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PHYSICIAN'S USAGE OF MOBILE CLINICAL APPLICATIONS IN A COMMUNITY HOSPITAL: A LONGITUDINAL ANALYSIS OF ADOPTION BEHAVIOR

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Abstract

It is widely believed that mobile clinical information systems can facilitate patient care, increase treatment capacity, reduce healthcare costs, and improve efficiency. Yet, there is limited research to substantiate these claims in healthcare delivery settings, partly due to lack of widespread adoption and use. This study summarizes our results on the adoption and usage trends in a community hospital which deployed several mobile clinical applications for daily patient care. We analyze twenty-two months of usage data to understand trends in physicians' adoption and use of specific mobile applications. Applying a novel, semi-parametric, group-based, statistical methodology, we obtain developmental trajectories depicting how usage evolves from initial 'trial' adoption to long-term institutionalization. We examine this longitudinal developmental pattern to understand how users can be clustered and profiled, and provide insights indicating that the potential impact of social influence needs to be further explored to develop new approaches to facilitate adoption.

Keywords: Mobile Clinical Information Systems, Technology Adoption, Developmental Trajectory Analysis, Social Influence, Opinion Leaders

1.0 Introduction

Clinical care takes place in multiple, diverse, delivery settings such as inpatient, outpatient, emergency and office practice environments. Hence, mobility is a critical aspect of health care delivery (Sarasohn-Kahn, 2010, Bardram et al., 2005, Istepanian et al., 2004). Information technology solutions such as Electronic Health Records and Electronic Prescribing Systems are facilitating the availability and utilization of patient information in some settings more than others (Radley et al., 2012, Holroyd-Leduc et al., 2011, Sykes et al., 2011, Edmondson et al., 2001), due either to the lack of mobile channels of access to the information or to the lack of usage of such technologies at the point of care (Gamble, 2009, Zheng et al., 2005). Mobile information systems can significantly improve access to data and information wherever and whenever it is needed (Istepanian et al., 2004, Fischer et al., 2003), and have shown some positive impacts on reducing medical errors, saving costs, improving usability and convenience, and enhancing positive attitudes toward wider use of such applications (Harkke, 2006). However, as noted in a recent study (Prgomet et al., 2009), while mobile devices are increasingly being used in healthcare, there are few studies that provide an assessment of the range of mobile clinical applications being deployed, the types of uses and users accessing them and the adoption and usage patterns among large groups of physicians, and the impact of usage on outcomes, particularly in community health settings (Holroyd-Leduc et al., 2011, McAlearney et al., 2005). Furthermore, theories of technology adoption also indicate that social influence can play a significant role in enhancing or inhibiting adoption and use (Zheng et al., 2010). Physicians practicing in groups vs. solo may thus exhibit different trends in their usage patterns of technology for clinical care if they are influenced by their professional social networks, such as peers or opinion leaders.

This study summarizes our results on the analysis of adoption and usage trends in a community hospital setting which has deployed several mobile clinical applications for daily patient care. Approximately 250 physicians across solo and group practices have been using mobile devices since June 2006 to access the applications. We analyze twenty-two months of usage data to understand the trends in physicians' use and adoption of specific clinical applications. Applying a novel, semi-parametric, group-based, statistical methodology, we obtain developmental trajectories depicting how usage evolves from initial 'trial' adoption to long-term institutionalization. We examine this developmental pattern to understand which applications get adopted, who adopts them or not, and how these users can be clustered and profiled. Additionally, we provide some preliminary estimates of the potential of social influence on adoption. These insights may provide better guidance for the design and deployment of appropriate, targeted interventions to improve adoption and use in diverse care delivery settings.

In the following sections, we describe the background, study setting, datasets analyzed, methods used, a descriptive and analytical summary of results, and finally, some discussions and conclusions on the adoption of mobile health technologies for clinical care.

2.0 Background

There is a broad range of literature on technology adoption using methods from the discipline of social psychology which is applied to information systems field, such as using the Theory of Reasoned Action (TRA, Ajzen and Fishbein 1980), Technology Acceptance Model (TAM, Davis 1989), and Theory of Planned Behavior (TPB, Ajzen 1991). These models utilize surveys to gather information about technology adoption in order to find empirical evidence of the motivation or factors influencing the adoption. Such surveys typically collect users' self-reported, subjective opinions about the usefulness and ease of use of the technology, and not objective, actual usage of a newly implemented information technology system.

In his classic book, *Diffusion of Innovations,* Rogers (2003) noted that technology adoption is a continuous process that evolves over time. Initially, people observe an innovation with uncertainty, hence they may be reluctant to adopt the technology immediately, but instead they seek out others who have already adopted the innovation in order to learn from them and thus reduce their uncertainty. Thus the innovation will diffuse from the early adopters to their circle of acquaintances over time. Rogers' book emphasizes two aspects of adoption behavior: first, it is a learning process over time, and second, adoption does not happen in an isolated manner but develops under social influence, such as peer effects and opinion leader effects, in a social system during the adoption process (2003).

