CHARACTERISTICS OF MOBILE HEALTH INFORMATION SEEKERS IN INDIA: UNDERSTANDING EARLY ADOPTERS

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ABSTRACT

There is a growing expectation that the rapid proliferation of mobile phones would increase patients use of these devices for own healthcare needs. But to what extent are patients ready for mobile health? A fundamental assumption is that the increased use of mobile phones would increase its use for health information seeking. However little research has focused on the factors that determine health-seeking behavior amongst mobile phone users. This study uses Indian data sets from global attitude survey conducted by Pew in 2014 to provide a baseline for the use of mobile phones for health information seeking (MHISB), The aim is to find association between MHISB, demographics, socio-economic status, internet use, social media and mobile information use for the purposes other than using for healthcare. The result of the study indicates that there are potential new media use determinants for mobile health information seeking. As divide in access is narrowing with increased adoption of mobile phones by lower strata of society, there appears to be an increasing "usage divide" between health information seekers and non-seekers. Using binary logistic regression analysis, the study finds 'use affinity effect' in which, more user engages in one type of information seeking, the higher are their probability of using mobile for health information seeking. An alternative explanation of complementary information use is suggested.

KEYWORDS: *Health Information Seeking Behaviour, Mobile Phones, India, Early Adopters, mHealth, Information and Communication technology (ICT) Binary Logistic Regression.*

INTRODUCTION

The thrust given to mHealth initiatives and widespread availability of health-related Internet websites and apps have raised hopes for new, tailored modes of health communication to meet the specific requirements of the patients and other stakeholders in the healthcare setting (**Yellowlees, 2015**). Use of mobile phones for health is seen as a disruptive application of new information and communication technologies (ICT) that can significantly alter the modalities of healthcare delivery and patient responses.

Self-care has emerged as one of the primary strategies for improving the outcome for the patient and to reduce the burden on health care services, both in public and private domains (Jung, 2013). MHealth applications and services are seen as a means to improve the quality of healthcare, its affordability, accessibility, security, and efficacy are considered (**Athavale, 2010; Prabhu, 2013**). The growth of mHealth in

India has been predicted on the typical mobile use by patients. In India, mobile phones have reached an estimated 833.02 million active subscribers (Urban share stands at 58.33% as compared 41.67% of rural subscribers) (**TRAI Annual Report, 2015**) in 2014. mHealth has received significant attention as a potential facilitator for addressing the core problems facing the healthcare sector in the country (**Jaroslawski, 2014**)

MHealth initiatives in India anticipate substantial engagement from the patient as a central stakeholder through the use of new information and communication technologies. Patients are expected to be empowered enough to access health information about their health status, risk factors, treatment options, potential side effects, self-management strategies, and provider's interests and motives (**Kaphle, 2015**). Mobile phones are also expected to reduce costs in terms of finance, time and human resources. Improvements in care delivery and coordination are also seen as a potential beneficial outcome of using mobiles for healthcare (**Jaroslawski, 2014**)

A fundamental assumption is that the increased use of mobile phones amongst the general population would increase patients use for health information seeking. However, little research has focused on the factors that determine health-seeking behaviour amongst mobile phone users. There is also little baseline data on the use of mobile phones for health information seeking amongst the general population. As a consequence, there is also a lack of empirical evidence for the patient's engagement in mobile health information seeking behavior (MHISB).

This research seeks to fill this gap by attempting to establish baseline data for MHISB. Such baseline data are vital for understanding the characteristics of early adopters of new technologies and hence can help in anticipating the trajectory of use of mobile phones for healthcare. The absence of data on MHISB in general population might frustrate early efforts in mobile healthcare intervention as it might lead to a mismatch between target audiences and actual patients at risk. On the other hand, data on early adopters can help improve both curative measures as well as preventive measures by enabling development of better profiles of target groups. Further such bass line analysis can help in the recruitment of people for testing various mHealth apps, information services, the conduct of RCTs and better segmentation of the market for tailored health communication interventions using mobile phones.

Hence two fundamental questions need to be addressed: 1) To what extent general public use mobile phones for health information seeking? What are the characteristics of early users engaging in MHISB? What factors contribute to an increase in the likelihood of health-related use to mobile phones? Based on the literature on health information seeking behavior (HIS), diffusion of innovation and findings from studies on the digital divide, this paper attempts to provide empirical evidence for the above two questions.

