The Role of Effectiveness, Appeal and Functionality on Evaluation of Health Apps

Full Paper

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Abstract

Mobile health applications (health apps) are enabling health care service delivery through access to patients beyond service walls. A number of health apps have emerged that help patients to collect information on diseases, provide treatment regimes, and aid in informed health decisions. To sustain a health app in the market, questions such as what functionalities influence a patient’s decision to use and evaluate the apps needs to be answered. A benchmark for sustained health app use is the impact that the current evaluation by patients. This study explores the impact of health app effectiveness and different health app functionalities on service appeal and week wise changes in patient evaluations. A dataset of 2,292 apps were used to conduct empirical analysis. We find that patients evaluate certain functionalities higher than others. Functionalities and service appeal moderate the influence of effectiveness on evaluation changes. Managerial and research contributions are discussed.

Keywords

Health apps, apps effectiveness, apps functionality, health apps evaluation.

Introduction

Health providers are looking to capitalize on the growing popularity of smartphones and maximize their ability to reach patients. Smartphone technology is emerging as an platform to integrate and provide a variety of services to patients (Nah et al. 2005; Persaud and Azhar 2012). The Pew Research Center (2013) reported that ninety percent of American adults own a cell phone, that sixty-four percent of those devices are considered smartphones, and fifty percent of smartphone owners regularly download mobile applications. With the increase in application functionality, from paying bills to tracking footsteps, a growing number of adults are turning to technology for help when it comes to their healthcare and wellness (Källander et al. 2013). In order to keep up with the growing demand, the healthcare industry is investing in mobile healthcare applications.

Mobile health apps vary in their functions, for example the ability to monitor a patient’s vitals and promote adherence to their treatment plan (Phillips et al. 2010). When patients access the digital market to download an app, they are given the opportunity to view ratings and reviews of the application. In most cases, after downloading the application and using it for a short period of time, a message will pop up prompting the user to rate the application and to leave a review. This rating process allows the user to leave both an overall rating and to share candid feedback regarding their experience. In addition, existing ratings of apps determine the adoption of the app by a new user.

In this study, we explore the factors that determine the change in patients’ evaluation of an app. Prior research suggests that service effectiveness, service functionality, and service appeal are determinants of patient’s evaluation changes (Huang and Korfiatis 2015; Park and Kim 2003). Service effectiveness is the
direct impact of a service provided by the app on the user’s health outcome (Jennings et al, 2015; Khare and Chougule 2012). Service functionality can be defined as the sum of the tasks a particular app can perform for the user (Cenfetelli et al. 2008). Service appeal refers to the purchasing decision patients make, based on the interest, curiosity and excitement, to determine which services among the variety available on the market appeal to them (Rosa et al. 1999).

We posit that health service effectiveness positively influence patient’s evaluation change. In addition, we posit that service functionality and appeal interacts with the health service effectiveness to amplify the influence on patient evaluations. We propose a model with these relationships, and draw testable hypotheses. We empirical test our hypotheses using text mined data from 2,292 health apps from android market, and find support for hypotheses. Managerial implications and contributions are discussed.

**Prior research**

Despite the availability of mobile applications in the digital market, there has been limited attention toward the relationship between patient health effectiveness and patient evaluation of apps. There is, however, a vast extent of literature that investigates online health information seeking behavior. Online health information empowers patients to investigate health concerns and facilitate the shift of health management toward patient-centric model (Xiao et al. 2014). Online health information is becoming prevalent phenomenon. In 2013 a survey by Pew research found that eighty one percent of U.S. adults use the internet. Seventy percent of the internet users said they have looked online for health information in the past year. The Pew survey also found that that fifty-three percent of US adults went online to diagnose a medical condition. Interestingly, thirty percent of those who went online ended up not visiting a clinician.

Due to the emergence of web 2.0 health information seekers are shifting from being passive to more active role. Users can comment on and evaluate the Health Information (HI) they find online. A cross functional study by Andreassen et al (2007) found that twenty seven percent of the health information seekers participated in online forums and online self-help groups. Part of the growing interest in online Health Information is due to the bevy of personal experience available, the Pew survey found that one in four internet users read someone else’s medical or health experience.