Peer effects are a type of social interaction which have been investigated in many fields, such as agriculture (Munshi 2004), marketing (Hartmann 2010), pharmaceuticals (Ching and Ishihara 2010), healthcare (Valente 2007), impact of social networks on Electronic Health Record adoption (Zheng et al. 2010; Sykes et al. 2011), and information appliances (Hong and Tam, 2006). Some studies have investigated asymmetric peer influences, or opinion leader effects, such as opinion leader physicians influencing other physicians on new drug prescriptions but not vice versa (Nair et al., 2010), or attractive consumers impacting average consumers' consumption experiences (Argo et al. 2008). The classic Bass model also shows that consumers' adoption time scales are different as some people adopt earlier and others later (Bass, 2004). The 'S' curve associated with innovation diffusion trajectory captures the early adopter effect and shows that users do not adopt a new technology or a new product at the same time (Rogers, 2003). Thus the early adopter may affect the later adopter, not vice versa, and this is also asymmetric peer influence. There is limited empirical research on peer and opinion leader effects on information technology adoption in health care delivery.

This study contributes to the existing literature on technology adoption and diffusion by using actual usage data rather than surveys to understand the evolution of physicians' mobile technology usage behavior over time and the potential influence of their social system in the care delivery environment.

3.0 Study Setting, Data and Methods

3.1 Study Site

Our study site is a progressive, community-based healthcare delivery system located in southwestern Pennsylvania in the United States. In partnership with more than 500 physicians and nearly 4,000 employees, the health system offers a broad range of medical, surgical and diagnostic services at two hospital locations with over 500 beds and five affiliated community satellite facilities. In June 2006, the health system deployed a Mobile Clinical Access Portal (MCAP), which is a secure, wireless, Personal Digital Assistant (PDA) based client-server solution providing physicians with 3 years of online clinical data accessible via their PDAs through any WIFI or broadband connection point. Thus, the MCAP solution provided a view of patients' electronic health records.

MCAP initially deployed 266 clinical applications, such as entering patient demographic data, accessing medical histories, electronic prescribing, placing lab orders, checking lab results, reviewing patient summary data, real-time decision support and other related functionality. Not all the features were deployed at the same time, but over 75 percent of the features were tried or used in the first three months of deployment. The requirements analysis and system design were updated and many features were revised and changed over time. After one year, approximately only 24 features continued to be frequently used, with lab-related and search-related applications being the most frequently utilized.

The system was made available to all physician users free-of-charge, but not all the users received the PDAs at the same time; however, around half the users received the hand-held devices in the first five months of deployment. Usage was 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.

The opinion leaders defined in this study are physicians who were identified exogenously by the health system administration based on their longtime dynamic observations, referred to as the informants' rating method (Rogers, 2003). These opinion leaders were early adopters and also the influential people in this health system; they were enthusiastic supporters of MCAP implementation and use, which they encouraged the health system administration to launch. They received the hand-held devices to access MCAP as its early users, and adopted the new technology within the first two months of deployment.

3.2 Data

The MCAP usage data consisted of approximately 363,000 records, representing all applications used at any time by any physician from June 2006 to March 2008. Two datasets were merged for this analysis. One dataset captured de-identified demographic information about 250 physicians, including a unique identifier, gender, age, primary specialty, sub-specialty, medical title, the date when the hand-held device was received, and, most importantly, which physicians practiced together in groups and which physicians were solo practitioners. The group practices were formed according to physicians' specialty areas and all the physicians in the same group came from the same or related specialty fields, such as Cardiothoracic Surgery and Cardiovascular Disease. The size of the group practices was based on market demand.

The second dataset was the log file of MCAP usage data from the MCAP server. This included physician identifier, usage date and time, and the clinical application that was accessed, representing MCAP usage over 22 months of 266 clinical applications by the 250 physicians. During data pre-processing, it was necessary to exclude 58 out of the 250 physicians from the first dataset due to missing demographic information or missing patient visit information, leaving 192 physicians in the merged file for the data analysis described in this study. Since almost 23 percent (58 out of 250) of the physician records were dropped due to incomplete data, a series of t-tests were performed to check for non-response bias. None of the t-tests were statistically significant.

Thus the merged data set in this study included 192 physicians with complete demographic and usage information: 54 physicians practicing by themselves (solo practice) and 138 physicians practicing in groups of varying sizes. All physicians were full time practitioners in 31 different specialty areas. For purposes of data analysis, we divided these 31 specialty areas into two categories, General Practitioner and Specialists, in order to examine how medical specialty areas may affect physicians' use or adoption of MCAP. General Practitioner included internal medicine, family practice and pediatrics, while Specialists included the remaining specialty areas. In addition, we grouped the physicians into three nominal age cohorts: under 45 years of age, between 46 and 55 years of age, and above 56 years of age.

Table 1 presents some basic descriptive statistics about the participating physicians. The female/male physician ratio was around 1:4. Their ages ranged from 30 to 78, and both the mean and median ages are around 50 years. The total number of physicians in general practice was about the same as the total number of physicians in all the specialties combined.