LITERATURE REVIEW

Models of health information seeking (HIS) have an extensive empirical grounding in academic literature (**Li, 2015**). The relationship between new media and HIS has been explored whenever a new technology has received widespread adoption and use amongst the general population and the patient communities. Several models have been used to study HIS behavior (**Johnson and Case, 2012**), the widely adopted being 1) Health Information Acquisition Model 2) Expanded Conceptual Model of Information Seeking Behaviour 3) Risk Information Seeking and Processing 4) Comprehensive Model of Health Information Seeking. The HIS research tradition has been extended to the study of online health information seeking, especially since the widespread adoption of the Internet (**Scrivener, 2002**). The Internet as a source of online health information has been subjected to a critical empirical examination with a two-primary focus (**Jones, 2014; Boot, 2010**). Firstly, studies have examined the quality of health content available online (**Clarke, 2015**). These studies applied content-analytic techniques, typically with an expert assessment of source credibility (**Rice, 200**). The second set of studies, rooted in information needs assessment methods, has taken a user-centric approach focusing on behavioural dimensions of active and passive users (**Johnson and Case, 2012**). Patient care in the various setting is a recurring theme in these studies (**Clarke, 2015**). Several studies have been undertaken from the perspective of health consumers (**Lewis, 2005; Dey, 2004**) and health informatics, which focuses on the design of information systems within health administration (**Walker, 2005, Hayes, 2010**). HIS studies have also examined the information behavior of doctors and other caregivers (Y**ounger 2010**). Patients experiencing a wide range of disorders or disease type have been covered under HIS studies. For example, extensive work has been conducted for HIS in the context of 1) cancer (**Desai, 2015**) 2) diabetes (**Jamal, 2015**) 3) Hypothyroid (**Perumal, 2015**) 4) mental health (**Kauer, 2014; Ayers, 2013; Weaver, 2010**) 5) genetic information (**Hamilton, 2015**) 6) pregnancy and antenatal care (**Pfaff, 2010**). Many of these studies have incorporated concepts from the Comprehensive Model of Information Seeking (**Johnson, 1995**), which suggests the continuity of HIS research tradition across diseases types, information carriers, user groups, and information categories.

Given the rapid developments in mobile communication, it is surprising that HIS literature has not paid sufficient attention to the use of mobile phones for health information needs. For example, one of the most comprehensive and authoritative works on the field by **Johnson and Case**, (2012) does not include any studies exploring the potential of mobile phones for HIS. However, the emphasis of HIS research has been shifting with the popularization of concepts like mHealth and the widespread availability of health apps on smart phones.

Studies related to mobile phone use in the healthcare setting have focused on themes that are in continuity with HIS research. These include HIS studies that focus on 1) health professionals' use of mobile phones (**Dexheimer, 2013**) (2) smart phone apps as a source of cancer information 3) changing trends in health information-seeking behavior. (**Pandey, 2013**) 4) user acceptance of mobile phones for health information (**Lim, 2011**) 5) comparative analysis of using personal computers and smartphones for consumer health information (**Jadhav, 2014**) 6) culturally sensitive tailored communication (Rushing, 2011) 7) provision of mobile access to healthcare services older adults (**Shahrokni, 2015**). 8) Use of mobile phones for improving conditions of patients with chronic diseases (**Ramachandran, 2015**) 9). provision of clinical guidance for rural health providers in India using mobile devices (**Gautham, 2015**).

There are very few studies on mobile health information seeking in the Indian context. Therefore, it was felt that the appropriate approach would be to establish a baseline of the user profiles of early adopters of mobile phones for HIS behavior. Previous studies on HIS has indicated that gender, education, income, SES, geography, ethnicity, family structure play a role influence HIS behavior. In addition to these, complimentary use of media also affects mobile phone usage for HIS (Ruppel,2012).

From this, we arrive at the following research questions:RQ1: Are socio-demographic characteristics (as indicated by gender, age, marital status,) associated with mobile health information seeking? RQ2: Are socio-economic characteristics (as indicated, employment status and education, income) associated with mobile health information seeking? RQ3: Does the frequency of Internet use associated with mobile health information seeking? RQ4: Does social media usage associated with mobile health information seeking? RQ5: Does mobile phone usage (as indicated by other activities done with mobile phones) associated with mobile health information seeking? Overall this research seeks to examine the determinants of HIS behavior using mobile phones in the Indian context.