Information Systems and Health IT research has shown us that mobile health apps have the ability to deliver health care in a more efficient way (Kumar et al. 2013; Odeh et al. 2015). Apps empower users to adopt a healthy lifestyle (Free et al. 2013), allows patients to manage chronic conditions (Terry 2010), enables patient self-monitoring (Ramanathan et al. 2013), and provides healthcare professionals with additional intervention (Klasnja and Pratt 2012) and treatment options (Dahne and Lejuez 2015; Gustafson et al. 2014; Milward et al. 2015). Given the potential benefits of apps for both providers and patients, Kumar et al (2013) endorses the need for more research in the area of mobile health.

Many of the available apps run on Apple’s iOS and Google’s Android operating systems and are available over the digital market places: itunes.apple.com and play.google.com, commonly known as app stores. The app stores also provide a platform to share reviews and ratings between users. This influences the potential users decision to download an application or not (Huang and Korfiatis 2015). Users can also leave comments and feedback for developers regarding possible improvements. This reciprocal relationship fuels an evolutionary environment for mobile health apps.

Existing research suggests that the decision to download a certain mobile application from the digital market is influenced by the existing ratings and evaluations of other users (Huang and Korfiatis 2015; Senecal et al. 2005). Although the mobile application rating and evaluation are subjective, the existence of multiple ratings that are similar in nature will increase the objectivity of the overall rating and evaluations (Flanagin et al. 2014). Apps ratings and reviews are becoming increasingly important for developers to differentiate their products as industry grows, with more than a million applications developed in the last few years (Spriensma 2012).

In order to achieve positive evaluation, developers should be aware of the factors impacting user's attitude. Huang and Korfiatis (2015) relying on the work of Kempf (1999), found that both the user's rational evaluation (based on whether the app will provide the benefits expected or not) and the emotional evaluation (based on the hedonic attributes of the app) are critical in formulating the users
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attitude towards the app. In the context of health technology, scholars found that effective health technology is positively associated with patient’s satisfaction (Delpierre et al. 2004; Jamal et al. 2009). In addition, healthcare scholars have been arguing that there is a relationship between the emotional aspect of the healthcare delivery and patient’s satisfaction (Lown et al. 2011; Weng et al. 2011).

The mobile applications stores contain different types of applications in order to appeal to a wide market of users. The abundance of applications available makes the users evaluation an important factor in order for users to differentiate a particular product from its competitor, which is necessary in order to gain prominence in the digital market. Baird and Raghu (2015) investigating Personal Health Records (PHRs) with different business models tethered PHR for standalone provider and group of provider, and Integrated PHR. The PHR digital business models found that even when users have similar preferences regarding a digital service their perceived value may be associated with the service business model. Baird and Raghu (2015) also found that variations in user’s digital services valuations are due to their business models.

Sunyaev et al. (2015) states that although there are over 35,000 health apps available in the digital market only 600 are most commonly used. With so many available applications developers continue to encounter the issue of service and feature duplication. Therefore, both developers and providers need to better understand how adopting a service functionality can impact user’s evaluation and differentiate their apps (Weinstein et al. 2014). To our knowledge, researchers have not yet investigated how functionality models influence the relationships between health effectiveness and user’s evaluation. Such is important to assist in differentiating a mobile application in the digital marketplace and enhance user’s evaluation. This study tries to address the existing gap in the context of health applications and the change in patient’s evaluation in the digital marketplace.

