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SOCIAL INFLUENCE AND NETWORK EFFECTS IN THE DIFFUSION OF A HEALTHCARE INFORMATION EXCHANGE SYSTEM

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"How have social networks managed to shoot to such prominence? … The most important reason for their phenomenal growth is something called the network effect." (The Economist, January 2010)

Abstract

The current paper analyzes the diffusion of a Healthcare Information Exchange system. We analyze 2.25 million Emergency Room referrals in seven hospitals during three years since the deployment of the system. We find that social learning within hospitals is a good predictor of physicians' decisions to use the new system. Similarly, the existence of data on the system, a type of network effects, is also significantly associated with system usage.

The paper contributes by addressing both social-influence and indirect-network-effects and testing their effects empirically. We also show that social influence is much stronger than network effects, as can be expected in the strong professional culture of healthcare. Thus, healthcare organizations that deploy technology should focus on social and organizational influence and invest only gradually in populating data in systems and networks.

Keywords: Diffusion of Innovation, Network Externalities, Technology Adoption, Health Information Technology.

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1 INTRODUCTION

The growing importance of technologies that are subject to network effects creates both incentives and opportunities for research of the social and network influences in the diffusion of innovations.

Social influence on diffusion has been studied for more than a century (Tarde 1903, Simmel 1908). The Diffusion of Innovation research tradition studies the attributes of the innovation, the individuals and the social system which are relevant to the diffusion process; it focuses on the *communication* by which individuals who have experienced the innovation influence others who have not experienced it yet (Rogers 2003). A basic principle of this literature is that the exchange of ideas is more frequent and more effective between individuals who are alike, or homophilous (Lazarsfeld and Merton 1964, Rogers 2003). A more recent literature stream focuses on the *value* of innovation under network effects, or network externalities (Rohlfs 1974, Katz and Shapiro 1985, Farrell and Saloner 1985). Network effects exist when the value of participating in a network increases as more people participate; this applies to literal-networks such as telephones and to complementary-goods such as DVD-players and DVDs (Goolsbee and Klenow 2002).

In reality, communication and value complements each other; for example, communication is needed to let non-adopters know about the value of the innovation. The current research tests the combination of communication and value by comparing the effects of social influence, or social contagion, within an organization with a complementary-network effect. The empirical context is the diffusion of a healthcare information exchange system (HIE). We study physicians' decisions to observe patient historical data in 2.25 million Emergency Room referrals, performed in seven hospitals of a large Health Maintenance Organization (HMO), during the first three years of the deployment of a medical data exchange system (Shabtai et al. 2006, Ben-Assuli et al. 2009). This unique dataset allows us to identify the hospital influence on usage decisions, as well as the effects related to the existence of data coming from community surgeries and other hospitals of the HMO.

We test whether homophilous communication within the HMO is indeed effective by the hypothesis that past usage rates at the physician's own hospital are predictors of his/her usage decision. At the same time, we test whether the gradual deployment of the system at the HMO and the gradual accumulation of data increases usage rates. In analyzing these two effects, we control for each physician's learning curve, as well as for patient's characteristics that influence usage decisions.

Our results support the importance of social influence, and show that previous local usage influence physicians strongly. We show also that although the complementary-network effect is important, at least in the strong organizational and professional context of healthcare, the effect of data accumulation is secondary.

The contributions of the current study are twofold. The incorporation of social influences and network effects adds to similar efforts, such as Tucker (2008), in explicitly defining and measuring social influences in the context of network effects. The second contribution is related to the diffusion of healthcare information technology (Greenhalgh et al. 2004, Angst et al. 2008, Angst et al. 2009). The current study demonstrates the nonlinear process characterized by multiple shocks, setbacks and successes (Greenhalgh et al. 2004) of healthcare innovation diffusion. It also supplement, with its large dataset, the in-depth case-studies of the diffusion of similar systems, such as Greenhalgh et al. (2008).

The main limitation of the current study is the difficulty to generalize from its specific context. Our results – strong social influence, weak network effects – are clearly the result of the strong organizational and peer influence in the medical profession.