METHOD

The data for this study was drawn from the 2014 Pew Research Centre India survey (2014). The Survey in India conducted between December 7, 2013, and January 12, 2014. Adults over 18 (N=2,464) were interviewed in local language and responses recorded through a structured questionnaire. The survey covered fifteen of the seventeen of the states and Union Territories with most population, which together represents about 91% of the adult Indian population (**Pew, India Survey, 2013-14**).Area probability design was used for sampling, by proportionally allotting 1876 interviews to regions and urbanity (with over-sample of 588 interviews in urban regions. The sampling unit was urban settlements and rural districts; with a margin of sampling error is ±3.8 percentage points and confidence levels of 95%. Details about the PEW have been published elsewhere Pew, India Survey, 2013-14). Thus, PEW data collection appears to be geographically representative and approximates the demographic distribution of the population matched from the 2011 Census of India (**GOI, 2011**).

Data were extracted from the PEW as save file and was read into SPSS to a data set for all analyses. The final sample for this paper was drawn (N=1740, after removing outliers and respondents with too many missing data) from four regions of the country (North=35.4%, South=22%, East=23.4%, and West=22%) and rural and urban regions (rural=61.8% and urban 38.2%).

The Pew includes questions on a variety of health outcomes, demographic variables, and individual characteristics and media use. Respondents profile and the relationship were crossed with MHISB after collapsing the ordinal and interval measures into two and three category variables (age, education, income, household size). SES was constructed by summing education and income. The operational measures of the variables under consideration are presented along with preliminary exploratory analysis done using the chi-square test (Table - 1). Independent sample t-test was used for examining the mean difference in education, income, SES, social media use, mobile information use between MHISB users and non-users (Table - 2).

In order to understand the characteristics of respondents who engage in the MHISB, a multivariable binary logistic regression was computed. Odds ratio was used to assess the use of the mobile phones for health information seeking across exploratory variables; multivariable logistic regression models were built to determine which variables were related to MHISB (**Anker, 2011**).

Demographics, SES, Frequency of Internet Use, Social Media Use and Mobile Information Use (MIU) measures were included as independent variables in the logistic model. While MHISB activities are reported less frequently than using the mobile for general information use, the mobile information use (MIU) factor was included in a second analysis to test the association between MHISB and individual MIU items. In line with the previous studies, the results of the logistic regression are presented as odds ratios (OR) with the corresponding standard errors, 95% confidence intervals, coefficients, and Wald Statistic.

RESULTS

Mobile Health Information Seeking (MHIS) was the response to the item "get information about health and medicine for you or your family, coded a dichotomous variable (1-yes). The answer to the question about the use of the mobile for health information was the dependent variable. Of the total sample (N=1740), 11.8% responded in affirmative to the question, with slightly more men (12.6%, n=1006) answering yes than women (10.6%, n=734). The notion that people are increasingly using the mobile as a source for obtaining health and medicine related information needs to be moderated in the light of the low response to MHISB question.

Age wise (M=36.76, SEM=12.94), a higher proportion of 30-39 yrs. old used mobile for health information (12.3%, n=381) than the younger respondent (11.4%) and older respondent (11.9%), suggesting that middle-aged people are more likely to use mobile for health information. However, chi-square did not find a significant difference in MHISB with gender or age or urbanity. This implies that some of the traditional sources of digital divides are not likely to be a factor in mobile health information seeking.

Table - 1: Demographic and Socio-Economic Characteristics of Respondents with MHISB

		Seek Mobile Health Information					
Variables		Yes %	No %	N	χ^2	df	p
Gender	Male	12.6	87.4	1006			
	Female	10.6	89.4	734			
	Total %	11.8	88.2	1740	1.629	1	.202
Age Group	40 Yrs and Above	11.9	88.1	691			
	30-39 Yrs	12.3	87.7	381			
	18-29 Yrs	11.4	88.6	663			

