

Examining the Social Influence on Information Technology Sustained Use in a Community Health System: A Hierarchical Bayesian Learning Method Analysis

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Abstract

This paper develops a hierarchical Bayesian learning model to investigate the social influence on sustained use of technology in healthcare. First, this post-adoption Bayesian learning model study makes a contribution to the limited literature on sustained technology use. Second, in the post-adoption stage, our sustained use Bayesian learning model shows that the difference between peer effects and opinion leader effects are not significant. This finding differs from those found in the existing literature examining social influence on technology adoption. This phenomenon reveals the technology user's psychological changes in response to social influence at different stages of technology adoption and use. Therefore, this brings up a practical policy implication regarding how to leverage this change and what type of social influence should be considered to leverage during the technology implementation stage, for promoting early adoption or for encouraging sustained use.

1. Introduction

Technology adoption has been a major topic in many fields, such as the pharmaceutical industry [1] [2], information systems field [3] [4], and healthcare [5] [6]. However, an individual's acceptance of a new technology is only the beginning of technology adoption. Post-adoption or sustainable use is the long-term goal of any new technology being implemented, particularly in healthcare. The present study examines the social influence on sustained use of technology by using a Bayesian learning model in order to provide a practical solution to how to improve the technology's long term implementation in healthcare.

There are a growing number of studies on the topic of social influence on information technology implementation in healthcare. A qualitative study on implementing IT technology in a clinical setting concluded that recognition of special people, such as opinion leaders, should be among the highest priorities when implementing the computerized physician order entry [7]. Zheng et al. found that personal friendships have a stronger influence on a physician's adoption

decision of Electronic Health Records (EHR) than professional connections [5]. Sykes et al. examined the electronic medical records (EMR) system use and consequent performance at the individual physician level by using a holistic model, and found that male and younger physicians are more likely to use the EMR, but the social network centralists are less likely to use the EMR [6]. Also, in the famous book on the social networks, *Connected*, Christakis and Fowler discuss why emotions, health behaviors, people's ideas, politics etc. would spread and be influenced to each other through our social networks [8]. However, not many studies on social influence on the sustained use of the new IT in either general information systems or healthcare.

Agarwal and Prasad (1997) is one of the first studies that stated that researchers should examine both the current use and future use of the technology by examining different Technology Acceptance Model (TAM) constructs. Looking at the different constructs reveals that in terms of World Wide Web adoption and use, different characteristics had different relevance for the two stages [9]. Jaspersion et al. (2005) [10] discussed a comprehensive conceptual two level stage model of post-adoption for information technology. This conceptual model already noted the importance of the fact that organizations are social systems and the interactions within the social systems impact individual's learning. This important fact is very similar to what the current paper wants to examine empirically by using a quantitative model: how social influence impacts individuals' learning about the sustained use of a new information technology within an organization. Narayanan et al. found temporal marketing communication effects on a new prescription drug. That is, 6 to 14 months after introduction, marketing communication has an indirect effect on the drug adoption. After that, the other indirect effects dominated [11]. Also, Manchanda et al. suggested that while marketing effects were more significant in affecting the early adoption behavior, interpersonal communication dominated from month

four onward, which is an instance of social influence on sustained use of a new product [12].

In the classic book, *Diffusion of Innovations* by Rogers (2003) [13], the author noted that technology diffusion is a process. Initially people perceive the innovations with uncertainty and risk, so most people would not adopt the technology immediately, but would seek out others who have already adopted the innovation to reduce their uncertainty. Thus the innovation will diffuse from the earlier adopters to their circle of acquaintances over time. Rogers' book emphasizes two points for the diffusion process: first, it is a learning process over time, and second, the diffusion does not happen in an isolated way but in a social system under the social influence during this dynamic diffusion process. However, Rogers' work was limited to the surveying of many field studies and the conducting of case analyses on the social influence on new technology adoption and diffusion. His work did not examine the social influence on the technology diffusion process quantitatively.