Research Model

In this paper, we base our conceptual model on the Comprehensive Model of Information Seeking (CMIS), developed by Johnson and Meischke (1993). CMIS divides the information seeking process into three parts: antecedents that explain why people first start looking for information (information seeking purpose), information carrier characteristics that influence how the users search for information, and information seeking actions that explain the outcome of the search (Johnson and Meischke 1993). Information seeking purpose is the reason why a user searches an information, and for health context, it may be to manage a disease. Information carrier characteristics refers to the qualities and specifications of the system used to search. This includes the functional utilities offered by the system, such as the option to search based on symptoms rather than disease. Information seeking actions are the details of a user’s search. For example, how many different sources they investigated, the scope of their search, and whether they find the information helpful. This third facet of the model results from—and is influenced by—the previous two, leading to the possibility of dramatic differences in the actual actions users carry out (Han et al. 2010; Johnson and Meischke 1993). CMIS model was utilized by a multitude of researchers within the health communication, health information, consumer health IT, health psychology disciplines (Or and Karsh 2009; Rains 2008; Robson and Robinson 2013). The model’s implications have also been considered for the assessment and interventions to enhance adherence to health protective regimens. Originally, the model was designed to predict and explain information seeking behavior (Anker et al. 2011).

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When applied to the context of health apps, CMIS explains the post-information seeking actions that are determined by the characteristics and utilities of health applications. CMIS’ main schemas can be applied to these applications, as there is little functional difference in the applicable factors across platforms. Based on these anchors to the CMIS, the conceptual model (see Figure 1) we developed for this study states that for health applications, health and psychological effectiveness have direct positive impact on the change in the evaluation of an application. Three functionality models (Information Access and Harness, Diagnosis and Discovery, and Adherence and Compliance) moderate the relationships of health effectiveness and psychological effectiveness on the evaluation of an application. Lastly, we hypothesize that patient interest for an application also moderates the relationships of health effectiveness and psychological effectiveness on the evaluation of an application.

**Hypotheses**

When people use an online resource to obtain health information or diagnosis for disease they will judge the accuracy of the information they obtain. If the information or diagnosis attained are not accurate that will cause users to evaluate the online resource poorly (Metzger and Flanagan 2013). Health app effectiveness refers to how the usage of the health app improves the overall health of the user. In other words, health app effectiveness is the reflection or measure for which patients would seek to use the health app. Patients use health apps to help them cope and deal with medical or health conditions. In addition to health effectiveness, the mobile applications literature suggests that users’ evaluations are also influenced by the psychological component of the apps. Some health applications include both health and psychological dimensions, like providing information about a disease, diagnose a condition, offering connection to social media, connect users to others with similar conditions, or connect users with friends and family (Huang and Korfiatis 2015). Some health applications for example, will help patient to reduce anxiety and cope with depression by using different techniques like dancing to favorite songs or encourage walking instead of driving. The impact of effective health apps will result in positive impact on the user's health, resulting in good evaluation. In addition, users may share their good experience in the digital market and influence others to use the app. Thus, we hypothesize:

**H1:** *Health app effectiveness is positively associated with change in patient evaluation.*

According to CMIS model, technology functionality and characteristics influence the people’s actions (Han et al. 2010). We argue that health application characteristics such as app functionality will moderate the relationship between the app health effectiveness and the change in the patient evaluation. For the health service functionality we looked if the apps have the following functionalities: information access and harness, diagnosis and discovery, and adherence and compliance. Information access and harness apps provide patients with information about a specific disease or condition. Diagnosis and discovery apps ask patients a set of questions then display the appropriate diagnosis for them. The adherence and compliance apps provide patients with appointments reminders, pills reminders, and allow patients to connect to their support group (Liang and Yeh 2011; Pihlström and Brush 2008). For the psychological component, apps can display information to cope with emotional issues, for example some apps display aspirational quotes to motivate positive thinking. Diagnosis and discovery apps can provide patients with emotional training, relaxation audio, and a diary to log their emotions. The adherence and compliance apps may allow patients to connect with their support network to help them cope with their emotional and psychological issues. These functionalities will make the app more effective towards patient’s health and patient will value them higher, thus we hypothesize:

**H2:** *Health service functionality of a health app positively moderates the relationship between health app effectiveness and the change in patient evaluation.*