Number of physicians (included in the analysis)	192
Number of female physicians	40

Number of male physicians	152
Physician's average age	50
Number of physicians in General Practice (i.e., Family Practice, Internal Medicine, and Pediatrics)	94
Number of specialists	98
Number of specialties	31
Number of clinical activities supported by MCAP	266

Table 1. Descriptive statistics

Table 2 shows the number of physicians distributed across group practices by group size. Most groups have less than three physicians and only two large groups have nine and eleven physicians, respectively. There are 54 solo practitioners and 138 group practitioners. Not all practice groups had an opinion leader amongst them and some practices had several. Three of the early user opinion leaders were solo practitioners.

Group size	The # of groups	The # of practitioners	# of groups having opinion leader
1 (solo users)	54	54	3
Group users			
2	22	41*	3
3	11	30*	3
4	8	26*	3
5	3	13*	2
6	2	8*	1
9	1	8*	0
12	1	12	1
Sub-total	48 groups	138	13

* Demographic Information missing on some group members, thus they are excluded from further analysis

Table 2. Physician Practice Group Distribution (192 total users)

In the next subsection, we present the model used to understand physician's adoption behavior as they actually test the clinical applications available via MCAP in daily use. This model facilitates an understanding of the developmental pattern of adoption behavior from initial trials to institutionalized use/non-use, temporal dynamics of this evolution and group characteristics of the users.

3.3 Developmental Trajectory Analysis (DTA)

DTA is a semi-parametric, group-based, statistical approach, technically a finite mixture model, which describes the course of a developmental behavior over age or time (Nagin, 1999). DTA identifies rather than assumes groups of distinctive developmental trajectories. Such group identification enables estimation of the proportion of population following each such group, and measurement of the effect of individual characteristics and circumstances on probability of group membership. Furthermore, this group membership probability can be used to create profiles of members. DTA has been applied to studies of physical aggression among youth (Nagin, 1999) and technology adoption by residents in an outpatient clinical environment (Zheng et al., 2005, 2013) among others. In this study, we use DTA to help identify groups of similar users (similar patterns of usage over time) of the mobile applications and to identify demographic characteristics within each group that are statistically related to mobile application usage.

A brief overview of the statistical theory underlying the DTA method is given below. Let the vector $Y_i = \{y_{i1}, y_{i2}, \dots y_{it}\}$ represent the longitudinal sequence of individual i's behavioral measurement during t time periods. Let $P^j(Y_i)$ denote the probability of observing Y_i given membership in group j, and π_j denote the proportion of the population comprising group j. The unconditional probability of observing Y_i equals the sum across the j groups of the probability of Y_i given membership in group j, weighted by the proportion of the population in group j:

$$P(Y_i) = \sum_j \pi_j P^j(Y_i) \qquad (3.1)$$

Let $P^j(Y_{it})$ denote the probability distribution function of y_{it} given membership in group j at time period t. For a given j, conditional independence is assumed for y_{it} over t periods of measurement; thus:

$$P^j(Y_i) = \prod_1^T p^j(y_{it}) \quad (3.2)$$

The likelihood for the entire population of N individuals is:

$$L = \prod_1^N P(Y_i) \quad (3.3)$$

DTA models the linkage between time and behavior by assuming polynomial relationships. For the censored normal model, a quadratic relationship is given as:

$$y_{it}^j = \beta_0^j + \beta_0^j Month_{it} + \beta_1^j Month_{it}^2 + \varepsilon_{it} \quad (3.4)$$

where ε_{it} is a disturbance assumed to be normally distributed with a mean of zero and constant variance of σ^2.

In addition, a special effect of the analysis is the modeling of cohort effect that allows, for example, an examination of the impact of the cohort of opinion leaders on their peers, hence the revised model (3.4) is:

$$y_{it}^j = \beta_0^j + \beta_0^j Month_{it} + \beta_1^j Month_{it}^2 + \ \dots . + \beta_{n-1}^j Month_{it}^n + \delta X + \cdots + \varepsilon_{it} \quad (3.4)'$$

For the censored normal distribution, the probability distribution function of y_{it}, given membership in group j, is:

$$p^j(y_{it}) = \frac{1}{\sigma}\Phi(\frac{y_{it} - \beta^j x_{it}}{\sigma}) \quad (3.5)$$

Where Φ is the density function of a normal random variable with mean $\beta^j x_{it} = \beta_0^j + \beta_0^j Month_{it} + \beta_1^j Month_{it}^2 + \ \dots . + \beta_{n-1}^j Month_{it}^n + Cohort$ and standard deviation σ. The model parameters of interest, β_0^j, β_1^j, β_2^j, etc. can thus be estimated by maximum likelihood approach. The maximization is performed using a general quasi-Newton procedure. Note that the model parameters, β_0^j, β_1^j, β_2^j,, etc., may differ from cluster to cluster, which is the key feature of this method since it allows for easy identification of population heterogeneity not only at the level of behavior at a given stage, but also in its development over time (Nagin, 1999).