Besides Roger's technology diffusion theory, similar work was conducted in the field of psychology research. Bandura (1976) [14], one of the most influential psychologists of all time, also explained a social learning theory that emphasized the idea that human beings' thoughts and behavior can be significantly influenced by observing people around them. People's learning motivation originates not only internally, but also from observing others' actions. This is another theory that provides support for the idea that social influence has an impact on people's technology adoption process. In other words, in a social system, people may observe other people's behavior and then mimic this behavior. Therefore, social learning is an important learning component of a human being's learning process, as people do not typically live in isolation. In marketing research, many studies have used Bayesian learning models to investigate consumers' dynamic learning during the brand switch and product choice decision process [15] [16] [17] [18] quantitatively. In the present study, we are interested in integrating the above theories to examine the social influence on users' dynamic learning process of sustained use of technology by using a Bayesian learning model.

2. Data

The study site is a progressive, community-based healthcare system located in Southwestern Pennsylvania. In partnership with more than 400 physicians and nearly 4,000 employees, the health system offers a broad range of medical services at many small clinical group practices and two major hospital campuses with over 500 beds. In June 2006, the health system deployed a Mobile Clinical Access

Portal (MCAP), which is a secure, wireless, client-server solution providing physicians with three years of on-line clinical data accessible from Personal Digital Assistants (PDA) via any Wi-Fi connection. Physicians were provided PDAs free of charge and are able to use the PDA to access MCAP anywhere, anytime, such as in the office, at home, or while traveling. Use of the MCAP is voluntary, but it was hypothesized that the convenience of using the device in a variety of care delivery settings would incentivize the physicians to become accustomed to accessing electronic patient information at the point of care, thus facilitating the move to a completely paperless electronic record system in the future. MCAP is a supplement to the health system's desktop EMR system, Clinical Access Portal (CAP), with no requirements or incentives for using it. Thus the use of MCAP technology over time should primarily reflect physician users' preferences based on the utility of the technology. The above factors provide good fundamentals for the current study on technology adoption and sustained use behavior.

2.1 Dataset

The community health system provided four datasets to the present research.

The first dataset includes de-identified demographic information about 250 physicians, comprised of a unique coded physician ID, gender, age, primary specialty, sub-specialty, medical title, and date when the hand-held device was received. The second dataset includes the group practices' information, and indicates which physicians practice together and which physicians are solo practitioners. The group practices are formed according to physicians' specialty areas and all the physicians in the same group come from the same or related specialty fields. For example, Cardiothoracic Surgery and Cardiovascular Disease are grouped together. The third dataset contains MCAP use data over 22 months. It consists of approximately 1,076,894 records; 363,000 records remained after removing the automatically generated default census records. Each record represents a certain application that was being used at a given time by a physician from the time physician users received the PDA until March 2008. The fourth dataset includes patient visit information over 21 months, which contains four types of patient visits: inpatient visits, outpatient visits, physician office visits, and emergency visits. This dataset contains information for 233 physicians from July 2006 to March 2008, almost the same time period as the MCAP usage. Each record indicates a type of visit at a given time with a given physician.

It was necessary to exclude 58 out of the 250 physicians with some missing demographic

information or missing patient visit information, leaving 192 physicians in the merged file for the data analysis in this study. Since almost 23 percent (58 out of 250) of the physician records were dropped due to incomplete data, we performed a series of t-tests to check for non-response bias. None of the t-tests were statistically significant.

2.2. Important Concepts and Variables

2.2.1 Social Structure, Peer Groups and Opinion Leaders

Because this study is particularly interested in the social influence on physician's information technology use behavior, understanding the health system's social structure and how to construct the peer group is critical.