The paper continues as follows. The next section reviews briefly the relevant literature and develops a single hypothesis. Section 3 describes in detail the empirical setting, and briefly the method. Results are presented in Section 4 and discussed in Section 5.

2 RELATED LITERATURE

"The main idea of diffusion theory [is] that interpersonal communication with near peers about an innovation drives the diffusion process" (Rogers 2003; p. 342). Indeed, diffusion is defined as "the process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers 2003; p. 11). This focus on communication is supported in many ways, including the fact that certain innovations are adopted by clusters of individuals, that opinion-leaders and change-agents are often critical in the adoption of innovations, and that learning is often social. Social learning (Bandura 1977) posits that individuals learn from observing other people's activities, and that both verbal communication and non-verbal behaviour are important in behaviour change. This final point is the basis for the communication side of the current study, as we explain in Section 3.

The emerging Economics literature about network externalities focuses on value: "there are many products for which the utility that a user derives from consumption of the good increases with the number of other agents consuming the good" (Katz and Shapiro 1985; p. 424). It should be noted that diffusion is a critical element of this line of work, because without co-consumers the product is useless. Katz and Shapiro (1985) explain that netwrok externalities are the result of three main sources: 1) direct physical effect, as with litteral-networks such as telephones; 2) indirect effect, such as in computers where the amount and variety of software for a given computer is dependent on of the number of computers that have been sold; and 3) when the quality and availability of post-purchase service depend on the experience and size of the service network which vary with the number of units sold. They also mention in a footnote more subtle sources of externalities that include product information that is more easily avaialble for popular brands, market share as a signal of quality and "Purely psychological, band-wagon effects" (Katz and Shapiro 1985; p. 424). So, the focus is value, and the indirect effect (point 2 above) is the basis for the value side of the current study, as we explicate in Section 3 below.

These two streams of literature are clearly applicable to the specific sectors of healthcare and IT. We mention here only the review of the Diffusion of Innovation literature prepared for the UK Department of Health (Greenhalgh 2004). One conclusion which is relevant to our context is the realization that much of literature focuses on simple, product-based innovations and individual adopters, and that " … it is important not to use this literature to over-generalize to complex, process-based innovation in service organizations, for which the unit of adoption is the team, department, or organization in which various changes in structures or ways of working will be required" (Greenhalgh 2004, p. 600).

Reviews of the literature relevant to IT include the reviews by Fichman (2000, 2004) and by Jeyaraj et al. (2006) and Sabherwal et al. (2006). Fichman (2004) describes the research of IT innovation diffusion by organizations as focusing on economic rationality and having pro-innovation bias. He suggests going beyond this dominant paradigm by considering wider perspectives including configurations, social-contagion, management-fashion as well as the destiny, quality and impact of innovation. Jeyaraj et al. (2006) report on roughly two hundred studies of individual and organizational adoption of IS. The best predictors for organizational adoption are external pressure, external information sources, top management support and the professionalism of the IS unit (Jeyaraj et al. 2006). Following these reviews, Jeyaraj and Sabherwal (2008) emphasize that IS diffusion is an emergent process involving actions by both the adopter and other individuals within the organization.

3 EMPIRICAL CONTEXT

Israel's Clalit ('general' in Hebrew) Health Services is one of the world's largest non-governmental HMOs. It is a not-for-profit organization that serves 3.8 million customers and employs 35,000 staff, including 9,000 physicians. Its annual budget is about USD 5 billion, funded mostly by the state through the National Health Insurance, but also through its customers' contributions. The HMO owns 7 general hospitals, 7 other hospitals, including geriatric and paediatric ones, and more than 1,300 community clinics.

During 2004, the HMO deployed a Health Information Exchange (HIE) system. The HIE retrieved data from other systems, but did not provide order entry functions to its users. This data retrieval architecture allowed to provide a comprehensive integrated and real time virtual patient record available at all points of care of the HMO. The system gathered historical patient data from the other healthcare information systems at the HMO's hospitals and clinics. Data included patients' demographic, chronic drugs, adverse reactions, detailed labs and imaging results, past diagnosis and healthcare procedures. At the same time, the HMO was moving from a manual order entry practices towards electronic order entry in many of its other systems. Although the HIE was available immediately, the connection of other systems to the HIE was gradual, done both by a central unit of five technicians and by distributed hospital teams, totalling about thirty technicians. According to senior medical professionals and administrators of the HMO, the system was perceived useful to achieve better medical quality, service levels and safety; privacy concerns were negligible because of well established access authorization. Actual usage of the system at each of the seven hospitals was idiosyncratic because of differences in management policy relating to the system, electronic order entry in general, as well as the influence of technology and medical champions at each hospital.

