributions theory perspective, as long as the total number of learning periods is large enough, or users receive enough learning signals, regardless of what the initial prior distribution parameter values are, the posterior distribution will converge to the true distribution (DeGroot 1970). Previous studies have also recognized that the initial condition is a critical issue for estimation if the data from the beginning is not included, which is not the case for us because we have the data since the inception of the MCAP initiative. Also, the initial mean and the initial variance are relative values for the learning parameters (Narayanan et al. 2005). In this study, in order to keep the utility within a positive range, we assume the initial mean value to be one and the initial variance to be five. Another major difference between this study and previous ones is how we estimate the parameters of the Bayesian learning model with hierarchical Bayesian structure for users' risk coefficient using a hybrid Markov Chain Monte Carlo method (Gelman et al. 2004), which adds both the observable heterogeneity with user demographic characteristics and unobservable user heterogeneity. The Bayesian estimation procedure executes 20,000 iterations and the first 10,000 iterations are regarded as the burn-in period. For generating the posterior distributions, we use 50 as the thinning interval. Figure 1 displays the rejection rate of Metropolis-Hasting algorithm and every 50th draw is retained for analysis. The rejection rate is stable and in a reasonable range. Figure 2 displays the log likelihood values of the data evaluated at posterior draws of individual-level estimates where every 50^{th} draw is again retained for analysis.





6. Empirical Result and Simulation

This section we present the estimated hierarchical Bayesian learning model parameters and the policy simulations based on those parameters.

6.1 Model Result

Table 4 presents the estimated posterior means and posterior standard deviations for the parameters of the Bayesian learning model, estimated using a hybrid Monte Carlo Markov Chain method. These parameters are the self-learning effect variance ($\sigma^2_{\varsigma 1}$), the opinion leader effect variance ($\sigma^2_{\varsigma 2}$), the mean quality of the new PDA technology (α), the heterogeneous risk coefficient(r_i) with demographic characteristics at the individual level, and the covariance for random effects r_i (V_β).First, we observe that both self-learning effect variance and opinion leader effect signal variance exist during learning process of the new technology adoption and their 95% confidence intervals do not include zero, which indicate that learning occurs and there is uncertainty about the quality of the new mobile technology. Note that we set the initial prior variance to be five, so both signal variance parameters are values relative to the initial prior variance and the absolute values do not have any meaning. Also, in order to keep those signal variance parameters always positive, we re-parameterized those estimators as exponents during the estimation procedure. Therefore, the estimated signal variance values in Table 4 should take exponents for checking their ratios. The ratio of the opinion leader effects signal and the self-learning signalis4.7:1, which indicates that one single self-learning signal is as informative as 4.7 opinion leader effect signals. Certainly this is not a surprise for two reasons. First, people usually trust their own personal experience (or, self-learning) more than what they learn from others. Second, the definition of self-learning is endogenous to the adoption definition, and when a physician's usage reaches 30 times per month, that is considered to be adoption. However, self-learning is more challenging to directly influence other than through mandates. In addition, the user population usually is generally too large to influence everyone. Although opinion leader effect variance is larger than the self-learning signal variance, opinion leaders area small fraction of the user population and it is much easier for management to target them through incentives, better training, etc. Thus, once opinion leaders adopt the new technology, they can influence their peers naturally.

Table 4 Estimated Bayesian Learning Model Parameters

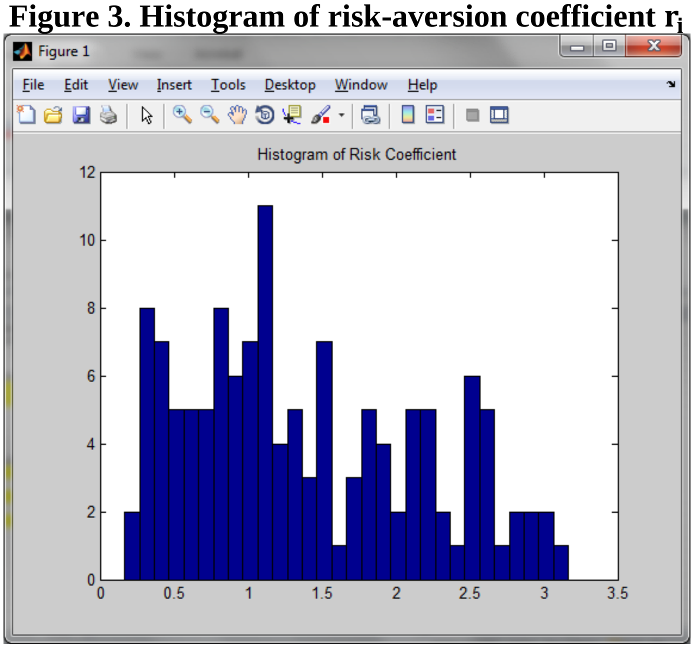
Parameter		**Posterior Mean**	**Posterior Std. Dev.**
Log(Self-learning signal variance)	$\ln(\sigma^2_{\varsigma 1})$	3.409**	1.133
Log(Opinion Leader signal variance)	$\ln(\sigma^2_{\varsigma 2})$	4.965**	2.344
Technology true mean quality	A	0.927	0.774
Heterogeneous risk aversion	r_i	0.705	0.838