A fundamental question to start with is: what is the main social structure of this community health system? A community health system has its own special characteristics compared to other health systems: many clinical group practices are spread throughout the community, and physicians in the health system are loosely associated with hospitals and practice quite independently. For example, many physician offices are far away from each other, and different group practices do not have interactions if they do not share patients, facilities, or clinical related business; still, they do share the system-wide EMR system and patient database via networks. Therefore, we assume that physicians from the same group practice will have more social interactions within their own groups than across groups. Also, usually we would not assume that the peer influence would be symmetrical because the early adopters or influential people would have a stronger influence on their peers than vice versa. We call these asymmetrical peer effects "opinion leader effects" because the influential people are opinion leaders.

After examining the major social structure of this community health system, which consists of many medical group practices, the next question is: is the formation of those group practices endogenous to the technology use behavior that the present study wishes to investigate? In another word, is the group practice formation in this health system independent from the physicians' decision to use the new technology? Endogeneity is a serious problem when the explanatory variables are correlated with unobserved factors. For example, if opinion leader effects are endogenous to the unobserved group formation rule (technology taste), then we cannot tell whether the technology sustained use behavior is affected by the opinion leader effects or the technology taste of users. However, the current study has little concern about this issue for several reasons. First, the group practices were initially formed a long time ago, far earlier than the

MCAP implementation in 2006. Second, the groups are based on the physicians' specialties, and the size of each group is based on the market demand, not on the physicians' taste in information technology or interests in MCAP, which is the behavior that the current study examines. Therefore, the endogenous issue of the present research would be less severe because what we want to study is the social influence on physicians' use of new information technology, which is independent from the formation of the group. Thus, the above discussions all provide the important theoretical foundation for identifying peer effect/opinion leader effects on their peer members, as Manski (1993) [19] discussed.

Third, it is important to determine how to exogenously identify the opinion leaders (OPLs) in a social influence study. The OPLs in this study are physicians who have been identified by the administration of the health system based on their longtime dynamic observations, referred to as the informants' rating method by Roger (2003) [13]. These OPLs are early adopters and also the influential people in this health system; they are enthusiastic about MCAP implementation and use, and they encouraged the administration to launch MCAP. Also, these OPLs are randomly distributed across various group practices (for which validation tests have been performed) in the community health system.

2.2.2 Technology Sustained Use

In this study, sustained use refers to users who not only adopted the new technology at the initial implementation stage, but also use the technology continuously in the long run. We defined a user who uses the new technology 30 times in a month as an adopter (sensitivity tests have been performed that show that between 26 and 35 times in a month, there is not much change in the data distribution). Similarly, it is important to provide a clear and reasonable definition of a sustained user. After empirically analyzing the technology usage data that we have, a physician user should meet the following requirements in order to be defined as a sustained user: a) the user has adopted the technology; b) the adopter used the technology 90 times in at least one month after adopting the technology, as this is an indicator of continuous use. Continuous use means that a user has to use the technology during more than 40% of the total months since he received the PDA (except for a couple of outliers). After conducting our empirical analysis, 61 users out of 113 adopters met the sustained user criteria. We also tried using 60, 70, 80, or 100 as the threshold values. For those values, the model results are quite similar qualitatively.

2.3 Descriptive Statistics

Table 1 exhibits the descriptive statistics for the adopters, which will be used for our sustained use model estimation. The table illustrates that 54% of the total adopters, 61 out of 113, became sustained users. Also, we can see that the sustained user rate is the highest among the adopters who have OPLs in their groups (66%). The sustained user rate is second highest among the adopters from the groups without OPLs (60%). Finally, solo adopters have the lowest sustained use rate (31%). Table 2 shows the descriptive statistics of OPLs, and we can see that all OPLs became sustained users.