DTA has a distinctive advantage over classical clustering methods by using the Bayes factor to compare models; it is thus able to determine the optimal number of clusters as well as appropriate order of the polynomial used to model each group's trajectory. The Bayesian Information Criterion (BIC) (Schwarz, 1978) for a given model is calculated as follows:

$$BIC = \log(L) – 0.5*Log(n)*k \quad (3.6)$$

n is the number of data points and k is the number of free parameters. BIC is the model selection criteria used in our analysis.

4.0 Results

4.1 Descriptive Summary of Physician Usage Data

In the following discussion, we present some general trends in usage over 22 months by physicians in various demographic groups. Figure 1 shows the total MCAP usage by all the physicians over the 22 months. The total usage by all users over time does not vary significantly (between 15,000 and 20,000 per month), although the number of users increased significantly over the first five months (see Figure 2). The number of physicians using MCAP in any month remained fairly steady as well. This seems to indicate that early users, though fewer, were more active users of the mobile device and its deployed applications than later users.

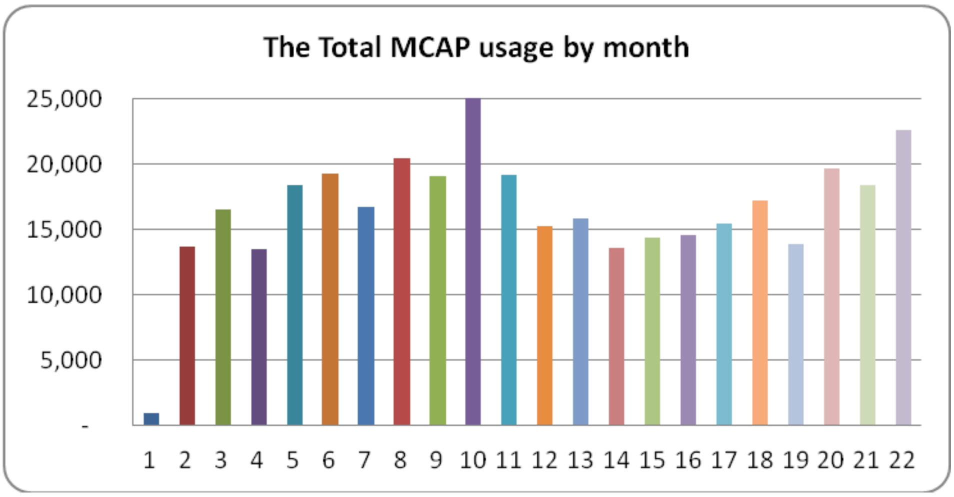

Figure 1. Total MCAP usage by month

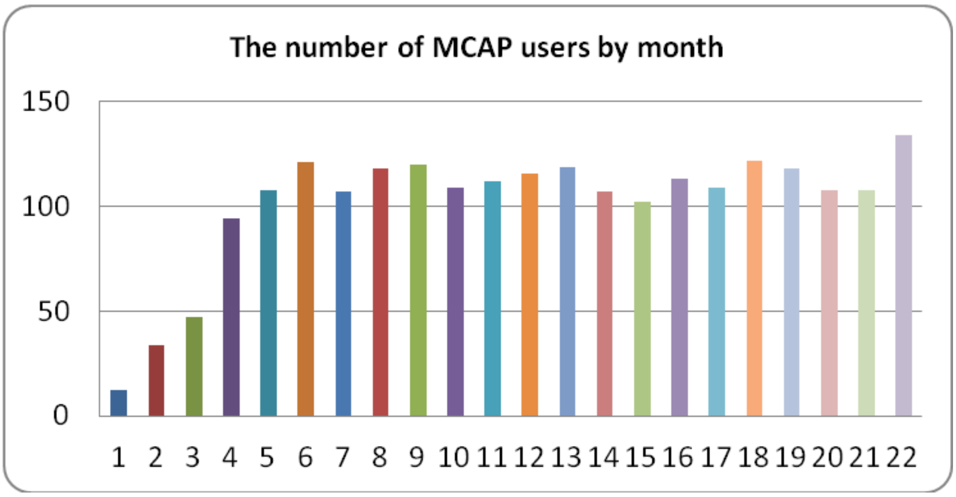

Figure 2. The number of MCAP users by month

In the first few months, there were only two female users and both of them were heavy users, as depicted in Figure 3. This tapered off considerably as more female users were given access to MCAP. Similarly, Figure 4 shows that specialist physicians have higher average usage than general practitioners while Figure 5 shows that for most months, older physicians (> than 51 years) have higher average usage compared to those below 35 years or those between 35 and 50 years, particularly remaining steady after the tenth month.