	Row Total	11.8	88.2	1735	.189	2	.910
Highest Educational Qualification	Some College/PG	20.2	79.8	187			
	Up to 9 Yrs Schooling/SSC/HSC	10.6	89.4	1169			
	Illiterate/Up to 4 Years School	10.6	89.4	380	15.086	2	.001
	Total %	11.7	88.3	1736			
Monthly Household Income	Above Rs 10,000	15.9	84.1	456			
	Rs 5001-Rs10,000	18.5	81.5	524			
	Up to Rs 5000	4.4	95.6	752			
	Total %	11.7	88.3	1731	70.53	2	.000
Employment Status	Yes, employed	14.4	85.6	833			
	No, not employed	8.7	91.3	888			
	Total	11.4	88.6	1721	13.87	1	.000
SES	High SES	16.5	83.5	738			
	Middle SES	11.1	88.9	541			
	Low SES	4.1	95.9	449			
	Total %	11.6	88.4	1728	41.30	2	.000
Marital Status	Married	11.1	88.9	1338			
	Not Married/Others	14.1	85.9	395			
	Total %	11.8	88.2	1733	2.704	1	.100
Internet Use	Yes	26.6	73.4	271			
	No	8.2	91.8	1424			
	Total %	11.2	88.8	1695	77.39	1	.000
Frequency of Internet Use	Several times a day	30.2	69.8	84			
	Once a day	33.1	66.9	82			
	At least once a week	27.5	72.5	61			
	Less Often	6.7	93.3	36			
	Total %	27.3	72.7	263	9.888	3	.020
Mobile Phone Use	Yes	11.8	88.2	1740			
	No	0.0	0.0	0			
	Total %	11.8	88.2	1740			
Smartphone Use	Yes	21.7	78.3	275			
	No	10.1	89.9	1423			
	Row Total	12.0	88.0	1698	29.83	1	.000
Social Media Use	Yes	32.2	67.8	198			
	No	6.1	93.9	155			
	Total %	20.8	79.2	353	36.94	1	.000
Social Media Usage	High	42.2	57.8	85			
	Moderate	24.5	75.5	83			
	Low	29.1	70.9	23			
	Total %	32.9	67.1	192	6.409	2	.041
Mobile Information Usage (without health information)	High	21.8	78.2	439			
	Moderate	17.5	82.5	570			
	Low	0.5	99.5	698			
	Total %	11.7	88.3	1707	146.24	2	.000

Comparing educational status with MHISB, we find that respondent with some college or postgraduate degree indicated higher MHISB (20.2%, n=187) than those with only high school level education (10.6%, n=1169) and illiterate or those with primary school education (10.6%, n=380). Chi-square test showed a statistically significant difference in MHISB along educational level (χ^2=15.08, df=2, p<.001). Respondents with fulltime employment showed a significantly higher MHISB (14.4%, n=833) than those unemployed or working part-time (8.7%, n=888) with significant chi-square statistic (χ^2=13.876, df=1, p<.000). Middle income group earning about Rs 5000 to 10,000 showed higher MHISB (18.5%, n=524) than higher income group (15.9%, n=456) and lower income group (4.4%, n=752) with significant difference in chi-square (χ^2=70.533, df=2, p<,.000). Combining income and education we constructed a socioeconomic status (SES) variable (Mean=5.67, SD=.048) which indicated a statistically significant difference in mobile health information use, with higher SES (16.5%, n=738) having higher MHISB than middle SES (11.1%, n=541) and lower SES (4.1%, n=449), (χ^2=41.309, df=2, p<.000).

Household size was operationalized through the question, "How many people live in your household including yourself"? (Mean=5.67, SD=.048) which was categorized into three groups with one to four household members (36.4%), five to six household members (35.4%) and family of more than seven household members (28.2%). We find a significant difference in MHISB between users from nuclear family (15.2%) than from large households (6.2%) and moderately sized (12.3) (x2=21.26, df=2, p<.000).

Internet Use was indicated by the question 'do you use the Internet, at least occasionally?'.Internet users indicated higher MHISB (26.6%) than non-users (χ^2=77.40, df=1, p<,.000, n=271).The frequency of internet use measured using the question 'how frequently do you use the Internet" and responses were recorded along Less Often, At least once a week, Once a day, Several times a day. MHISB indicated a significant difference (χ^2=9.89, df=3, p<020). This suggests a positive relationship between the frequency of internet use and MHISB.

Mobile Phone use was indicated by two questions 'do you own a cell phone? Also, 'some cell phones are called "smartphones" because they can access the internet and apps. Is your cell phone a smartphone?' Smartphone use (χ^2=29.84, df=1, p<.000, yes=21.7%, n=275).Social media use was measured using the questions "do you use social networking sites like (examples)?' and the analysis suggests that social media use (χ^2=36.95, df=1,p<.000,32.2%, n=198) was significantly associated with MHISB.