Table 1: Descriptive Statistics for Adopters

Variable	Mean	Std. dev	Min.	Max.
Sustained user rate in total	54% (61)	Total # of users		113
Sustained solo user rate	31% (9)	# of solo users		29
Sustained users from non-OPL groups	60% (33)	# of users from non-OPL groups		55
Sustained user from OPL groups	66% (19)	# of users from OPL groups		29
Male	81%	N/A	0	1
Age	49	10	30	78
Age 45 years old and under	37%	N/A	0	1
Age between 46 and 55 years old	35%	N/A	0	1
Age 56 years old and above	28%	N/A	0	1
General Practitioner	50%	N/A	0	1
Group Size	4	3.4	1	12
Total months used	15	5	1	20
Total MCAP use	1,188	2,186	31	13,438
Average monthly MCAP use (solo/non-OPL/OPL)	58/ 102/ 102	74/ 143/ 96	9/ 10/ 10	243/ 611/ 400
Average monthly inpatient visit	43	37	0	145
Average monthly outpatient visit	481	514	0	2,153
Average monthly physician office visit	404	418	0	1,551
Average monthly emergency visit	42	82	0	586

Table 2: Descriptive Statistics of Opinion Leaders

Variable	Mean	Std. Dev.	Min.	Max.
Sustained User rate	100%(18)	N/A	1	1
Male	89% (16)	N/A	0	1
Age	49.5	6.69	39	60
Age 45 years old and under	33%(6)	N/A	0	1
Age between 46 and 55 years old	50%(9)	N/A	0	1
Age 56 years old and above	16%(3)	N/A	0	1
General Practitioner	78% (14)	N/A	0	1
Group Size	4.1	2.25	2	12
Total months use	15	5.1	1	20
Total MCAP use	5,655	8,372	196	35,027
Average monthly MCAP use	257	380	9	1,592
Average monthly inpatient visit	91	46	25	170
Average monthly outpatient visit	1,149	736	36	2,584
Average monthly physician office visit	706	589	1	1,998
Average monthly emergency visit	69	49	0	184

3. Model

A Bayesian learning model is a structural model that serves to estimate a user's utility function based on the user's behavior. That is, a user would become a sustained user when the utility of becoming a sustained user is higher than that of not becoming a sustained user. A Bayesian learning model is constructed under the assumption that the utility of using the technology would be affected by its quality. That is, a user would learn about a new technology by receiving the dynamic learning signals around the quality of the new technology. Thus, the uncertainty will be reduced and the real quality will be reached, and then the user may become a sustained user.

This research explicitly accounts for two types of information signals affecting users' learning during the

sustained using process of a new mobile information technology: self-learning signals and social learning signals. The social learning signal effects include both peer effects (the influence from general peers) and opinion leader effects (the influence from the opinion leaders who are early adopters and influential physicians). We are particularly interested in the social learning effects, opinion leader effects and peer effects in this research, on this dynamic learning process, as social influence might be adjustable, unlike demographics, in encouraging users' technology long-term sustained use under certain deployment policies.

3.1 A Bayesian Learning Process

We develop a Bayesian learning model that exhibits the mechanism by which users learn about the mobile information technology in a social system. In this manner, users' uncertainty about the technology's quality is resolved via self-learning signals, peer effect signals, and opinion leader effect signals in a Bayesian updating process, thus leading to the subsequent long term sustained use.

3.1.1 Utility Function

It is assumed that, on average, users are rational in a social system and that they will become sustained users of the new technology when the utility of using it is higher than not using it. The utility of using this new technology can be approximated by a quadratic functional form in the technology's quality, considering that users might be risk-averse or risk-seeking [16]. Therefore, a user i 's utility function at time period t for using a new technology can be expressed as follows:

$$U_{it} = A_{it} - r_i A_{it}^2 + \beta_1 \text{In_P}_{it} + \beta_2 \text{Out_P}_{it} + \beta_3 \text{Phy_P}_{it} + \beta_4 \text{Em_P}_{it} + \varepsilon_{it} \quad (1)$$

where A_{it} is the experienced quality of the new technology by user i at time period t ; r_i is the risk coefficient for user i and its sign will indicate whether the user is risk-averse or risk-seeking; In_P , Out_P , Phy_P and Em_P are the four types of patient visit volumes by physician user i at time period t : Inpatient Visit Volume, Outpatient Visit Volume, Physician Office Visit Volume, and Emergency Visit Volume, and β_i are their coefficients respectively. 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, for several reasons. First, the technology itself may have hardware or software quality of imperfect variability, or random shock, over time. Second, users' use or learning of the new technology may not be exactly the same each time when they use it and some randomness may exist too. 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} . Hence, the