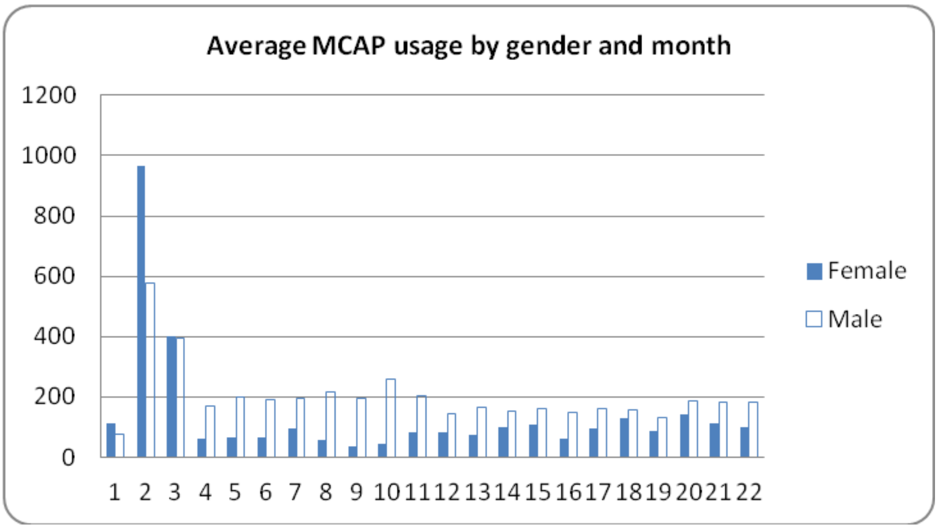

Figure 3. Average MCAP usage by gender and month

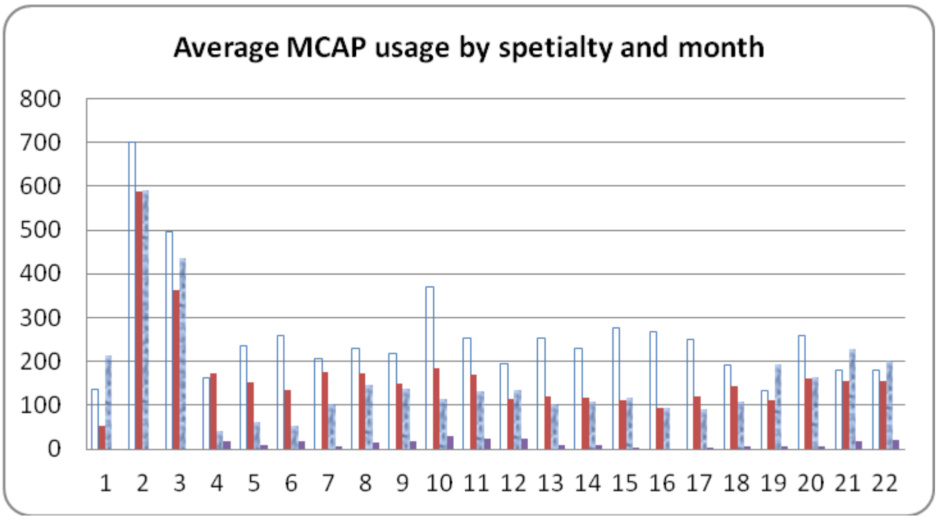

Figure 4. Average MCAP usage by specialty and month

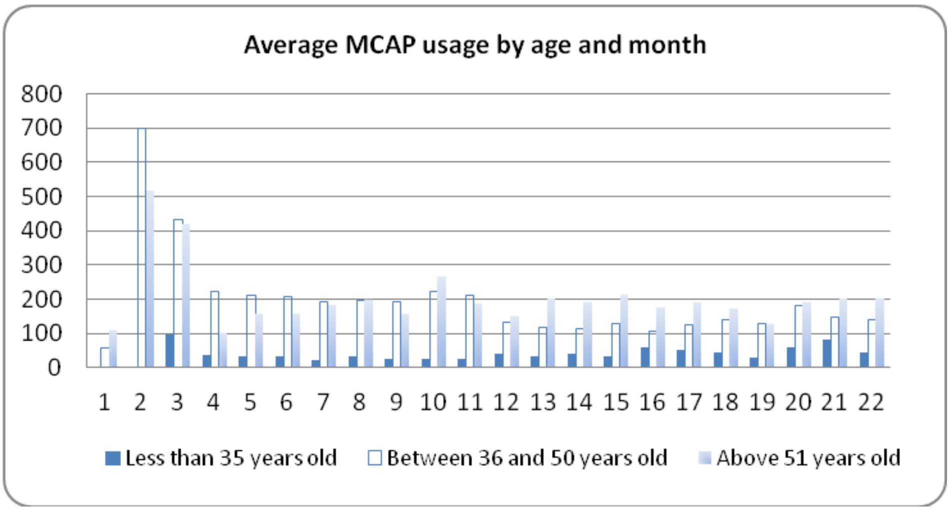

Figure 5. Average MCAP usage by age and month

Figure 6 is a single snapshot of the average monthly MCAP usage, which is the total MCAP usage adjusted by the total number of months each physician had access to the PDA. We observe that most physicians used the PDA under 10 times per month, on average. The second largest group used the PDA between 10 and 50 times per month, leaving around 66 physicians who used the PDA more than 50 times per month. We consider this last group to be quite a stable group of users who have adopted the mobile device to access the various clinical applications deployed.

