Chapter 50
Remote Patient Monitoring for Healthcare:
A Big Challenge for Big Data

Andrew Stranieri
https://orcid.org/0000-0002-4415-5771
Federation University, Australia

Venki Balasubramanian
Federation University, Australia

ABSTRACT

Remote patient monitoring involves the collection of data from wearable sensors that typically requires analysis in real time. The real-time analysis of data streaming continuously to a server challenges data mining algorithms that have mostly been developed for static data residing in central repositories. Remote patient monitoring also generates huge data sets that present storage and management problems. Although virtual records of every health event throughout an individual's lifespan known as the electronic health record are rapidly emerging, few electronic records accommodate data from continuous remote patient monitoring. These factors combine to make data analytics with continuous patient data very challenging. In this chapter, benefits for data analytics inherent in the use of standards for clinical concepts for remote patient monitoring is presented. The openEHR standard that describes the way in which concepts are used in clinical practice is well suited to be adopted as the standard required to record meta-data about remote monitoring. The claim is advanced that this is likely to facilitate meaningful real time analyses with big remote patient monitoring data. The point is made by drawing on a case study involving the transmission of patient vital sign data collected from wearable sensors in an Indian hospital.

DOI: 10.4018/978-1-6684-3662-2.ch050

INTRODUCTION

Continuous remote monitoring of patients using wearable sensors and Cloud processing is emerging as a technology that promises to lead to new ways to realize early detection of conditions and increased efficiency and safety in health care systems (Chan, Estève, Fourniols, Escriba, & Campo, 2012). The approach combines body area wireless sensor networks (BSN) with systems that are designed to process and store the data for the purpose of raising alarms immediately or for data analytics exercises at a later point in time (Balasubramanian, Stranieri, & Kaur, 2015). Real time remote monitoring systems have been described for a number of remote monitoring applications including: continuous vital signs monitoring (Balasubramanian & Stranieri, 2014; Catley, Smith, McGregor, & Tracy, 2009), arrhythmia detection (Kakria, Tripathi, & Kitipawang, 2015), regulating oxygen therapy (Zhu et al., 2005), monitoring of pregnant women (Balasubramanian, Hoang, & Ahmad, 2008), fall detection (Thilo et al., 2016), chemotherapy reaction (Breen et al., 2017) and glucose monitoring(Klonoff, Ahn, & Drincic, 2017). Ultimately, a multitude of condition specific applications, each using different subsets of each patient's health data commissioned by diverse healthcare practices can be expected to emerge in the near future. For instance, a rehabilitation clinic may be interested in tracking a patient's gait, while a counselling service may be interested in tracking heart rate variability to detect suicidal depression (Carta & Angst, 2016) and a hospital may be interested in detecting post-operative sepsis (Brown et al., 2016).

Remote patient monitoring (RPM) applications often generate high volumes of data with great velocity and variety to produce valuable diagnostic information. For instance an ECG wearable sensor alone can produce 125 to 8000 samples per second (Shimmer, 2018), that can be used to predict various heart conditions in real time. In many occasions, a RPM application uses more than one wearable sensor to monitor vital signs, such as ECG, body temperature, blood pressure, oxygen saturation (SpO_2) and respiratory rate, to analyze and predict the health condition of the patient. This leads to large data repositories that present serious challenges for Big Data analytics algorithms (Kalid et al., 2018). A review by (Mikalef, Pappas, Krogstie, & Giannakos, 2017) reveals that Big Data is characterized in terms of the five main 'Vs:' volume, velocity, variety, veracity and value. Although a great deal has been written about the Big Data explosion, little is known of the conditions under which Big Data Analysis (BDA) leads to the generation of value for an organization (Wang, Kung, & Byrd, 2018).

In this chapter, the observation is first made that BDA for remote patient monitoring is difficult to perform due to the volume, velocity, veracity and diversity of data. Consequently, few electronic health records include RPM data despite the increasing prevalence of data from continuous monitors because electronic health records were designed for structured and less variable health data. In addition, explicit decisions about the way in which RPM data is collected, processed and interpreted in practice are rarely made by analysts acting in isolation in health care, but by diverse stakeholders working in teams in sociopolitical contexts. For instance, in the data analytics exercise with an Australian hospital described by (Sharma, Stranieri, Ugon, Vamplew, & Martin, 2017), the problem, and interpretation of analytics results depended on stakeholder priorities at the executive, management and operational levels of the hospital. The data analytics process model CRISP-DM (Shearer, 2000) cannot readily accommodate diverse stakeholder priorities and also cannot easily be adapted for continuous analytics with RPM data.

The openEHR (open Electronic Health Record pronounced open A'yr) standard that depicts the pragmatics of health care concepts described by (Kalra, Beale, & Heard, 2005) provides an important precursor to facilitate the application of Big Data analytics for RPM data. The use of openEHR has the potential to ensure data is correctly interpreted in analytics exercises and facilitate diverse stakeholder