expected utility to user i from using the new technology at time period t is

$$E[U_{it}] = E[A_{it}] - r_i (E[A_{it}])^2 - r_i \sigma_{it}^2 + \beta_1 \text{In_P}_{it} + \beta_2 \text{Out_P}_{it} + \beta_3 \text{Phy_P}_{it} + \beta_4 \text{Em_P}_{it} + \varepsilon_{it} \quad (2)$$

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 usually unrealistic). One of the contributions of this research is that the risk coefficient r_i is estimated as a random parameter that is a combination of the observed individual demographic characteristics and the unobserved individual heterogeneity across users. Because it is assumed that users perceive risk-aversion differently, we introduce individual-level user demographic characteristics into the model with a hierarchical Bayesian structure [20], as shown below.

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

3.1.2 Learning in a Bayesian Mechanism

A Bayesian learning model assumes that there is a true quality, α , of a new technology or a product that users are unlikely to know at the beginning of its availability, resulting in user uncertainty. But users will learn about the true quality over time via various noisy signals in a Bayesian mechanism, thus decreasing the uncertainty.

Usually, when a user is introduced to a new technology, before using it or adopting it, he or she may 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 by, the user may learn more about the new technology via various information sources or signals, at certain time periods (i.e., time period t), and will update his/her prior belief about the technology's quality to a new level based on those signals; this new level is referred to as the posterior belief. This posterior belief at the end of time period t will be a prior for the next time period $t + 1$. 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 with the true "quality value", α , at some time point in the future.

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

$$\text{Prior: } A_0 \sim N(\alpha_0, \sigma_0^2) \quad (4)$$

Over subsequent time periods t , $t = 1, 2, \dots, n$, if user i receives one or more signals about the new technology, these signals will help the user to learn about the true quality of the technology. More

specifically, there are three types of signals: an intrinsic signal 1 (self-learning effects), S_{it1} ; an extrinsic signal 2 (peer effects), S_{it2} ; and another extrinsic signal 3 (opinion leader effects), S_{it3} for user i at time period t . All of these signals provide some noisy information around the true quality, α , with random errors, Q_{it1} , Q_{it2} and Q_{it3} , respectively (as modeled in (5), (5)' and (5)''). To simplify the Bayesian updating mechanism, it is also assumed that all of the three noises follow normal distributions with mean zero and variances $\sigma_{\epsilon_1}^2$, $\sigma_{\epsilon_2}^2$ and $\sigma_{\epsilon_3}^2$, which reflect the probabilities that the noisy signals around the product quality a user experiences are not precise. Hence, users' perceived quality distributions mixed with the signals around the true quality value, α , are denoted as shown in (6), (6)' and (6)''.
 Noise 1 distribution: $Q_{it1} \sim N(0, \sigma_{\epsilon_1}^2)$ (5)
 Signal 1 distribution:
 $S_{it1} = \alpha + Q_{it1}, S_{it1} \sim N(\alpha, \sigma_{\epsilon_1}^2)$ (6)

$$\begin{aligned} \text{Noise 2 distribution: } Q_{it2} &\sim N(0, \sigma_{\epsilon_2}^2) & (5)' \\ \text{Signal 2 distribution:} & & \\ S_{it2} = \alpha + Q_{it2}, S_{it2} &\sim N(\alpha, \sigma_{\epsilon_2}^2) & (6)' \end{aligned}$$

$$\begin{aligned} \text{Noise 3 distribution: } Q_{it3} &\sim N(0, \sigma_{\epsilon_3}^2) & (5)'' \\ \text{Signal 3 distribution:} & & \\ S_{it3} = \alpha + Q_{it3}, S_{it3} &\sim N(\alpha, \sigma_{\epsilon_3}^2) & (6)'' \end{aligned}$$