However, recognizing that average usage cannot represent the real patterns of adoption and use by each user over time, we apply the more dynamic method of DTA to examine this evolution.

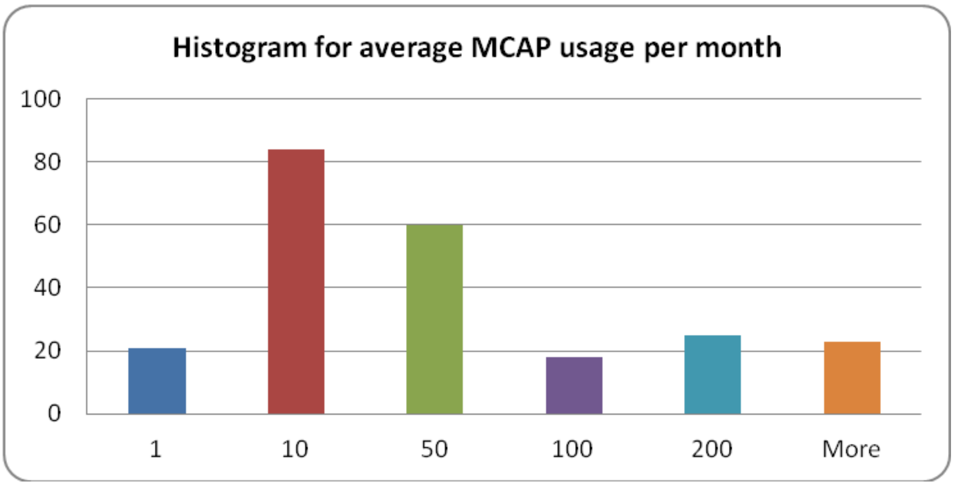

Figure 6. Average MCAP monthly usage

4.2 Analysis of Mobile Clinical Features Used

An analysis of the deployed applications used by any physician in any month indicates that the number of applications accessed decreased dramatically from a high of 266 clinical features available at the time of initial deployment to just 24 at the end of a year. Based on MCAP usage data, we find that 218 out 266 (81%) PDA–based activities were used less than 10 times and 31 out of 266 (11.6%) such features were used between 10 and 400 times in this two year time period, which indicates extremely low usage of the whole system. Only 24 features continued to be used after the first year, of which 18 features were used more than 400 times over this study period.

We categorized all the features into a few groups according to their functions, such as lab related features which include all features such as ordering new labs, checking lab results, looking up abnormal labs, and so on. Another group is search related features, which encompass all features including a search function, e.g. searching patient names. The third group is the e-prescribing feature, which led physicians to an external e-prescribing website. This application was offered late in the study period, and as expected, general practitioners were the heavy users of this activity. The fourth group encompassed order related features which allowed physicians to place orders for their hospital inpatients. Table 3 shows that lab related features were the most frequently used feature, and on average, almost 60 percent of all the MCAP usage was lab related, and accessed by specialists and general practitioners alike. In some months, about 80 percent of MCAP usage was lab related.

Average usage	Specialists	General Practitioners
Total features	1565	1664
Lab-related features	1162	895
Search-related features	36	43
E-Prescribing	0.04	120
Order-related features	4	4
The number of users	80	94

Table 3. Average usage of different types of features

4.3 DTA Results

To conduct the developmental trajectory analysis (DTA) on physicians' MCAP adoption and usage, we removed three physicians who were extraordinary outliers. They were very heavy users, at a level 10 times more than any other physician per month. Different model specifications were tested using demographics for trajectory grouping. Most model results were qualitatively the same, such as that they all have the same trajectory clustering for best fit, and the same direction for the significant variables. There were minor differences in group compositions or the estimated parameters across the different models, as well as the BIC values. The BIC value indicated that the model with time, opinion leaders' cohort, and the interaction between time and opinion leaders' cohort, was the best for identifying the trajectory groups for this data.

The best model was based on the model (3.4)' along with the interaction terms of the peer cohort and time periods. The best fit was obtained when dividing the 189 physicians (three heavy outlier users were removed) into four groups, with a linear fit for the first two groups, a quadratic fit for the third group, and a cubic fit for the fourth group. Figure 7 depicts the four groups of physicians according to the DTA model and Table 4 presents the demographic characteristics within each group that are statistically related to mobile usage.