Heterogeneous risk coefficient			
Intercept		0.808**	0.193
Male		-0.493**	0.142
Age<=45		0.080	0.154
Age between 46 and 55		0.444**	0.176
General practice		0.109	0.137
Covariance	V_β	1.063**	0.170

Notes: the reference age group is the group with age above 56 years old. ** indicates the 95% interval does not include zero.

The true mean quality of this new technology is positive and is a little smaller than the assumed initial prior mean, one, which may suggest that this new technology's quality is lower than users expected. Learning does occur as discussed earlier. There is a substantial heterogeneity across individual users in the risk-aversion coefficient even after controlling the demographic variables, as Figure 3 indicates.

Figure 3. Histogram of risk-aversion coefficient r_i



Among the individual level demographic variables, male users are less risk-averse than female users, and more actively seeking to use this PDA system. Surprisingly, users in the age group 46-55 are more risk-averse than users in the older group (the reference group), the reason for which needs further study. The largest impact on the risk coefficient is the individual intercept, which indicates that heterogeneity is strong across users. The covariance of the heterogeneous risk coefficient is also rather significant, which is another indicator of the heterogeneity across the individual users.

6.2 Policy Simulations

In this sub-section, we use the estimated Bayesian learning model parameters from the previous section to run policy simulations in order to investigate how changes in opinion leaders' technology use behavior will affect their peer users' technology adoption behavior. We simulate: (1) to increase opinion leaders' technology use frequency, (2) to decrease opinion leader signal variability, and (3) to add opinion leader effects to non-opinion leader groups to examine the variety of ways in which opinion leaders impact their peer users.

6.2.1 Simulating Changes in OPL Use Frequency

Figure 4 exhibits the simulation results from changing opinion leaders' use frequency based on the estimated model parameters from Table 4. The solid line is the aggregated PDA adoption probability in a given month and the dashed line is the simulated aggregated PDA adoption probability in a given month by users who are in a group with OPL. Figure 4(a) shows that when there is a 10-instance increase in the monthly technology use frequency by opinion leaders, the adoption probability by their peer users will increase by a modest 2.3%, on average, over the 22 months. Figure 4(b) shows a little more significant increase than 4(a) when the OPL use frequency is doubled in each time period, where the aggregated PDA adoption probability increased by 4.4%, on average. Figure 5 shows the impact on learning variance, or the posterior variance, when OPL use frequency changes. The lower the learning variance, the closer is the technology quality to its true mean. Ideally, when the learning variance is zero, the true mean is reached. Thus, we observe that when OPL use frequency increases, either a 10-instance increase or doubled in each time period, the users' learning variance decreases by 3.9% and 6.1%, respectively, on average.

