ADR Reporting Through Twitter from Patient Perspective

Completed Research

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Abstract

Adverse Drug Reaction (ADR) has become a central concern for many healthcare providers (FDA, 2016). It is well known that adverse reactions to drugs are a reason for several health problems. According to the Food and Drug Administration (FDA) estimation, ADRs are the 4th leading cause of death. The prevalence of ADRs demands a simple ADR reporting process. The ADR reporting process involves many stakeholders such as the FDA, the patient, and the health professional. The research uncovered a significant lack of communication among the stakeholders, thus the research goal is to improve this lack of communication. This research paper is an extension of a previous research in progress; Toward Improving Adverse Drug Reactions Reporting From Twitter (Alghamdi S, & Mujallid O, 2016); that provided the research problem, method, methodology, and designs the artifacts. This paper provides iterations of the design process, evaluation and presented findings as a descriptive analysis.

Keywords

Health Informatics, Design Science Research (DSR), Media Richness Theory (MRT), Adverse Drug Reactions (ADRs), Social Network, Twitter

Introduction

As Adverse Drug Reactions (ADRs) are considered one of the leading causes of death in health care (FDA, 2016). Medical researchers have become increasingly interested in studying ADR due to its importance as a significant public health problem that can be prevented. In fact, Sloane stated that ADRs are considered one of the main causes of illness, hospitalization, and mortality (Sloane et al., 2015). As a consequence, the drug reactions have received a considerable amount of attention by drug scientists and health professionals.

Recently, a study found that 42% of the patients involved in social networks discuss their current health conditions online (Sarker, Nikfarjam, & Gonzalez, 2015). Thus, social networks become a potential vital source of information to monitor the effects of medical drugs after they have been licensed (Sloane et al., 2015), yet there are different issues when it comes to report an ADR from online data sources. One issue is that patients post their drug reactions on different social networks, such as Twitter, which does not necessarily mean their doctors will receive it. Another issue is that there are criteria that need to be fulfilled in order for the report to be recognized by the Food and Drug Administration (FDA) (2015). Based on the FDA recommendation the communication between the doctors and the patient should be a priority to help the patient to avoid circumstances of drug reactions as well as help to monitoring patient to determine whether the drug reactions may cause a future complication.

This paper is an extending of a previous research in progress (Toward improving adverse drug reactions reporting from Twitter), which stated the research problem, methodology and the artifacts design. In this phase the evaluation of the artifact were conducted as further iterations of the design process. These findings are presented a descriptive analysis in this paper.

The proposed solution addresses three objectives. The first objective is to provide a reliable solution that works as a communication channel between patients and health professionals. A second objective is to provide a solution that helps the patient to report ADRs to their health professionals. A third objective is to provide a solution for health professionals to report ADRs through Twitter while taking into consideration the FDA criteria. The research focus on how the (ADR) reporting can be improved based on patients' posts on Twitter and also what solution can be provided to improve the communication between the patient and the primary doctor during the ADR reporting process. This study provides a reliable tool called an Easy Reporting (EZ-R) that will allow users to report ADRs and aims to enhance such communication, which will eventually benefit all involved stakeholders. To enhance a rich communication among stakeholders during the reporting process, this study draws upon Media Richness Theory (MRT) (Warters, 2015).

Background and Related Work

An Adverse Drug Reaction is defined as any serious undesirable experience that a patient has associated with the use of a medical product (Baniasadi, S., Fahimi, F., & Shalviri, G., 2008). ADRs make around 30% of hospital admissions in the US and costs up to 30.1 billion dollars per year (Sultana, Cutroneo, & Trifirò,2013). ADRs can occur to any number of patients after a drug enters the market. This led to the establishment of the ADR reporting processes.

The current ADR process has a few limitations. The ADR process involves many stakeholders, two of which must be present to complete a report. The FDA is one stakeholder and they are responsible for protecting the public health, investigating drug complaints, and monitoring drug reactions (Reisman, 2012). Either the patient or the doctor may submit an ADR to the FDA. Moreover, a new study found that 86 % of Adverse Events (AEs) went unreported (Sultana, Cutroneo, & Trifirò,2013). Even if a patient files an online complaint, the process often poses a big challenge because the current online process has many limitations; according to Ying et. al. (2010). One of those limitations is the dependence on volunteers to report ADRs. This makes it a passive system that is limited by latency and inconsistency, which resulted a significant lack of communication between healthcare providers and patients. Therefore, a solution is needed in order to prevent more ADR related to deaths and costs for the country.