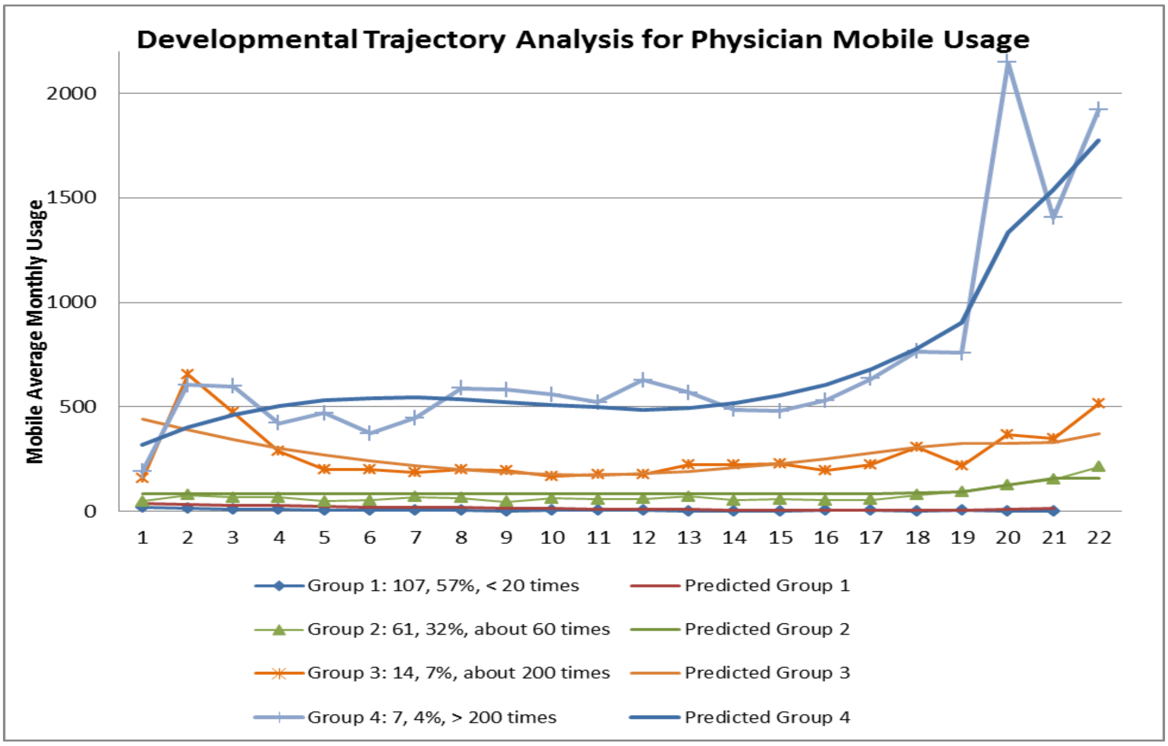

Figure 7. Developmental Trajectory Analysis Results

Group	# of Users	Average Age	# of GP	# of male	Less than 35	Between 36 and 50	Greater than 51
1	107	51	37	81	32	35	40
2	61	48	42	49	23	27	11
3	14	50	7	13	6	5	3
4	7	47	3	6	4	2	1

Table 4. DTA Group Characteristics

Group 1 is the largest group, consisting of 107 out of 189 physicians, with monthly usage at less than 20 times, on average. The monthly usage of this group is stable but decreasing slightly, until a small upsurge at the end of our available data. Thus, this large group of physicians appears to be unenthusiastic about the MCAP system, perhaps not convinced of its value, or these individuals may be relying more heavily on other forms of technology (e.g., desktop computers in their offices). This group includes many physicians who had zero usage during many of the months. We conclude that this group never really adopted the mobile accessible system or used it in their daily work. While the average age of each of the groups did not differ significantly, as shown in Table 4, Group 1 had a much larger proportion of specialists and older physicians than other groups.

Group 2 consists of the second largest group of users, with 61 out of 189 physicians (32%). They used the mobile device around 50 to 100 times monthly in the first 20 months, then increased to around 200 times. Given their higher average level of usage, we conclude that this group of physicians adopted the system and began using it regularly at a slightly increasing rate, i.e., slowly rising over the final seven months of the data series. Groups 3 and 4 are small groups (only 14 and 7 physicians, respectively), but are heavy users. Group 3 shows an unusual pattern, with an early peak, a decline, and then a steadily increasing average usage over the second year of usage. Group 4 includes the heaviest users among the four groups. Monthly usage rose to around 500 per month almost immediately, and increased further over the study duration. In addition, a potentially fifth group could be the two omitted physicians who displayed the heaviest usage. These two cases seemed to be unique outliers. Thus, altogether, about 42 percent of the physicians (Groups 2, 3, 4, and the three outliers) show evidence of some level of adoption of the system, and some increase in usage over time. However, we could not obtain additional data from the health system about physicians' motivations, behavior, constraints, or subjective opinions to further clarify the determinants of adoption and usage.