Figure 4. Simulation of OPL use frequency changes impacting adoption probability

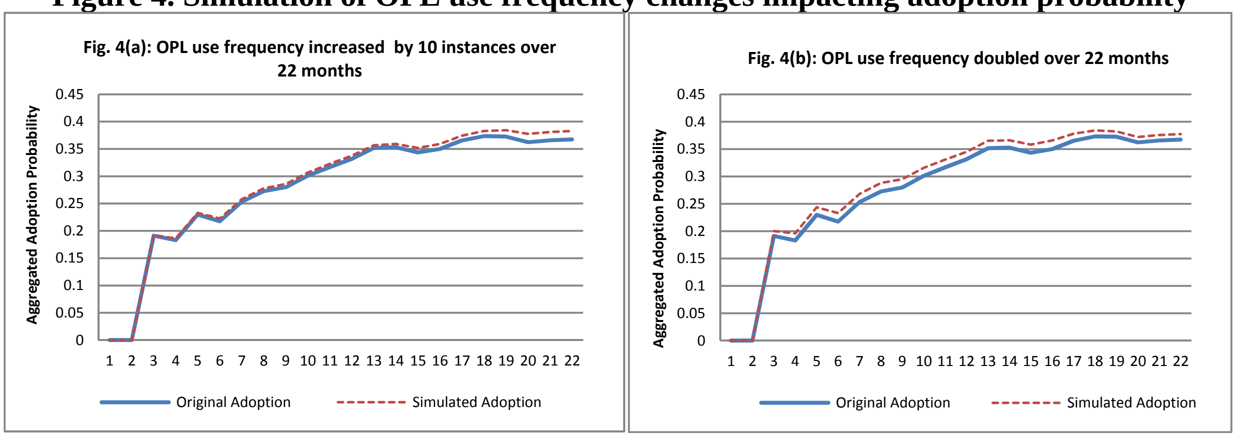
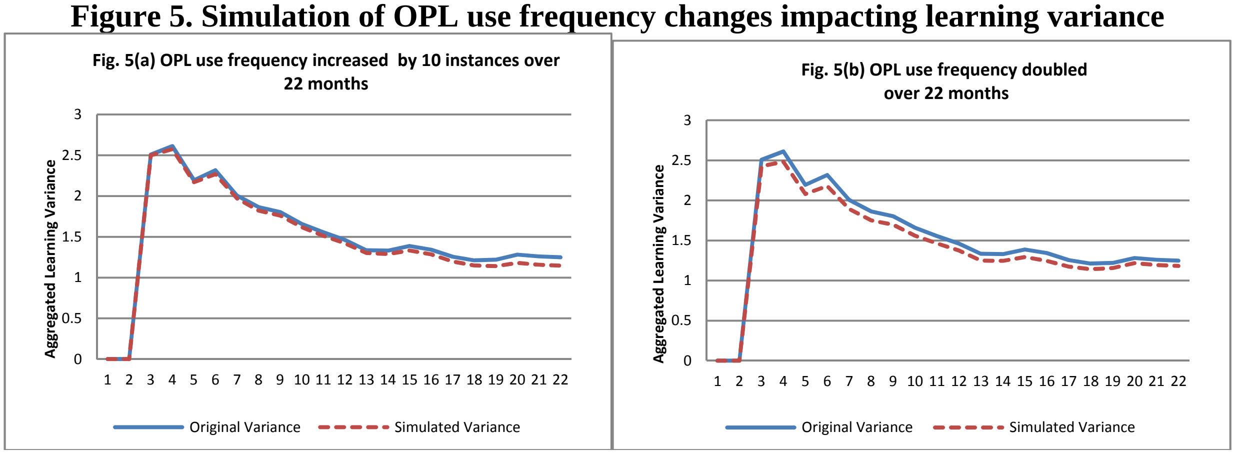


Figure 5. Simulation of OPL use frequency changes impacting learning variance



6.2.2 Simulating Changes in OPL Effect Variance

While users’ technology adoption behavior is affected by the behavior of their OPL, as indicated by the previous simulation results, those changes are not significant. On the other hand, Figure 6(a) and Figure 6(b) display simulation results for changes in the variability in opinion leader effects which show that when opinion leader effect variability decreases by 50%, their peer users’ aggregated adoption probability increases significantly over a 22 month time period. On average, the adoption probability increases by 24% compared to the adoption probability without this simulated policy intervention, and the learning variance decreases by 39%. This simulation result suggests that if opinion leaders adjust their influence to be more consistent, or less variable, over time, or they send more consistent signals to their peer users, their peers will learn faster and will be more likely to adopt the new technology. This finding has a very practical policy implication, which is that management can target opinion leaders for promoting the adoption of a new technology because once the opinion leaders decide to adjust their effects to be more consistent, this will impact their peers' adoption behavior significantly.

In comparing the first and second simulation results, we can conclude that both opinion leader behavior changes affect the peer users’ behavior. Furthermore, decreasing the variability in opinion leader effects has a much larger impact than increasing the frequency of the opinion leaders’ technology use, although these two quantities are not on the same scale and should not be compared directly. Despite this, it indicates that if opinion leaders behave more consistently, the peer users would be more likely to be convinced, or to be less confused, by the opinion leader effect signals, which will improve new technology adoption or utilization.