Today, patients are increasingly turning to social networks as a source for health-related information, health and wellness advice, and to share experiences (Alabbasi et al., 2014). According to a recent study, 26% of adult that use Internet discuss their personal health problems online and 42% of them discussing current conditions on social network (Sarker, Nikfarjam, & Gonzalez, 2015). Twitter, one of the most popular social network websites, has around 320 million users monthly as of December 31, 2015. According to Ginn, R., et. al., Twitter users generate more than 9000 tweets every 4 seconds. With this volume of data, healthcare providers and agencies tried to analyzing and predicting ADRs from the content of Twitter using data mining techniques (Sloane et al., 2015). Yet, this approach lack the FDA four criteria as a requirement to accept ADR reports based on social network data mining, specifically: 1. An identifiable patient which is the patient information that includes patient name, or patient identification number; 2. An identifiable reporter which is the person who is in charge of reporting to the FDA such as a family member, doctor, or pharmacist; 3. The drug name that causes the ADR; 4. An adverse event or fatal outcome that caused by the drug (FDA Guideline , n.d.).

Theoretical Foundation

The theoretical foundation of this study draws upon Media Richness Theory (MRT), developed by Richard L. Daft and Robert H. Lengel in the 1980's (Warters, 2015). MRT categorized different levels of communication media to carry information, ranging from low (or lean) richness to high (or full) richness (Warters, 2015). For instance, a higher richness level of communication that provides rapid response and feedback channels are vehicles such as face-to-face communications and videoconferencing (Warters, 2015).

The MRT provides a theoretical basis for the propose tool (EZ-R). In fact, in this study, the MRT inspired the researchers to build an artifact considering the communication aspect between the doctor

and the patient. Such an artifact that will mediate the ADR reporting process and improve the current passive low richness method into a richer, and more active method.

Research Approach

This research follows the Design Science Research (DSR) approach, introduced by Hevner and Chatterjee (2010), which includes a set of artifacts that solves a wicked problem. DSR is composed of three related cycles: "the relevance cycle, the rigor cycle, and the design cycle". The DSR artifact outcome can be one or more namely, *models*, *methods*, or *instantiations* (Hevner and Chatterjee, 2010).

Therefore, based on the DSR approach, the goal of this research is to provide a reliable solution as a communication channel between patients and health professionals, and improve ADR reporting. The outcome solution consists of three main artifacts: a patient mobile application (instantiation), a doctor mobile application (instantiation), and an algorithm (method) that run in the backend of both applications.

Designing & Building the Artifacts

Technical Requirements

To develop the applications, android studio was used to implement both doctor and patient applications. The following tools were used during the development phase: android Software Development Kit (SDK), Java, Android Mobile OS, Twitter API, MySQL database, and JSON (JavaScript Object Notation).

Design & Build the Artifacts

From DSR perspectives, each of the artifacts designed to play a different role in reporting ADR namely, Dashboard (doctor's application), Mobile Application (patient's application), and an algorithm to looks up and detects side effects in patient tweets (both patients and doctor applications). The three artifacts have been designed and developed in iteration process. Both applications and algorithm have been constructed and tested to build the final artifacts. The source of the data was from Drugs.com and collected based on the top 20 drug names and the relevant 700 side effect terms, that being looked up on searches engines. This collected data have been stored on a database on the server. This sample has been used to test both applications and algorithm functionality.

The EZ-R works under two assumptions. First, the research team assumes that the doctor has a list of patients' Twitter usernames. Another assumption is that the patient agreed that all of their tweets will be monitored by the doctor. Each doctor will have an application that works as a dashboard. The next sections will describe both applications in detail.

Artifact 1: Doctor Dashboard Application (Instantiation)

In this dashboard, the home page contains the main functions which are "View Report", "Lookup for Patient on Twitter", "Chat with Patient", and "Send SMS to Patient". These functions empower doctors to help their patients to report the side effects. With taking into consideration of the previous assumptions, the doctor will use the "lookup for patients" function, which runs the algorithm to find out whether or not the patient's tweets contain mention of side effects. If the algorithm found that the patient's tweets contain a side effect, then the doctor's screen will show this side effect. Next, the doctor can initially use "Send SMS" function to send an SMS to the patient to download the patient application on his/her smartphone. After the patient downloads the application, then the doctor will be able to use the following functions: the "View Report" function shows a list of reports or questions that are submitted by the patient. The "Chat with Patient" function enables the patient and doctor to communicate over messaging with each other. Thus, the doctor application can help doctors to monitor his/her patient on social network and empower them to help patients to report the side effects.