Service appeal indicates the interest of users in an app. The interest in the health apps could be because they allow easy access to medical information, services, and support. For example, a diagnosis app would have a great benefit to users who want to diagnose medical conditions and get more information without the need to visit a medical professional. Patients who value the flexibility and the easy access to the health apps will be more excited and passionate about the technology and the services they provide. The excited users will provide app developers with good feedback to help them improve the apps. Those users will be
more excited about the apps and more likely to generate positive evaluation and influence other users. That being said, patient interest due to service appeal will positively impact the relationship between health app effectiveness and patient evaluation. Based on that, we hypothesize:

**H3: The positive effect of health app effectiveness on the change in patient evaluations shift is stronger for apps with high service appeal.**

**Method**

**Data and Variables**

For our analysis, we are using secondary data from the android market place. Our units of analysis are based on the tracking information about the health apps for two and a half months from 13 October 2014 to 1 January 2015. The first week is the focal reference week, and the second week is used as the reference for the increase in ratings and reviews to calculate the variables used in this study. We found 3,292 health, wellness, and medical apps in the android market in the focal week of 13 October 2014 to 20 October 2014. We could not consider 521 apps for our analysis, because they did not have any usage information in the market place until the focal week. After we examined the data more closely, we found 177 apps in languages different than English, had unreadable names, or were duplicates in the market. In addition, we excluded 302 apps as there were no change in ratings or number of people who rated or reviewed the apps in the focal week and the subsequent weeks. We were left with 2,292 apps for our analysis. We created a panel data set that consist of 28,331 observations.

In Table 1, we provide a description of the variables we used in this study. In Table 2, we provide descriptive statistics for the key variables and the pair-wise correlation amongst them. The dependent variable in our model is the change in patient evaluations in the week's span. This variable is calculated as the net change in the application of average rating and raters in that week, per original rater in the beginning of the week (see the calculation description in Table 1). Using both average ratings per week and the total number of raters provides both a measure of score, and a measure of popularity in a single variable that assesses overall rating impact. By measuring the change in overall impact score between the two time periods, an index is developed based on the benchmark measure of the first week. This index is our dependent variable, Change in patient evaluations. Combining two important app rating measures, the average rating score and total number of raters, Change in patient evaluations measures the shift in an app's overall impact rating between two time periods, both in terms of quality and quantity.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description and Operationalization</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables</strong></td>
<td></td>
</tr>
<tr>
<td>Change in patient evaluations (cPE)</td>
<td>The change in the net user rating of the app, considering both the total users who rated the app and the ratings that the app received in the span of the week. The cPE index is calculated as follows: $cPE = (R2N2 - R1N1)/N1$. Where, $R2/R1$ = Average rating of the app in week 2/week 1, $N2/N1$ = Total number of users who rated the app in week 2/week 1</td>
</tr>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
</tr>
<tr>
<td>Health App Effectiveness (HE)</td>
<td>This variable is the average of the following two measures:</td>
</tr>
<tr>
<td></td>
<td>Health Effectiveness: Health effectiveness felt by the users for the app in the market. This variable is coded by mining the text reviews of each app in the weeks’ time. The index measures the percentage of reviewers that discuss Health Effectiveness of the app within the focal week.</td>
</tr>
<tr>
<td></td>
<td>Psychological Effectiveness: Psychological effectiveness felt by the users for the app in the market. This variable is coded by mining the text reviews of each app in the weeks’ time. The index measures the percentage of reviewers that discuss Psychological Effectiveness of the app within the focal week.</td>
</tr>
</tbody>
</table>
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This variable is the count of the following functionalities:

Information Access and Harness: Health Applications that display medical and health information, display pre-loaded instructions, and present specific condition Information.

Diagnosis and Discovery: Health Applications that display common symptoms and conditions provide specific diagnosis based on users input and questionnaire answers, and some may provide a communication with medical professionals.

Adherence and Compliance: Health Applications that assist with healthy eating, weight management, fitness, healthy living, smoking cessation, stress management, sleep, provide medication reminders, and medication trackers. The apps also allow patients to communicate with support network.