The dataset analyzed in this paper was prepared by the HMO in support of a study of the value of medical information (Shabtai et al 2007, Ben-Assuli et al. 2009). The dataset includes all patient visits (referrals) to the HMO's all general hospitals during three years, starting at the HIE deployment. There are about 2.25 million records that include patient data, physician identification, and indications what data was used by the physician. Table 1 presents numbers about the size of the dataset.

Hospital ID	Wards	Physicians	Referrals
120	9	696	342,774
121	10	386	223,639
122	7	281	114,259
123	9	169	326,528
124	10	634	514,053
126	12	568	311,838
128	8	527	408,766
Total	65	3,261	2,241,857

Table 1: Dataset Size Statistics

The decision to use the system, at each specific referral, was taken by the physician in charge of that referral. Physicians were autonomous to use or not use the system, given the patient circumstances, data available on other information systems at the emergency room, and the procedures of the emergency room. In addition – the focus of the current study – usage decisions might have been influenced by social influence and the value of data that was available on the system. Before developing the theoretical model and describing the method and dataset in detail, Figures 1 and 2 present a summary of the diffusion process over the twelve quarters (on the x-axis) covered by the dataset. Figure 1 depicts average usage of the HIE system at each hospital (on the y-axis, as fraction of all referrals). Figure 2 brings the average data existence at each hospital (on the y-axis, referrals that had HIE data, as fraction of all referrals); hospitals are identified only by internal IDs.

The figures give a sense of the considerable differences between the hospitals. Usage rates (Figure 1) demonstrate the nonlinear process characterized by multiple shocks, setbacks and successes (Greenhalgh et al. 2004) of the diffusion of healthcare innovation. Data existence (Figure 2), on the other hand, demonstrates both the differences between hospitals and the HMO uniformity. Specifically, initial data existence rates are related to the level of adoption of each hospital electronic entry systems, while the uniform rate of data increase is mostly related to the HMO-wide rate of systems connection.