A more detailed question on Social Media Usage was included in the questionnaire. These are: "Do you ever use online social networking sites like Facebook, Orkut, Hi5.com, Friendster, Twitter?" 1) to stay in touch with family and friends or not? 2) to share your views about religion or not? 3) to share your views about politics or not? 4) to share your views about music and movies or not? A reliability test was performed on the four items which yielded a Cronbach's Alpha = 0.506. These four items were summed to get Social Media Usage (Mean=2.51, SD=.07062) with a higher score reflecting greater Social Media use. The total score was recorded into three social media usage categories, high (45.6%), medium (42.4%) and low (12%).

Mobile Information Usage (MIU) was measured through six indicators as a response to the question, 'do you use mobile phones for 1) Send text messages 2) Take pictures or video 3) Get political news and information 4) mobile user Access a social networking site mobile use 5) Get consumer information such as prices or availability of products 6) mobile use Make or receive payments. All items were coded as a dichotomous variable (1-yes). A reliability test was performed on the four items which yielded a Cronbach's Alpha = .753. These six items were summed to get MIU (Mean=1.23, SD=.0329) with a higher score reflecting greater MIU. The total score was recorded into three Mobile Information Use categories, high (31.2%), medium (33.5%) and low (35.3%).

TESTING MEAN DIFFERENCE IN MHISB

The results of the independent sample t-test are presented in Table 2. Does the average age difference between MHIS users and non-users? From the t-test, we find that those who get health information from mobile phones were significantly more likely to have lower age (M=33.51, SD=12.191, N=234) than those who did not use mobile for health information (M=36.29, SD= 12.807, N= 1640).t (1872) =-3.122, p =.002, and the t-test for unequal variances, t (311.065) = -3.240, p =.001, did not yield comparable results. This suggests that younger people exhibit more MHISB than older adults.

Does the average household monthly income differ between MHIS users and non-users? From the t-test, we find that those who get health information from mobile phones were significantly more likely to have higher monthly household income (M=11.06, SD=2.752, N=232) than those who did not use mobile for health information (M= 10.21, SD=2.951, N=1628).t (1858) =4.164, p =.001, and the t-test for unequal variances, t (4.387) =311.685, p =.000 yield comparable results. Higher income people exhibit higher MHISB than lower income group.

Does the average level of education differ between MHISB users and non-users? From the t-test, we find that those who get health information from mobile phones were significantly more likely to have higher educational qualification (M=5.62, SD=1.711, N=233) than those who did not use mobile for health information (M= 4.91, SD=.627, N=1640) .t (1871) =6.168, p =.000, and the t-test for unequal variances, t (294.741) =5.939, p =.000, yield comparable results. MHISB is positively associated with education.

Does the average SES differ between MHIS users and non-users? From the t-test, we find that those who get health information from mobile phones were significantly more likely to have high SES (M= 15.3286, SD=3.01276, N=201) than those who did not use mobile for health information (M=13.5898, SD=3.58, N=1527). t (1729.42) =6.259, p =.000, and the t-test for unequal variances, t (279.26) =7.51, p =.000, yield comparable results. SES is also positively associated with MHISB.

Table - 2: Results of Independent Sample t-test-Group Means

Variables	MHISB	N	Mean	Std. Deviation	Std. Error Mean
Age	Yes	205	38.38	15.690	1.097
	No	1531	37.34	14.116	.361
Family Size	Yes	205	4.93	1.739	.122
	No	1535	5.63	2.395	.061
No of Children	Yes	205	1.15	1.038	.073
	No	1535	1.55	1.520	.039
Detailed Urbanity	Yes	205	4.98	1.613	.113
	No	1535	4.85	1.773	.045
Highest Educational Qualification	Yes	203	4.43	1.652	.116
	No	1534	4.03	1.448	.037
Monthly Household Income	Yes	203	10.91	2.141	.150
	No	1529	9.57	2.956	.076
Socio-Economic Status (SES)	Yes	201	15.3286	3.01276	.21270
	No	1527	13.5898	3.57903	.09158
Frequency of Internet Use	Yes	72	3.0522	.85416	.10086
	No	191	2.7238	1.08094	.07819
Social Media Usage Scale	Yes	63	2.7187	.97843	.12312
	No	129	2.3905	.96870	.08545
Mobile Information Usage	Yes	199	2.8802	1.57572	.11169
	No	1508	1.0227	1.16976	.03012
All reported mean difference has significant t-values at p<.000					

Does the average house size differ between MHIS users and non-users? From the t-test, we find that those who get health information from mobile phones were significantly more likely to have smaller household size (M=4.93, SD=1.739, N=205) than those who did not use mobile for health information((M= 5.63, SD=2.39, N= 1535). t(1738) =-4.075 , p = .001, and the t-test for unequal variances, t(317.130) =-5.186, p =.001, yield comparable results. Household size seems to be inversely related to MHISB, with people with smaller household having higher health information seeking activities.