No Clear Functionality: Applications that has no clear health functionality. HSF was zero for these apps.

Service Appeal (SA)
A strong interest and desire by the user to download and acquire the application for the attractiveness of the service it provides. The variable represents the ratio of top rating to the total rating of the health application.

Control Variables

Age of the app (AGE)
How long the app has existed in the android market since its release. The variable was calculated by finding the difference between the focal week and the release date of the app.

Price of the app (PRICE)
The price of the health app in US dollars.

Category Dummy (C_N)
The category of the app, as pre-defined in the android market. We coded dummy variables for each category to include in the analysis.

Table 1: Description of Variables

The focal independent variables in this study are health app effectiveness. The variable is coded by mining the text reviews of each app in the weeks’ time. The index measures the percentage of reviewers that discuss psychological and health effectiveness of the app within the reference week. The reviews were coded using a hermeneutic coding process to code the health effectiveness and psychological effectiveness. For psychological effectiveness, we used terms like emotional support, success and efficacy. For health effectiveness we used words like BMI assessment, screening, care etc.

The second independent variable is the health service functionality of the app. This variable reflects the functionality model of the app, and was coded by categorizing the health application into four main categories according to their functionality (Information Access and Harness, Diagnosis and Discovery, Adherence and Compliance and No Clear Functionality).

The third independent variable is service appeal in the health app. This variable is operationalized to reflect the interest of users in the health app as a functional and effective product, and is measured by calculating the percentage of users that rated the health app with highest rating in the market. We controlled for many variables like the price of the app, the duration of the app in the market, and the average download per week. We also coded dummy variables indicating the category of the app and included them as control variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observation</th>
<th>Mean</th>
<th>Std. Dev</th>
<th>Min</th>
<th>Max</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>cPE</td>
<td>2,292</td>
<td>5.65</td>
<td>3.19</td>
<td>-7.1</td>
<td>21.54</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HE</td>
<td>2,292</td>
<td>45.6</td>
<td>10.32</td>
<td>5</td>
<td>96</td>
<td>0.09</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HSF</td>
<td>2,292</td>
<td>1.36</td>
<td>0.98</td>
<td>0</td>
<td>3</td>
<td>0.02</td>
<td>0.34</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>SA</td>
<td>2,292</td>
<td>0.43</td>
<td>0.16</td>
<td>0</td>
<td>1</td>
<td>0.08</td>
<td>0.06</td>
<td>0.05</td>
<td>1.00</td>
</tr>
</tbody>
</table>

The category dummies have mean < 0.05, and std dev < 0.20; and correlations are less than 0.1. All correlations greater than 0.10 are statistically significant at p < 0.01.

Table 2. Descriptive Statistics and Correlations amongst Key Variables
Estimation Models

We are using panel data for our analysis. We ran a Hausman, the test was significant and hence we used a fixed effect model. We used the panel data estimation with fixed effect to model the patient evaluation shift model because the change in patient evaluations is a continuous variable (Green, 2008).

\[ cPE_i = \beta X_{it} + \alpha + u_{it} + \varepsilon_{it} \]  

(1)

Where, Where, cPE is the dependent variable, X: is a set of explanatory variables, \( \beta \) is a vector of parameters, u is the between-entity error and \( \varepsilon \) are within entity error associated with each observation.

Results

We tested the direct relationship between health app effectiveness on the change in patient evaluation (Table 3, Column 1). We find support for H1 as the coefficient for health effectiveness is positive and significant (\( \beta_{21} = 0.36, p < 0.01 \)), the result shows that with 1% increase in health effectiveness, the change in patient evaluations increases by 36% in two weeks’ time.

We find support for H2, which predicted that the relationship between the health app effectiveness and evaluation change differs across different health functionalities. The interaction term of HE x HSF is positive and significant in the interaction effects model (refer to column 2 of Table 3, \( \beta = 0.26, p < 0.01 \)). Finally, we also find support for H3, which predicted that the relationship between the health app effectiveness and evaluation change differs across various levels of service appeal. The interaction term of HE x SA is positive and significant in the interaction effects model (refer to column 2 of Table 3, \( \beta = 0.12, p < 0.05 \)).