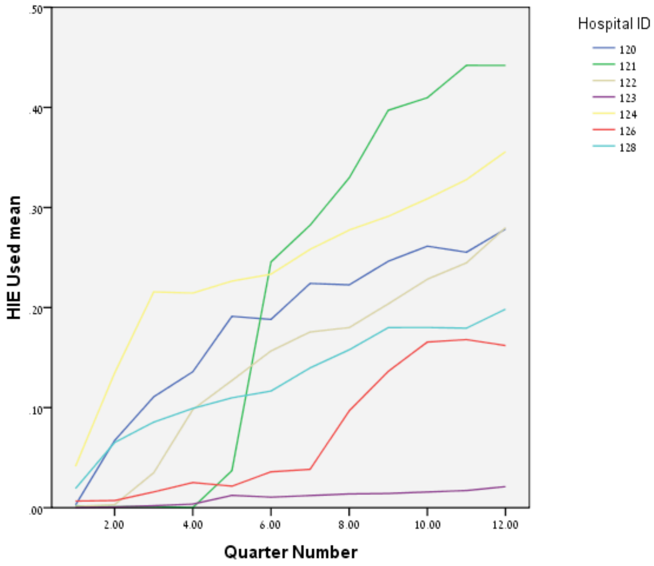

Figure 1: Mean System Usage at Hospitals

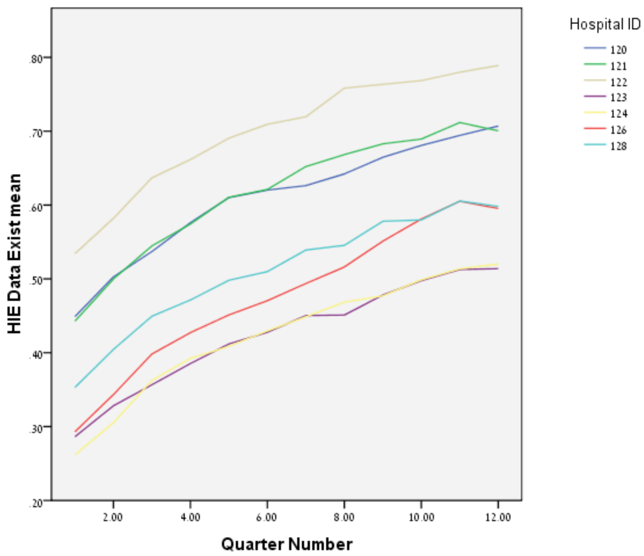

Figure 2: Mean Data Existence at Hospitals

4 MODEL SPECIFICATION

Given the deployment of the HIE system at the research sites and the detailed dataset we have access to, we study actual system use (Jeyaraj et al. 2006). We focus on the dichotomous choice facing a physician at an ER referral, namely, while treating a patient at the emergency room. The choice we study is either to observe the patient's historical data on the HIE system or not to observe it. We posit that this decision is related to 1) the local usage rate during the previous period, and 2) the local rate of data existence during the previous period.

The local usage rate represents the observed behaviour of peers at the physician's locality. We expect that a physician learns from his/her peers, namely that HIE usage is a result of social learning

(Bandura 1977, Rogers 2003, Fichman 2004). Specifically, a physician at a hospital where the usage rate of the HIE sytem at the emergency room was high at the previous time period, would mimic his/her peers and would be more likely to use the system; similarly, for ERs where usage rate is low, there would be no social learning of a new behaviour and the physician would be less likely to use the system.

Local rate of local data existence during the previous period represents indirect netweork effects (Katz and Shapiro 1985) or a complementary-goods effect (Goolsbee and Klenow 2002). Namely, the data is complemntary to the system: when detailed patient data are not available, the demographic data about the patient is of small value only; when the HIE system contains data about labs results, imaging results, etc. it is much more valuable. We reason about local data existance during the previous period because in Emergecny Rooms the patient-physician encounter is distinct and not continuous, and the physician does not know when encountering a patient if detailed patient data is available. Thus, the local experience of how much data is available is used as an indication of the value of the system. Namely, a physician at a hospital where data on patients were readily available on the HIE system (because local surgeries were connected to the system), would be inclined to use the system; similarly, if local experience that the system includes little or no data, the value of the system is perceived to be limited, and the physician would be less likely to use the system. Please note that although the above reasoning focuses on value, the communication aspect of diffusion appears in the assumption that local experience of the amount of data on the system is communicated to the decision maker.

The actual model follows Goolsbee and Klenow (2002) by using local usage rate and data existence rates during the previous period; this is analogous to epidemiology models in which disease spreads more quickly the larger the fraction of the population infected (Bass, 1969). In addition, to the main effects we study, the model includes controls for patient and physician observables, as follows:

$$Y(i, j, t) = a \text{ Local System Rate } (i, t-1) + b \text{ Local Data Existence}(i, t-1) + \\ c \text{ Patient Attributes}(i, t) + d \text{ Physician Attributes}(j, t) + E(i, j, t)$$

where:

- *Y(i, j, t)* is 1 if physician i observes patient j's historical data at time t, and 0 otherwise
- *Local System Usage(i, t-1)* is the fraction of ER referrals where the HIE system has been used at the physician i's hospital and ward in the previous time period
- *Local Data Existence(i, t-1)* is the fraction of ER referrals at the physician i's hospital and ward in the previous time period where historical data about patients (not necessarily patient j) exist
- *Patient Attributes(i, t)* are observable characteristics of physician i at time period t
- *Physician Attributes(i, t)* are observable characteristics of physician i at time period t
- *E(i, j, t)* is an error term

Local System Usage(i, t-1) captures the behaviour of the physician's immediate peers at the same hospital. If there are social influences, then a physician working in a hospital and ward where system usage has been high, is be more likely to use the system, leading to a >0 (Goolsbee and Klenow 2002).