Does the average frequency of Internet use differ between MHIS users and non-users? From the t-test, we find that those who get health information from mobile phones were significantly more likely to have a higher frequency of Internet use (M= 3.14, SD= 2.7403, N=140) than those who did not use mobile for health information. (M=2.75, SD=1.05, N=306). t (446) =3.830, p =.000, and the t-test for unequal variances, t (306.74) =4.038, p =,.000 yield comparable results. The frequency of Internet use is positively associated with MHISB.

Does the average amount of social media use differ between MHIS users and non-users? From the t-test, we find that those who get health information from mobile phones were significantly more likely to have higher social media usage (M= 2.75, SD= .978, N=128) than those who did not use mobile for health information (M= 2.37, SD=1.062, N=216). t (342) =3.326, p = 001, for equal variance assumed and the t-test for unequal variances, t (284.49) =3.397, p =.001, did not yield comparable results. The f-value for equal variance assume was not significant (F=.281, p=.597). Social media usage is positively associated with MHISB.

Does the average amount of mobile information usage differ between MHIS users and non-users? From the t-test, we find that those who get health information from mobile phones were significantly more likely to have higher mobile information use (M= 3.57, SD= 1.796, N=225) than those who did not use mobile for health information (M= 1.21, SD=1.29, N=1612).t (1835) = 24.081, p = .000, and the t-test for unequal variances, t (257.617) =18.902, p =,.000 yield comparable results. Overall mobile information usage (MIU) is positively associated with MHISB.

RESULTS OF LOGISTIC REGRESSION

Which factors increases/decreases the likelihood of using mobile for health information seeking? Logistic regression was conducted to find out which of the factors were significant predictors of MHIS. Beta values were used in an equation to calculate the probability of case falling into health information users and non-user category and the direction of the relationship-increase or decrease in likelihood. The results are presented in Table 3. We found that only Mobile Information Usage was able to predict MHISB (Beta=-1.073, SE=.184, Exp (B)=.342, p<.000). The model suggests that where the user sought health information, the predicted probabilities were high for mobile information usage and whereas for non-users of MHIS, the predicted probability was low.

Table - 3: Logistic Regression (Dependent is Mobile Health Information Seeking, 1-Yes)

							95% C.I.for EXP(B)	
	B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**Lower**	**Upper**
Frequency of Internet Use	-.051	.216	.055	1	.814	.950	.622	1.452
Age	-.010	.021	.210	1	.646	.990	.950	1.033
Educational Qualification	-.022	.125	.031	1	.861	.978	.766	1.249
Monthly Household Income	.067	.069	.932	1	.334	1.069	.933	1.225
Gender(1)	-.332	.463	.515	1	.473	.717	.289	1.778
Social Media	.320	.228	1.968	1	.161	1.378	.881	2.155

Usage Scale								
Mobile Information Usage	-1.073	.184	33.834	1	.000	.342	.238	.491
Constant	3.895	1.349	8.339	1	.004	49.180		

a. Variable(s): Frequency of Internet Use, Age, Highest Educational Qualification, Monthly Household Income, Gender, Social Media Usage Scale, Mobile Information Usage. The pseudo-R-Square value suggests that the exploratory predictors account for 63% of the variability of MHIS (-2 Log Likelihood=169.54, the Nagelkerke pseudo-R2=.366, p<.05). The model was also able to classify 72.3% of the MHIS correctly with an improvement of nearly 7.78% from the Block 0 classification of 64.5 % - were no predictors were included in the model. As expected Hosmer and Lemeshow test was not significant (chi-square=3.505, df=8, p>.899. Odds ration indicates that for three out of four users, we can make a reasonably accurate prediction that a mobile health information seeker is likely to be a high general information user. To further test this hypothesis, logistic regression was run with six mobile use items. Table - 4 presents the results of Binary Logistic Regression.