Figure 6. Simulation of changes in variability of OPL effects

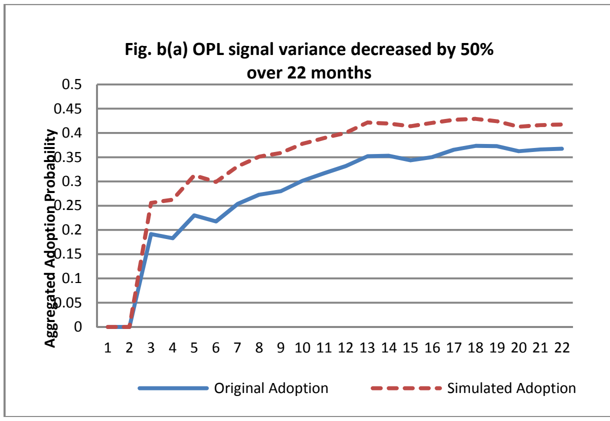


Fig. b(a) OPL signal variance decreased by 50% over 22 months

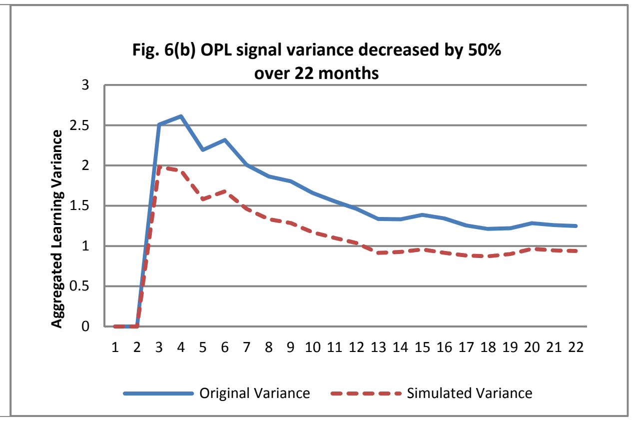


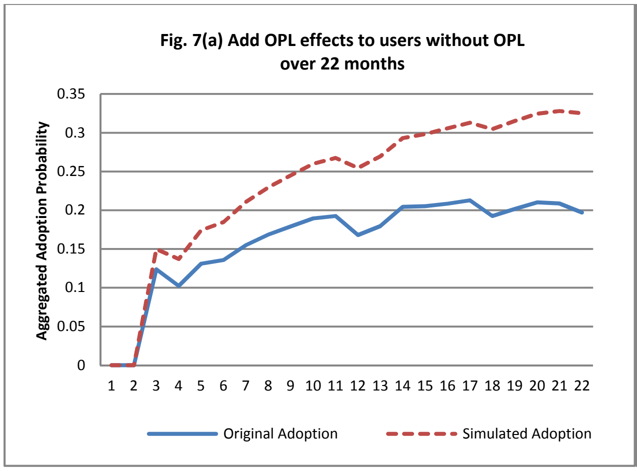
Fig. 6(b) OPL signal variance decreased by 50% over 22 months

6.2.3. Simulation of the Impact of Adding OPL Effects to Users without OPL

Thus far, we have only simulated the impact of opinion leaders on the users who have opinion leaders in their groups, which increase adoption probability or decrease learning variance for these users. In this subsection, we examine the gap between users with OPL and users without OPL by simulating the addition of opinion leader effects to users who have no opinion leaders and observe how this changes their adoption probability or learning variance.

Figures 7(a) and 7(b) show the impacts of adding OPL effects (5 instances to each time period) to users without OPL originally. The increased adoption probability and decreased learning variance are dramatically large comparing to the situations when they had no OPLs, which may be due to two possible reasons. First, the OPL use frequency change from zero to 5 is a significant change for users without OPL. Second, since we add the frequency evenly to each time period, the simulated OPL use variability is continuous and also consistent which can have cumulative effects on their peer users over time. Figures 8(a)-(d) show the simulated impact of adding OPL effects to users without OPL on the gap between the users without OPL and users with OPL. Figures 8(a) and 8(b) show that the adoption probability gap between those two groups has narrowed down significantly, which of course indicates the total adoption probability increased among the entire user population. The same impact is seen on the gap in learning variance between users with OPL and users with newly added OPL as well.