Local Data Existence(i, t-1) captures the amount of patient data that exist on the HIE system. The system and historical patient data are complementary-goods, namely the existence of such data increases the value of using the system. If indeed this complementary-goods effect is significant, then a physician working in a hospital where such data has been more likely to exist, is more likely to use the system, leading to b>0 (Goolsbee and Klenow 2002).

In order to control for other factors that affect the physician's usage decision, we include observable characteristics of the patient and of the physician. The patient history, such as age and previous incidents, as well as the nature of the current incident, affect the need to observe patient historical data. We have also some information about the physician, including the work load at his/her ward and the type of medicine he/she practices. In addition, we calculate the rate of quarterly system usage by each physician to represents the personal learning curve of the physician; we include also the square of this rate in order to accommodate possible non-linearity of the learning curve.

5 METHOD

5.1 Measures

The two main constructs – Local Usage Rate and Local Data Existence – are operationalized as the rates of usage at the hospital relevant to each referral, at the previous quarter (following Goolsbee and Klenow (2002)). Table 2 brings the description of these measures, the measures used for the dependent and control variables.

	Measure	**Description**
Y	*HIE Usage*	1 if the HIE system was used (by the physician, observing patient's data during the specific referral) 0 otherwise
Social Influence	*Local Usage Rate*	The fraction, in percents, of referrals in the hospital for which the HIE system was used, during the previous quarter
Network Effects	*Local Data Existence*	The fraction, in percents, of referrals in the hospital for which the HIE system included historical data, during the previous quarter
Patient Attributes	*Patient Age*	in years
	Patient Insured	1 if insured by the HMO 0 if not insured by the HMO
	Patient Prior Visits	1 if the patient visited the hospital during the year before the current referral 0 otherwise
	Patient Visit Length	the length in hours of the current visit at the emergency room
	Patient Admission Days	the number of days that the patient is hospitalized following the current emergency room visit, 0 if not hospitalized
Physician Attributes	*Internal Practices*	1 if the physician practices internal medicine 0 otherwise
	Ward Shift Load	the number of referrals at the same ward, during the day or night shift of the referral
	Physician Usage Rate	The fraction, in percents, of referrals treated by the physician for which the HIE system was used, during the previous quarter

Table 2: Measures

5.2 Referrals

The focus of this study is the choice facing a physician either to observe a patient's historical data on the HIE system or not to observe it. The dataset includes about 2.25 million referrals; each of them represents a single patient-physician encounter, and system usage choice made by the physician facing a patient. We use this dataset to compute the variables *Local Usage Rate*, *Local Data Existence, Ward Shift Load* and *Physician Usage Rate*. Descriptive statistics of the referral dataset are given in Table 2.

	N	Min	Max	Mean	Std. Dev.
HIE Usage	2,241,857	0	1	.15	.354
Local Usage Rate	2,061,628	.01	44.21	13.76	11.28
Local Data Existence	2,061,628	26.17	78.00	49.98	11.59
Patient Age	2,238,813	.01	97.00	40.05	25.24
Patient Insured	2,241,857	.00	1.00	.787	.409
Patient Prior Visits	2241857	.00	1.00	.465	.498
Patient Visit Length	2,241,423	.00	71.00	2.53	3.28
Patient Admission Days	2,230,367	.00	439.00	1.00	3.04
Internal Practices	2,241,857	.00	1.00	.340	.473
Ward Shift Load	2,241,857	1	124	32.98	20.46
Physician Usage Rate	2,061,628	.00	100.00	14.18	18.05