Artifact 2: Patient Mobile Application (Instantiation)

Initially, when the user runs the application for the first time, a login screen will be displayed. A username and password screen prompts for authentication. The user will provide unique username and password for the first time. If the username is correct, then the application will store the username on the server. If the patient tweeted about a drug side effect, the application gathers the tweet content using Twitter API. The API matches keywords in Tweets to those that are pre-stored on the server. If the tweet matches, then the application will automatically send a notification prompting the patient to report the side effect to the doctor. The patient can use the following three functions. One function is the "patient profile", which will allow the patient to and update demographic information. Another function is "send report" which helps patients report an ADR. In this function, the patient will be directed through workflow steps to complete an ADR report including patient identity, drug reactions, adverse drug event, drug name, and drug dosage. Last function is the "chat with a doctor" which allows doctors and patients to engage in a real-time transmission of text-based conversation.. Therefore, the patient application can help the patient communicate with his/her doctor any time, and to report the side effects easily.

Artifact 3: An algorithm to look up and detect side effects in patient tweets

The algorithm works in both the doctor dashboard application and the patient mobile application. The algorithm runs as a loop to detect patient tweets contains side effects that match the list of terms of side effect and drugs' names that stored previously on the server. The algorithm runs on the doctor application only when the doctor uses "lookup for patients". The following steps explain the algorithm:

Algorithm steps in doctor application

Assumption: It is assumed that the patient posted a tweet that has a side effect (Figure 3). For example, if a patient posts a tweet including this text: "I have chest pain for 2 days from using XYZ … etc.", then the application works according to the following algorithm description.

Algorithm description:

1.The doctor looks up the patient username (Figure 1 and Figure 3).
2.The application checks if this username has tweeted about a side effect.
3.If yes, the application retrieves the tweet content using Twitter API.
4.The application compares the KeywordMatch with tweet content with side effects that are pre-stored in the server.
5.If keyword is matching, then a message is sent to the doctor about side effect (Figure 1 and Figure 3).
6.The doctor sends SMS to patient to download the app.

Algorithm Steps in Patient Application.

Assumption: It is assumed that the patient is using his/her Twitter account using Twitter on desktop, or Twitter app on a smart device.

Algorithm description:

1. After the user logs into the mobile application, the application checks the username. (The application stores the username on the server when the user uses the patient application for the first time).
2. The application monitors tweet content that is posted on the user account (Figure 1 and Figure 3).
3.The application gets the patient tweet content using Twitter API. (Works as a repeated process each time of tweet).
4.The application compares keywords of tweet content to side effects that are pre-stored on server.
5.If KeywordMatch matches one of side effect that pre-stored on server.
6.Then automatically send a push notification to patient (Figure 1 and Figure 3).
7.Patient will use the mobile app to report his/her side effect.
8. Doctor will receive the report (Figure 1 and Figure 3).

Pseudo code explain the algorithm in patient application:

```
{    Get username From Server
     IF (username == True) THEN { get Tweet_Content from Twitter API
     IF (Tweet_Content == True)) THEN { KeywordMatch == Tweet_Content
Run_Function (Push_Notification)
IF Push_Notification == is_open
       {initiate_Patient_App
       }                  }
ELSE REPEAT
}
     ELSE      END

}
```

Pseudo code explain the algorithm in doctor application:

```
{      SET          initial username

     IF (username == True) THEN { get Tweet_Content from Twitter API

         IF (Tweet_Content == True))

THEN    { KeywordMatch ==  Tweet_Content

             Run_Function (Send SMS)      }

         ELSE REPEAT }

     ELSE      END }
```

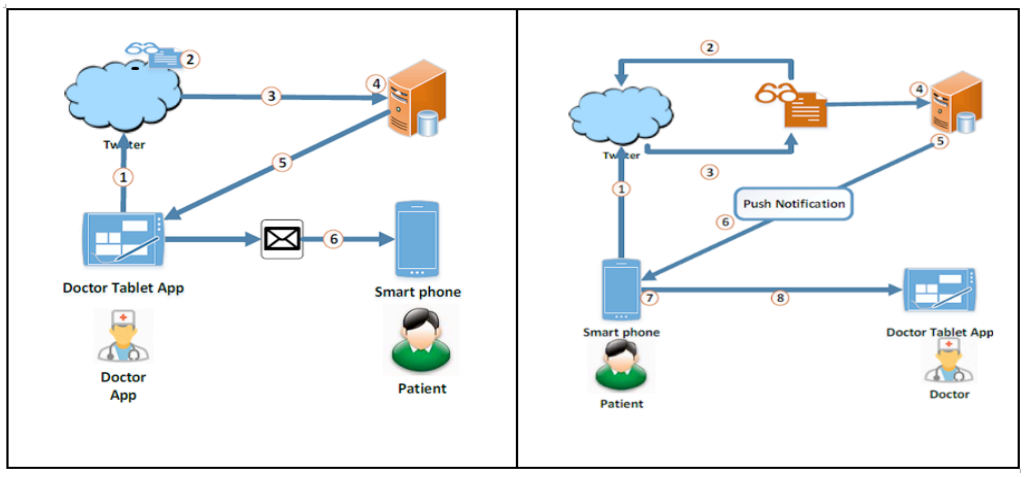

Figure 1: Algorithm steps of both doctor application (left) and patient application (right).