Figure 7. Add OPL effects to users without OPLs



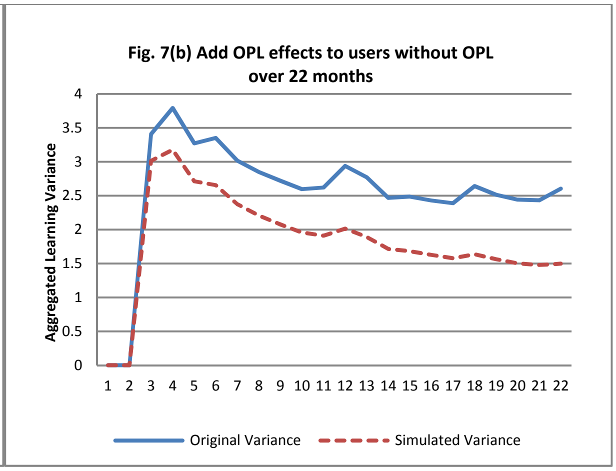
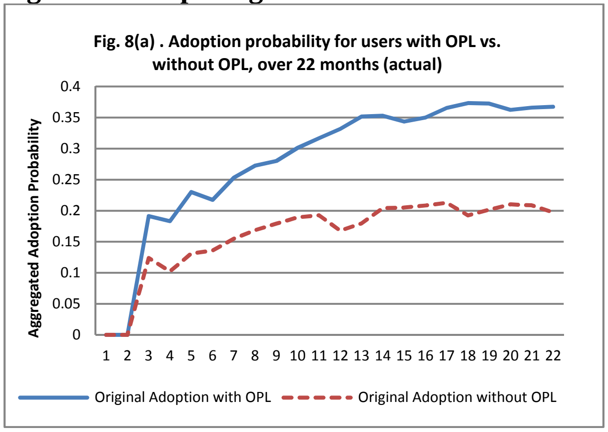
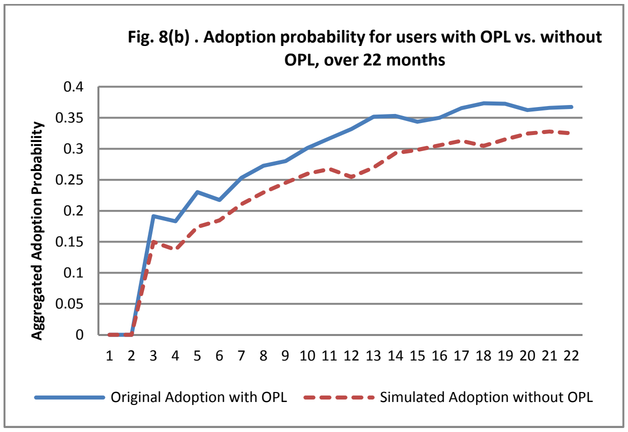
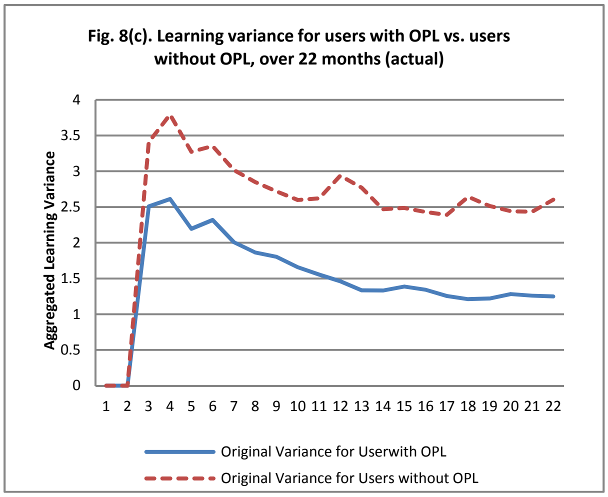
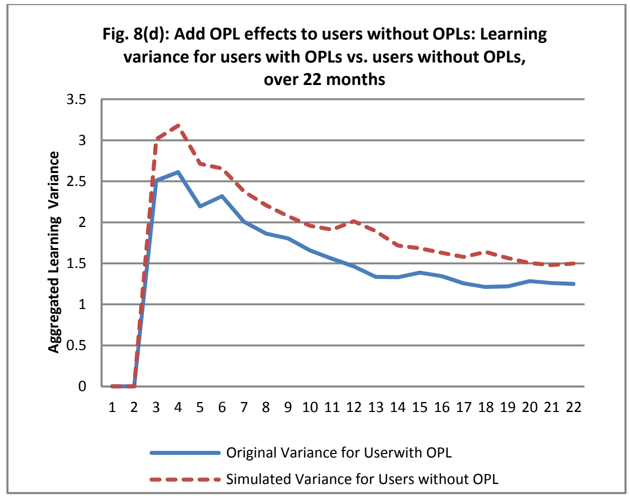