Since both the prior (4) and the perceived quality mixed with signals ((6), (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_{it}^2 (DeGroot 1970) [21], as shown in (7), (8) and (9).

$$\begin{aligned} A_{it} &\sim N(\alpha_{it}, \sigma_{it}^2) \\ \alpha_{it} &= \alpha_{it-1} + D_{it1} * \beta_{it1}(S_{it1} - \alpha_{it-1}) \\ &\quad + D_{it2} * \beta_{it2}(S_{it2} - \alpha_{it-1}) \\ &\quad + D_{it3} * \beta_{it3}(S_{it3} - \alpha_{it-1}) \\ \text{With } \beta_{it1} &= \sigma_{it}^2 / (\sigma_{it}^2 + \sigma_{\epsilon_1}^2), \beta_{it2} = \sigma_{it}^2 / (\sigma_{it}^2 + \sigma_{\epsilon_2}^2), \text{ and} \\ \beta_{it3} &= \sigma_{it}^2 / (\sigma_{it}^2 + \sigma_{\epsilon_3}^2) & (8) \end{aligned}$$

$$\begin{aligned} \text{and} \\ \sigma_{it}^2 &= 1 / (1/\sigma_0 + \sum_{\tau=1}^t D_{it1}/\sigma_{\epsilon_1}^2 + \sum_{\tau=1}^t D_{it2}/\sigma_{\epsilon_2}^2 + \sum_{\tau=1}^t D_{it3}/\sigma_{\epsilon_3}^2) & (9) \end{aligned}$$

D_{it1} here is the 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 ($n = 1, 2, \dots$). Otherwise, D_{it1} will be 0 and the mean of prior belief and the variance of the prior belief will not be updated as equations (8) and (9) show. The same logic applies to D_{it2} and D_{it1} .

The posterior information for time period t , as models (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 three types of signals in one time period, equations (7) to (9) can be naturally expanded with similar structural terms.

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

$$P_{it} = e^{E[U_{it}]} / (1 + e^{E[U_{it}]}) \quad (10)$$

Based on Equation (10), a hierarchical Bayesian approach can be used to estimate this Bayesian learning model with a demographic heterogeneous risk coefficient also incorporated.

4. Sustained Model

4.1 The Bayesian Learning Model on Sustained Use

The Bayesian estimation procedure is executed for 20,000 iterations on the technology use data of the adopters. The first 10,000 iterations are regarded as the burn-in period. For generating the posterior distributions, we use 20 as the thinning interval.

Table 3 shows the Bayesian learning model results for social influence on sustained technology use. First, the self-learning signal variance is the least variable signal or the most reliable signal for a user at the sustained use stage or post adoption stage, which is consistent with our general common sense expectation. Second, however, it is very interesting to note that the opinion leader signal variance (15.7) is not significantly different from the peer effect signal variance (14.3) for this sustained use model, which is different from the adoption model result (Hao, 2012) [22]. In the adoption model, opinion leader signals are more precise than peer effect signals, or in other words, users trust their opinion leaders more than their general peer colleagues. This change suggests a very interesting perspective on social learning by users, from the early adoption stage to the sustained use stage. That is, at the initial adoption stage, opinion leaders have a stronger influence on users' learning of the new technology because users believe that opinion leaders (or early adopters) "know" more about the value of the new technology than other general peers, and thus users trust them more than other general peers. At the sustained use stage, users have changed this trusting opinion because users may think the technology is not "new" any more and that everyone has learned about the value of the technology. Hence, opinion leaders are no longer privileged persons, and the influence from opinion leaders and general peers are not significantly different any more. This result is a little similar to the result of [11] which also found temporal effects on drug prescription adoption. Manchanda et al. (2008) [12] suggested that adoption behavior of a new prescription drug by physicians in Manhattan was affected by both targeted marketing communication and social contagion, but marketing effects were more significant in affecting the early

adoption behavior and interpersonal communication dominated from month four onward.