Figure 2: Screenshot of user interface drawing using Microsoft Word drawing tool.

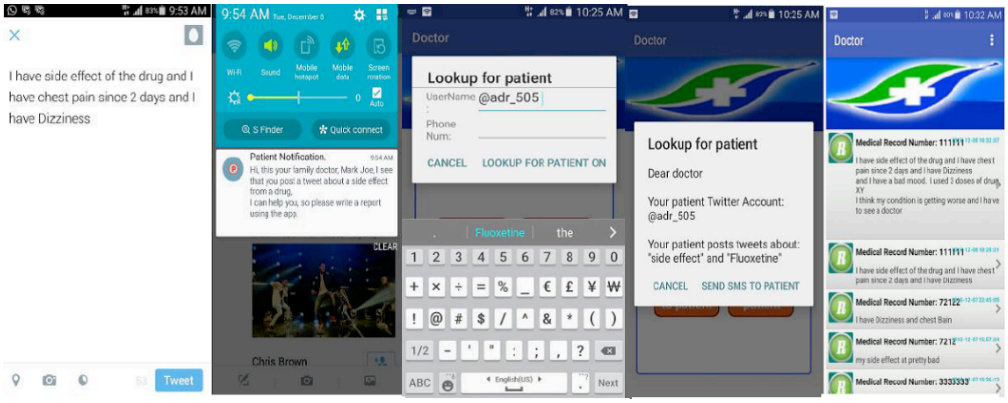

Figure 3: Screenshot of both doctor and patient applications.

Evaluation

The researchers conduct the evaluation upon two iterations. First iteration conduction was using paper prototyping method, where patients asked to reveal their opinions of about patient prototype UI drawing (MS. Word drawing Figure2 and description of intended functions. After that, data were collected using a pre-test survey. First iteration was helpful to measure user's current level of understanding about ADR topic as well as the collect feedback from the users and to design and build the real mobile application. The second iteration conducted to assure that collected feedback from first iteration was applied to the application.

Patient's survey

Participants

The pre-and post-surveys links were sent by emails to participants using random sampling method. All participants were students from Claremont Graduate University. The total participants in this research study were 15 individuals, 10 females and 5 males, with an age range of 15—54.

Procedure

Both surveys were conducted in order to assess the application usability and usefulness. The pre-survey is intended to measure the patient's current level of awareness about the importance of reporting an ADR and the patient's level of their familiarity with the FDA current reporting system. For example, participants were asked questions about the FDA current reporting system and social network usage to understand patient familiarity with FDA process. During the application testing, the participants requested to use Twitter to test the application detection function. After, participants finish testing the application, they were asked to fill a post-survey, to investigate the easiness, usefulness, functions ability that will help the patient to report an ADR to the doctor.

Results patient's survey

The majority of participants were not familiar with the process of reporting a side effect, based on the pre-survey, 31% thought it would be a difficult process. Moreover, participants spent more than four hours on social networking, which indicate the importance of the social network in their daily routine. Finally, 70% of participants see the importance of reporting an ADR and preferred using a smartphone application to do that. On the other hand, the post-survey 12 out of 15 participants found that it is very easy to report an ADR to the doctor using the EZ-R application. Finally, for overall usability the majority of the participant felt very confident when they were using the application and navigating through the function.

Limitation and Challenges

For this pilot study, the researchers examined the functionality of the application, however, there were some challenges and limitations. First, the researchers were limited in detecting false-positives to detect synonyms of symptoms of the side effect that not stored. Second, there remains a limitation in regard of misspelled words, unknown keywords, or incorrect drug names submitted by patients and were not previously stored on the server.

Conclusion and Future Work

Recently, a large number of patients discuss their health issues and ADRs on different social networks (Sarker, Nikfarjam, & Gonzalez, 2015), such as Twitter, which leave a large percentage of ADRs not reported to authorize health professionals or to the Food and Drug Administration (FDA) (Sarker, Nikfarjam, & Gonzalez, 2015). So far there is no reliable tool that might be used by health professionals to report an ADR based on their patient's tweets. This research provides a reliable solution that targeted patients whom discussing their current health condition on Twitter, and facilitates the submission of ADR by improving the communication with their health care professionals more easy and user-friendly.

Doctor's evaluation will be a target for the future work. Moreover, future enhancement should take into account the aforementioned limitations, as well as provide a sufficient doctor's sample size for the evaluation. This solution might incorporate video conferencing within the application. More importantly, the application can be connected with the FDA database. Also, a proper HIPPA and security procedures should be implemented to deal with patient's data privacy.

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