Table 3: Referrals, Descriptive Statistics

5.3 Physicians

The unit of analysis is a physician, as we focus on the physician's usage decisions. We computed the quarterly mean value of all measures, per quarter (three months), per physician. This has two advantages. The first is addressing simply the problem of temporary staff at the emergency rooms. Many of the 3,261 physicians identified in the referral dataset are employed only provisionally: on average a physician is active 5.6 quarters out of the 12 quarters we study (standard deviation 4.1). For an analysis of behaviour over time, the coming and going of subjects is problematic, for example, by requiring to fill-in many missing observations. In order to avoid this problem, we focus on the most active physicians; these are the ones that practiced at least half of the period (6 quarters) and had at least 1,000 referrals. These are 274 physicians, which on average practice 10.9 quarters (standard deviation 1.5); these 8.4% of all physicians are responsible for 32.4% of the referrals, and we label this group as *active* physicians. The second advantage is the ability to use a simple statistical procedure to address the dependence between observations related to the same physician, by using mixed linear regression with physician as the subject and quarter as the repeat unit (McCulloch and Searle 2000). Table 3 presents statistics for the active physicians.

Quarterly mean of ...	**n**	**Min**	**Max**	**Mean**	**Std. Dev.**
HIE Usage (%)	274	.00	81.73	16.8420	18.7185
Local Usage Rate	274	.85	27.32	14.8164	5.8746
Local Data Existence	274	30.86	71.99	46.9954	8.3616
Patient Age	274	3.51	66.06	36.0773	17.2147
Patient Insured	274	.58	.95	.7865	.0669
Patient Prior Visits	274	.20	.75	.4735	.1123
Patient Visit Length	274	.54	7.30	2.3065	.8918
Patient Admission Days	274	.00	3.01	.8852	.8159
Internal Practices	274	.00	.98	.2797	.4124
Ward Shift Load	274	6.43	71.75	31.7698	17.6465
Physician Usage Rate	274	.00	73.98	15.1994	17.0076

Table 4: Active Physicians (12 quarters), Descriptive Statistics

6 RESULTS

Table 5 summarizes the results of the mixed linear regressions for the active physicians' dataset. The full SPSS outputs are given in an online appendix[*].

Column 1 presents a baseline model; all active physicians are included; only control variables are regressed upon, excluding the diffusion-related variables. The independent variable is multiplied by 100 (fraction in percents) to make the results and their interpretation more readable. The covariance structure is the first-order autoregressive structure with homogenous variances (AR1); the correlation between any two quarters is equal to rho for adjacent quarters, rho^2 for quarters that are separated by a third, and so on; rho is .875 ($p<0.001$). As expected, the quarterly means of patients' age, mean number of prior visits, and mean length of the current visits *increase* the likelihood of system usage. The indication for Internal medicine also increases system usage. However, the mean value for the indication if the patient is insured by the HMO is not significant; similarly, the mean shift load on the physician. One significant relation is in an opposite direction to expectations – the mean patients' admission days (following the current ER incidents) reduces system usage; we expected this variable to proxy the severity of the patients problem and thus to increase system usage, but it does not.

Column 2 presents the main model including all active physicians (n=274). This model fits the data better than the baseline model of column 1, according to the different information criteria provided by the Mixed Linear procedure (please see the online appendix for details). The coefficients representing social influence and network effects are significantly positive, as expected ($a>0$ and $b>0$). However, they differ considerably by magnitude – a 1% increase at the hospital usage rate during the previous quarter, increases system usage by about half a percent; a 1% increase in data existence at the hospital during the previous quarter have only a small effect of 0.05%. The coefficient representing the physician's learning curve is positive as expected with a small negative correction of the square variable. The coefficients of the other control variables are similar to those in the baseline model.

[*] http://portal.colman.ac.il/users/www/83/diffusion_of_hit/

Column 3 represents a subset of the active physicians, those who practice internal medicine where data is more important. The model fits better the data then a baseline model on the same subset (not shown in the table). The results are similar to the main model.

Column 4 is another subset of the active physicians – only the physicians working at hospital number 124 (see Figure 1) that was the earliest adopter of the system. Because the variability of the Local Usage Rate and Local Data Existence variables is only per quarter (all physicians are affiliated with the same locality), we operationalized the local variables differently than in the previous models – usage rate and data existence were computed per ward and not per hospital. Again, the model is better than a baseline model on the same subset (not shown in the table). The basic result holds – positive social influence and network effects, while the social influence is much strong. However, there are differences in some of the control variables – no significant learning curve per physician and significant negative effect of the shift load and positive effect of the patient admission days.