Table 3 Estimated Bayesian Learning Model Parameters for Sustained Users

Dependent user)	var.(sustained		Posterior Mean	Posterior Std. Dev.
Self-learning variance	signal	$\sigma_{\epsilon 1}^2$	1.553	7.433
Peer effect signal variance		$\sigma_{\epsilon 2}^2$	14.370	28.364
OPL signal variance		$\sigma_{\epsilon 3}^2$	15.684	29.754
Technology mean quality		α	1.787	0.121
Physician office visits		Phy	0.124	0.088
Inpatient visit		Inp	0.260	0.305
Outpatient visit		Outp	1.207	0.378
Emergency visit		Em	-0.590	0.309
Heterogeneous risk aversion		r_i	3.678	0.765
Heterogeneous risk coef.				
Intercept			4.408	0.693
Male			-0.292	0.301
Age $\leq$ 45			-0.411	0.248
Age between 46 and 55			-0.115	0.240
General practice			-0.699	0.338
Covariance		V_{β}	1.0002	0.136

Notes: the reference gender group is female; the reference age group is the group with age above 56 years old; the reference group for general practice is the specialists group.

The technology quality is a relative value to the initial set up value, which is higher than not becoming a sustained user. Three coefficients of the four types of patient visits are positive, which indicates that the more inpatient visits/outpatient visits/physician office visits a physician has, the more likely that he/she will become a sustained user. On the contrary that the more emergency visits a physician has, the less likely that he/she will become a sustained user. All of the demographic impacts on the risk coefficient are negative or risk-seeking. The intercept is the largest estimate for the risk coefficient, which may suggest that at the post-adoption stage, physician users are more risk-seeking in order to have a wider or deeper exploration of the functions and usefulness of the technology.

How to understand and interpret the Bayesian learning model results quantitatively have been shown in Hao (2012) [22] by various policy simulations, and we skip that here.

5. Conclusion

5.1 Contributions

First, the present study makes contribution to the limited literature on sustained use of technology in healthcare by using a novel hierarchical Bayesian learning model. Second, this model's result suggests that users' perception of the social influence on their technology learning at the post-adoption stage is different from the early adoption stage. At the early adoption stage, users trust more in opinion leader effect

signals than general peer effect signals [22]; but at the post-adoption stage, peer effects and opinion leader effects are not significantly different any more. This is a new finding based on the authors' knowledge. Some similar findings were from past marketing literature, such as that marketing communication had a different influence on consumers' adoption behavior from the early stage to the later stage [11] [12]. Third, at the post-adoption stage, many demographic characteristics show a risk-seeking trend, which is also different from the adoption stage [22]. This might indicate that at the post-adoption stage, users seek more risk in order to deepen their learning about this new technology.

5.2 Limitations

There are still several limitations in this research. First, how to define sustained use is debatable, and we decided upon 90 times per month. When the threshold value changes, the model estimates will change a little quantitatively, but not qualitatively. Second, the peer effects and opinion leader effects are only represented by their monthly use, with no variables to catch other possible social learning signals. Third, it is assumed that users are Bayesian learners and this may not be true because some people may forget. Since this research examines the entire user population of a health system, this limitation would not be a major concern.

5.3 Future Research

The future research can extend this study in several directions. First, the current Bayesian learning model on social influence's role in sustained use of technology is based on observational data and the assumptions of what that data represents, and we do not have the exact social interactions within this community health system. Hence, any subjective survey data on the social network and social interactions of the health system will be a great complement to this study. Second, this study only uses the total number of the MCAP uses in one time period as the proxies of the self-learning and social learning signals, and it does not differentiate the learning at the medical feature level of the MCAP; for example, the number of uses of a lab result feature by an opinion leader should be a social learning signal for this lab result feature. Third, another extension could be to improve the Bayesian learning model by including heterogeneous learning signals, and not only the heterogeneous risk coefficient. That is, either self-learning signals or social learning signals should be treated heterogeneously since they are generated by different people.

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