Figure 8. Comparing the addition of OPL effects to users without OPLs









Based on the simulation results comparing the opinion leader effects on users with OPL to the users without OPL, we conclude that OPL effects have significant impact on users' learning process, and thus, the technology adoption probability. Additionally, if OPL effect signal is more consistent, or less variable, then the impact on their peers' learning will be more significant than if OPL were to simply increase their technology use randomly.

7. Conclusions

This study develops a hierarchical Bayesian learning model to examine opinion leader effects affecting information technology adoption behavior in healthcare by using a panel data from a community health system, which enables us to determine how changes in opinion leader technology usage behavior influence their peer users' adoption behavior. Our model results show that both self-learning effects and opinion leader effects impact users' learning process of the new information technology, and thus, the adoption behavior. Although self-learning signals are four times as informative as the opinion leader effect signals on users' learning process, it is not always practical or possible to force users to increase their self-learning or personal usage and make them adopt a new technology. On the other hand, it is possible to encourage opinion leaders to adopt a new technology or to adjust their initial technology use since opinion leaders are a small fraction of the entire user population, whom it should be relatively easier to incentivize. These opinion leaders will then influence their peer users in a natural setting, and thus facilitate the diffusion of the new technology among all the users.

Our policy simulation results suggest that, first, the more the opinion leaders use the technology, the higher is the adoption probability by their peer users and the lower is the learning variance. Second, if opinion leader effect signaling is more consistent, or less variable, then it would be a more effective factor in increasing their peer users' adoption probability(or decrease the peer users' learning variance)than opinion leaders increasing their pure usage frequency only. In other words, if opinion leaders' technology use is random with a large variance, then that may send out confusing signals to their peers, which would interfere with the peers' learning, and thus their adoption behavior. Third, the simulation scenario of adding OPL to the users without OPL shows dramatic adoption increase and confirms OPL effects on technology adoption. This result can be a practical solution to be used either by the management of an organization who wants to encourage new technology adoption or diffusion or by the marketing managers who want to promote a new technology in a certain sector. The key issue is to find the opinion leaders and educate them, then opinion leaders will naturally impact their peers to adopt the new technology. In addition, our hierarchical Bayesian learning model also suggests that individual level heterogeneity on risk-aversion exists even after controlling for the demographic characteristics.

There are several contributions made by the current paper. First, a key contribution of the present study is to introduce a structural Bayesian learning model, drawn from marketing literature on consumer choices among frequently purchased goods or services, to the important domain of healthcare IT adoption. Second, to the best of our knowledge, this is the first study to investigate the opinion leader effects on users' information technology adoption by using Bayesian learning model in either healthcare or information systems, more generally. Third, we develop a hierarchical component for the risk-averse parameter with individual demographic characters in a Bayesian learning model. Finally, this study distinguishes between one time purchase or one time use and adoption, and illustrates that adoption should be defined and modeled differently according to the technology context.

This study also has several assumptions and limitations. First, there may be more signals affecting consumers' learning about a new technology's quality; we include only two – self-learning and opinion leader effects. Second, self-learning could occur via many channels; we only include the self-trial as the signal. Third, opinion leader effects are not directly measured but constructed using observational usage data with the assumption that if opinion leaders use the new technology, then their peers will receive this signal, resulting in an effect on the peers. Fourth, lack of social network data across practice groups limits our ability to qualitatively explain the observed findings. Finally, the assumption of Bayesian learning for a user may not hold all the time, such as when users forget aspects of technology use. These limitations will be addressed in future studies.

There are several directions in which the present study can be extended. First, a future study can examine the self-learning and the opinion leader effects on the long term usage of the technology after the initial adoption time period, which is currently being investigated. Second, another extension could introduce a forward looking utility function to make the Bayesian learning model dynamic. Third, physicians' subjective opinion about the technology, or physician's workload and work outcomes, may also provide additional insights into this information technology learning process.

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