		1	2	3	4
	Quarterly mean of …	**Baseline**	**Active Physicians**	**Internal Practices**	**Early Adopter**
Social Influence	*Local Usage Rate*		.5539***	1.1608***	.7429***
Network Effects	*Local Data Existence*		.0535**	.1002*	.1318**
Patient Attributes	*Patient Age*	.1029***	.1004**	.1970*	.02188
	Patient Insured	2.6158	3.4324	12.3118*	-9.2861*
	Patient Prior Visits	19.1158***	11.0420***	23.1674***	17.3413***
	Patient Visit Length	1.2878***	1.3721***	1.7727**	4.4187***
	Patient Admission Days	-.5480**	-.2884	.6477	2.0353***
Physician Attributes	*Internal Practices*	26.2706***	27.2579***	n/a	20.1478***
	Ward Shift Load	-.0558	-.0578	.2129***	-.2477***
	Physician Usage Rate		.1939**	.2480**	-.0604
	(Physician Usage Rate)^2		-.0031***	-.0044***	-.0011
Physicians (n)		274	274	96	79
Quarterly Observations (N)		2,972	2,972	1,063	874

*** p<0.001, ** p<0.01, *p<0.05 + p<0.1; n/a not applicable

Table 5: Mixed Linear Regression Results

The results support the hypothesis that social influence and indirect network effects are significant through the diffusion process of the HIE system. On average, an additional 1% in average usage at the (active) physician's ward in the previous quarter, increases usage by 0.5% for the full dataset of active physicians, or by about 1% for internal medicine only. This result is more concrete on Figure 3: it shows the average usage for the 274 active physicians, and it is easy to notice that the diffusion rate ranges between 3% and 0.5% per quarter. Turning to network effects, on average, an increase of 1% in data existence at the hospital level, increases HIE usage by 0.05% for the active physicians, or by 0.1% for the internal medicine subset. This is about a tenth of the social influence coefficient in the respective models.

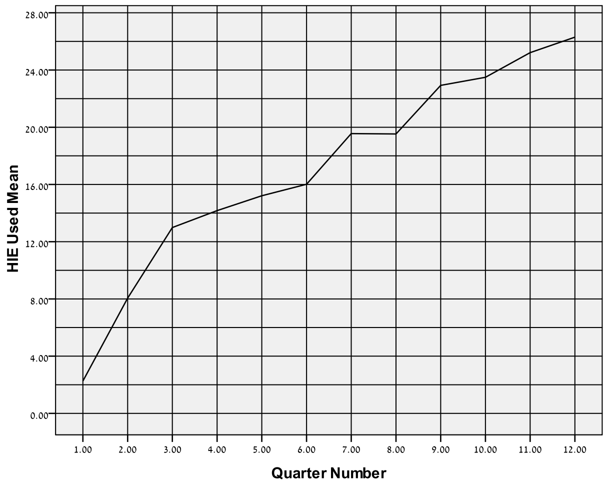

Figure 3: Mean Usage Rate for Active Physicians

7 DISCUSSION

The main result of the current study is the support it provides for the existence of both social influence and complementary-goods network effects in the diffusion of a Health Information Exchange system. We believe that the quality and size of the dataset makes this simple result robust and significant.

The second result is that social influence is much stronger – ten times stronger – than network effects. We interpret this as a consequence of the strong organizational and professional structures and culture in healthcare in general and in the specific HMO in particular. The nature of the data – an electronic patient record – may also explain the result, because these records are not yet considered critical for ER practices. The result is significant for other organizations that deploy complex healthcare information systems – most effort should be invested in social and organizational influence; investment in populating data in systems and networks should remain secondary.

The contributions of the study are in explicitly describing, measuring and comparing the effect of social influence and indirect network effects. Further contribution is the presentation of observations about the diffusion of healthcare information technology that could help other organizations involved in similar efforts.

One limitation of the current study is the difficulty to generalize from its healthcare context. An additional limitation is the less than fully developed analysis. There is clearly a need for further modelling and analysis of the dataset. Further research should also include additional development of the theoretical perspectives, possibly including aspects of social contagion and absorptive capacity (Fichman 2004).

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