Besides the polynomial fit, the opinion leader cohort (OPL variable) and the interaction between the opinion leader cohort and time periods (OPL x Time Period) for all four groups were other factors included in the model. As shown in Table 5 for each DTA grouping, OPL variable is positive and statistically significant for Groups 1, 2 and 4, which suggests that the presence of an opinion leader in these groups increased monthly usage for the groups. However, for Group 3, the interaction between opinion leader and time period is negative, which may indicate that while opinion leader may impact monthly usage, this impact can also change over time. The negative sign of the interaction term of OPL and time period may explain why Group 3 shows an early increase in MCAP and then a decrease later. However, the small size of Groups 3 and 4 and the heavy usage by group members make it difficult to infer any definitive effect of opinion leaders in these two groups. Yet, there is clearly an indication that opinion leaders can influence adoption and use of new mobile health technologies in the clinical care delivery environment. While DTA illustrates the evolving nature of technology usage in this environment, the ability of the model to include the cohort effect over time and its significance in some groups but not others indicates that more nuanced models need to be developed to better understand social influence.

Group		Parameter Estimate	Std Err.	T for H0: Parameter=0	Prob. > |T|
	Intercept	-175.69*	10.62	-16.537	0
	Linear	-104.65*	12.14	-8.623	0
	OPL	106.23*	20.10	5.285	0
1	**OPL*Time Period**	33.59	28.86	1.164	0.2445
	Intercept	28.42*	7.12	3.992	0.0001
	Linear	-6.11	9.24	-0.661	0.5085
	OPL	100.44*	13.33	7.537	0
2	**OPL*Time Period**	22.15	19.13	1.157	0.2472
	Intercept	150.22*	15.46	9.715	0
	Linear	142.63*	24.57	5.805	0
	Quadratic	268.03*	28.39	9.442	0
	OPL	38.98	20.40	1.911	0.0561
3	**OPL*Time Period**	-271.81*	32.25	-8.428	0
	Intercept	458.19*	21.60	21.216	0
	Linear	-99.49	51.22	-1.942	0.0522
	Quadratic	326.85*	51.70	6.322	0
	Cubic	483.77*	74.20	6.52	0
	OPL	187.71*	37.03	5.069	0
4	**OPL*Time Period**	179.44*	58.35	3.075	0.0021
	Sigma	147.77	2.60	56.79	0

* indicates statistically significant at 5%

Table 5. Opinion Leader and Temporal Effects using DTA

5.0 Discussion and Conclusions

From the analysis of physician usage, it appears that physicians who began using the system earlier, i.e., within the first three months of deployment, were heavier users. They were also stable and routine users of MCAP. In general, this community health system physicians were mostly non-users or light users (less than 100 times over the total 22 month time periods), likely due to the voluntary nature of MCAP deployment and access to patient information through other channels of access such as clinical workstations, and laptop and desktop computers. Even though the Developmental Trajectory Analysis identified four usage trajectories, only about half the physicians used the mobile clinical system regularly and consistently. The remaining may have tried the system but did not continue to really use it effectively. This argues for a more dynamic definition of the adoption decision as a function of physician users' own individual level demographic characteristics, the user group's level of social interaction, and the work environmental characteristics. The DTA analysis also provided preliminary indications of social influence via opinion leader effects that varied over time. The quantitative impact of this influence and the mechanism by which this influence reduces their peers' uncertainty about the value of MCAP for clinical care is ongoing research.

We may assume that there are two types of social influences in this study. The first social influence is the opinion leader effects discussed briefly in this paper, where opinion leaders are influential physicians who were also early adopters. The second social influence is peer effects, which are from general physician colleagues or peers who work in the same group who may not be influential or early adopters. However, peer effects may be present even though they may not be as strong as opinion leader effects. Hence, future research needs to examine these two types of social influence, opinion leader effects and peer effects, on a dynamic adoption decision in this environment.

The potential impact of opinion leaders on physician users' adoption decision may have important policy implications because, if these effects exist on peer physicians' technology adoption behavior, then decision makers can concentrate on working with a finite set of opinion leaders to incentivize and encourage them to adopt complex technologies early. This adoption could, subsequently and more naturally, influence their peer users' technology adoption behavior within an organization through social multiplier effects. In addition, examining other factors such as gender, age, specialty area, work environment and work load may also have positive and statistically significant impacts on mobile information technology adoption. Technology providers, implementers, and decision makers should be aware of these factors as well, because they may be utilized to encourage mobile IT adoption in the clinical care delivery environment.

From our analysis of the clinical features used, we observed that 81 percent of the clinical features were used less than 10 times during the entire study period, and only about 9 percent of the features were still being used one year after the deployment. One reasonable explanation that was given for this lack of use of the mobile channel was that the range of alternatives available to physicians to access this information, such as desktop applications and phone messaging, as mentioned earlier, and the health system provided little incentive to explore and adopt yet another channel of access to patient health data. E-prescribing, described in the literature as a critical function for motivating clinicians to adopt mobile technologies, was deployed too late in the study period to detect significant impact, but saw some uptake by general practitioners, but not by specialists.

Future research needs to explore this lack of uptake in mobile access to patient information despite the articulated benefits of this technology for a mobile work force. Furthermore, adoption and continued usage of these systems may also be motivated by local opinion leaders and peer groups. In ongoing research, we are exploring the impact of such socio-technical factors in this environment, and in particular, the theoretical and practical mechanisms involved in its development, and models and methods for quantifying the impact.

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