We tested for multicollinearity by computing variance inflation factors (VIFs) for all estimation models. The highest VIF was 1.91 in the direct-effect models, confirming that multicollinearity is not a serious concern. To reduce potential high multicollinearity issues due to the number of interaction terms in the models, all continuous variables were mean-centered by subtracting the corresponding variable mean from each value (Aiken and West 1991). The VIF of any individual variable in any of the interaction effect models was less than 7.0. Furthermore, mean VIFs in all the models were less than 5.0. Thus, we find that multicollinearity is not a serious concern in the estimation.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Direct Effects Model</th>
<th>(2) All Interaction Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health Effectiveness (HE)</td>
<td>0.36*** (0.05)</td>
<td>0.31*** (0.03)</td>
</tr>
<tr>
<td>Health Service Functionality (HSF)</td>
<td>0.21*** (0.04)</td>
<td>0.19** (0.04)</td>
</tr>
<tr>
<td>Service Appeal (SA)</td>
<td>0.18** (0.01)</td>
<td>0.16** (0.02)</td>
</tr>
<tr>
<td>HE x HSF</td>
<td></td>
<td>0.26*** (0.03)</td>
</tr>
<tr>
<td>HE x SA</td>
<td></td>
<td>0.12** (0.01)</td>
</tr>
<tr>
<td>Controls</td>
<td>Included</td>
<td>Included</td>
</tr>
<tr>
<td>Constant</td>
<td>-5.60*** (0.02)</td>
<td>-3.23*** (0.07)</td>
</tr>
<tr>
<td>Observations</td>
<td>27,504</td>
<td>27,504</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.38</td>
<td>0.27</td>
</tr>
<tr>
<td>Adj R-sq.</td>
<td>0.26</td>
<td>0.20</td>
</tr>
</tbody>
</table>

*Standard errors in parentheses

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

The focal independent variables and interaction terms are mean centered in the interaction effect models

Models include all the category dummies and none of them are significant

Table 3: Results of Estimation Models
To aid in the interpretation, we plotted the interaction effects (see Table 4-4A to 4B). The first interaction effect 4A shows that there is a greater change in evaluation of the apps for apps with high health service functionality. Similarly, figure 4B shows that greater change in evaluation of the apps for apps with high service appeal. We also compared the coefficients of service appeal and health service functionality using a t-test. Results showed that health service functionality has a greater impact on evaluation than service appeal.

![Figure 4A](image1.png)  ![Figure 4B](image2.png)

**Table 4: 2-way Interaction Graphs**

**Discussions**

This study finds that health app effectiveness is a critical positive determinant to influence change in patient evaluation of health apps. Second, we find that the health service functionality of an app helps to increase the positive effect of health effectiveness on the change of patient evaluation. A third finding is that if the service provided by the app has a higher appeal, it will have a favorable impact on the effectiveness and users evaluation. Another managerial implication of this study is that the apps functionalities play a valuable role in user’s evaluation of the health app. Hence, developers should pay more attention toward what type of functionality they adopt in their applications. In addition, identifying users who value health apps and take their feedback is very important to enhance future releases. This study contributes to existing literature of digital products, by identifying how technological and functional factors are associated with digital product success.

This study is a balanced panel study, we eliminated dead applications from our analysis. Future studies may include those apps and look at the validity of the reviews. Future studies can also look if the health application was recommended or prescribed by the provider and how that may impact user’s evaluation. In our study we only analyzed applications that came from the android digital market; future studies may include applications from other markets as well, like iPhone and Microsoft.

To conclude, this study explores the impact of health app effectiveness and different health app functionalities on service appeal and week wise changes in patient evaluations using a dataset of 2,292 apps. Findings show that patients evaluate certain functionalities higher than others. Functionalities and service appeal moderate the influence of effectiveness on evaluation changes. The findings have implications for appropriate app design and subsequent business models in health care.

**References**