Table - 4: Logistic Regression (Dependent is Mobile Health Information Seeking, 1-Yes)

Predictors	B	S.E.	Wald (df =1)	Sig.	Exp.(B)	Lower	Upper
Send text messages	-0.517	0.252	4.200	0.040	0.596	0.363	0.978
Take pictures or video	-0.492	0.226	4.717	0.030	0.612	0.393	0.953
Get political news and information	-1.279	0.211	36.780	0.000	0.278	0.184	0.421
Access a social networking site	-0.691	0.236	8.589	0.003	0.501	0.316	0.795
Get consumer information such as prices or availability of products	-1.096	0.247	19.663	0.000	0.334	0.206	0.542
Make or receive payments	-0.980	0.207	22.344	0.000	0.375	0.250	0.563
Constant	1.530	0.209	53.374	0.000	4.620		

Analysis of odds ratio suggests that the use of mobile phones for health information is increased by 1) sending text messages (59 times, probability 37.3 %), 2) taking pictures (61 times, probability 38%), 3) accessing political news (28 times, probability 28 %) and 4) using social networks (50 times, probability 33 %) 5)access to consumer information (33 times, probability 25% 6)make mobile payments (25 times, probability 27%) The findings were confirmed by rerunning logistic regression for predicting non-user of MHISB, which showed an expected reciprocal relationship.

DISCUSSION

While our model identifies that all the predictor variables are significantly associated with the MHIS outcome, and indeed can explain 72.39% of the variance in outcome, they do not predict the outcome for individual users very well. The omnibus effect of the scenario using demographics and socio-economic factors fell short of significance. This is a critical insight because it indicates that income, gender, employment, marital status, and overall social media use do not determine mobile health information use outcomes (even when they are significantly associated with it as was seen from t-test and chi-square test). There is substantial individual variability that cannot be explained by the exploratory variable. Thus there is likelihood that the digital divide might not be present in the case of mobile health information seeking.

Overall, we can conclude that using mobile phones for one purpose, e.g., consumption and financial transaction triggers its use for other purposes. This supports the complementary information use hypothesis, which suggests that health information use compliments information use for another related usage, paralleling the theory of complementary channel selection (**Ruppel, 2012**). In other words, from a user perspective, we can conclude that health information seeking is not dissimilar to consumer information seeking or financial service or social networking site use. We can suggest that seeking health information and health services parallels product and service consumption behavior.

CONCLUSION

As mobile phones penetration has increased exponentially, socio-economic and demographic factors will become less relevant in predicting mobile phone usage to use scenarios. Users' experiences with one kind of information environment catalyze their search and adaptation in another context of use. Mobile information seeking is a transferable cognitive skill.

In order to segment mobile users, we need to consider the cluster of use situations instead of compartmentalizing each use scenario. This has implications for apps or any information service developer's strategies for audience engagement. Decision makers and designers need to take into account the overall information ecology of users. New users of mobile phones enter into an engagement with the technology in anticipation of specific use. These uses then act as an attractor that draws health information seeking behavior.

In other words, mobile use for one purpose instigates its use for MHISB- the more users use mobile for one type of service, the more are they likely to be induced or nudged to use other types of services/ information. We can call this appetizer influence and can be stated as flows: Those who seek information for one purpose gravitate towards health information because increased confidence and self-efficacy in one domain can be transferred to another related domain of information use. There is a need to programmatically profile multiple information tracks to understand better how the various types of information or information context influences specific seeking behavior.

As the digital divide in mobile use is continuously narrowing, socio-economic and demographic factors seem less relevant for predicting mobile health information usage. As the cost of mobile drops and features increases so will the affordances of mobile and its consequences to usage—it is increasingly important to see mobile related predictors for understanding mobile health information seeking (**Donner, 2008**). Poor have more access to mobile, and hence there is levelling of access, while usage based divides will be accentuated.

Better, comprehensive indicators limit the current paper for MHISB. Multiple indicators would have enabled generation and validation of more complex hypothesis. **Pew survey** (2014), being an omnibus survey has limited items that deal with health beliefs and behavior. This study is constrained by lack of broad-ranging variable sets to test theoretical propositions of HIS. However, the advantage is that we get a valuable insight into the profile of early adopters.

Widespread use of smartphones has created new opportunities in healthcare. Healthcare practioners have high expectations but consumer interaction will determine the trajectory of mHealth. The pace of adoption will depend on the experience of early users and a significant contribution of this paper is to provide a profile of such users.

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