Mobile Health: Medication Abuse and Addiction

Upkar Varshney
Georgia State University
35 Broad Street
Atlanta, GA
01-404-413-7382
uvarshney@gsu.edu

ABSTRACT

Prescription medication abuse is a major healthcare problem and can lead to addiction syndrome, higher healthcare cost, and serious harm to patients. Mobile health can play a major role in addressing prescription medication abuse. This is due to the ability to (a) monitor patient's health conditions anywhere anytime, (b) monitor patient's medication consumption, and (c) connect with healthcare professionals and utilize suitable interventions in time. More specifically, medication behavior can be monitored using smart medication systems, specialized wearable sensors or mobile devices with patient-entered consumption data. This data can then be analyzed for certain patterns to detect medication abuse. The goal is to design and develop an advance warning system based on the patterns of medication use to alert healthcare professionals and/or family members. Such system will utilize additional contextual knowledge of patient's condition and past history, current use, and information on abuse and addictive potential of medications. In this paper, we present medication related challenges and a preliminary design of a system to monitor and analyze the patterns of medication use, and utilize an analytical model for performance evaluation. The known patterns are utilized to estimate probability of near-future addiction. Our results show that medication adherence can be estimated and probabilities of multi-dosing and super adherence (>100% medication adherence) can be computed based on thresholds supplied by healthcare professionals. The work applies to m-health analytics and decision support systems.

Categories and Subject Descriptors

C.2.1 [**Computer-Communications Networks**]: Network Architecture and Design. J.3 [**Computer Applications**]: Life and Medical Sciences

General Terms

Management, Measurement, Performance, Design

Keywords

Prescription abuse, monitoring, mobile health, addiction

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1. INTRODUCTION

Prescription medication abuse is any intentional use of a medication with intoxicating properties outside of a physician's prescription for a bona fide medical condition, excluding accidental misuse [6]. Addiction is defined as compulsive use of a substance for psychic effects and to satisfy a craving for the drugs [3]. Prescription medication abuse is a major health problem and can result in addiction leading to increased healthcare cost and injury to patients [10]. According to NIH, 20% of all prescription medications have been used in one or more types of medication abuse [15], while other studies estimate prevalence of prescription abuse as 4.5% of the population [2] and 36-56% among chronic pain patients [13]. Prescription abuse has been linked to more deaths than automobile accidents and results in $8.6 Billion in health and legal expenses and loss of productivity in US alone [7].

Mobile health [1, 8, 18, 22, 23, 25, 28, and 30] can play a major role in addressing prescription abuse and addiction. Addiction of prescription medications is a chronic disease, which can be treated with highly expensive treatments [2]. However, proactive monitoring and detection of prescription abuse can reduce the need for expensive treatment [10]. More specifically, the medication adherence [5, 11, 12 and 26] and consumption of certain medications can be monitored anytime anywhere and certain changes can be analyzed for patterns of current abuse and near-future addiction. The patient's medication taking behavior can be monitored using wireless smart medication systems, specialized sensors or mobile devices where patients can enter dose consumption data [19, 24, 27, and 29]. The goal is have an "advance warning system" based on pattern of medication use to alert healthcare professionals and/or family members. This will allow them to intervene before the patient becomes addicted.

In this paper, we focus on medication abuse by presenting a preliminary design of a system to monitor and analyze the patterns of medication use, and present an analytical model for performance evaluation. We note that medication use data is likely to be both unreliable and limited. Considering the chronic nature of medication abuse and millions of patients with vulnerability to medication abuse, we envision that some data will be generated by long-term monitoring of health and medication consumption. This will lead to better calibration of the model along with more accurate values of parameters to improve the prediction accuracy. The proposed work will help in the analysis of data for healthcare diagnostics, and we hope that other researchers will address abuse and addiction challenges identified in this paper.

Rest of the paper is follows. In section 2, we present the architecture and decision support for abuse monitoring system. Then in section 3, we present an analytical model and performance results. Section 4 includes concluding remarks and ideas for future research.

2. MEDICATION ABUSE MONITORING

In this section, we discuss medication abuse monitoring by including various insights from healthcare literature, deriving requirements for a monitoring system and then present the architecture and decision support components.

2.1 The Monitoring Environment

Medication abuse involves higher doses [6] and/or rapid escalation of the dose [3]. Although, there are individual variations [6], prediction of abuse is further assisted by any past history of abuse [6], co-ingestion of other drugs [6], and current health condition of the patient [2]. The goal is have an "advance warning system" based on medication consumption pattern to alert healthcare professionals and family members to intervene in time before the patient develops addiction syndrome. Such predictive system can be implemented based on additional contextual knowledge of patient's history, current health conditions and the type of medications [2]. Our work is on proactive monitoring of doses to detect current abuse and future addiction. The monitoring will lead to a decision support system to help healthcare professionals and family members to become aware of the current situation and implement suitable interventions [6].

The goal is to analyze the medication data for any gradual or sudden changes in medication taking behavior. The regular levels of medication adherence (80-100% and occasionally higher) generally lead to good health outcomes for patients (Figure 1). The super adherence, where patient consistently consumes more than 100% doses over certain duration (due to access to poly-pharmacy) is undesirable, especially in the context of potential abuse and addiction. If certain undesirable patterns are detected, the patient is likely to move towards abuse, addiction and/or overdose (Figure 1). The goal of any medication abuse monitoring is to detect such patterns and inform healthcare professionals and/or family members to implement a suitable intervention before the patient develops addiction syndrome leading to injury and even death. The proactive and effective interventions can improve the patient outcomes and quality of life, and could reduce future healthcare expenses.

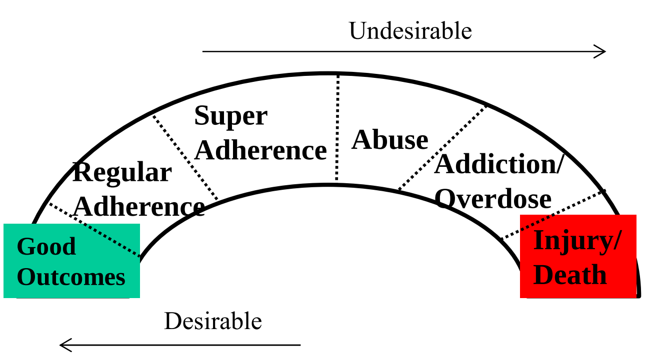


Figure 1. The Big Picture of Adherence, Abuse and Addiction of Medications

2.2 Requirements

The following requirements for abuse monitoring system are derived [2, 3, 6, 7, 10, and 13].

- It should monitor both average value of medication adherence as well as the patterns of adherence.
- It should be designed for long-term use as abuse and addiction appears to be chronic conditions.
- It should consider past history, patient's characteristics, and abuse potential of medications in analyzing medication data for current abuse and future addiction.
- It should be able to handle missing and/or incorrect information by extrapolating based on past history and current consumption.
- It should analyze the pattern of medication adherence to detect probabilities of multi-dosing and/or frequent dosing in determining current abuse and future addiction.

2.3 Abuse Monitoring System

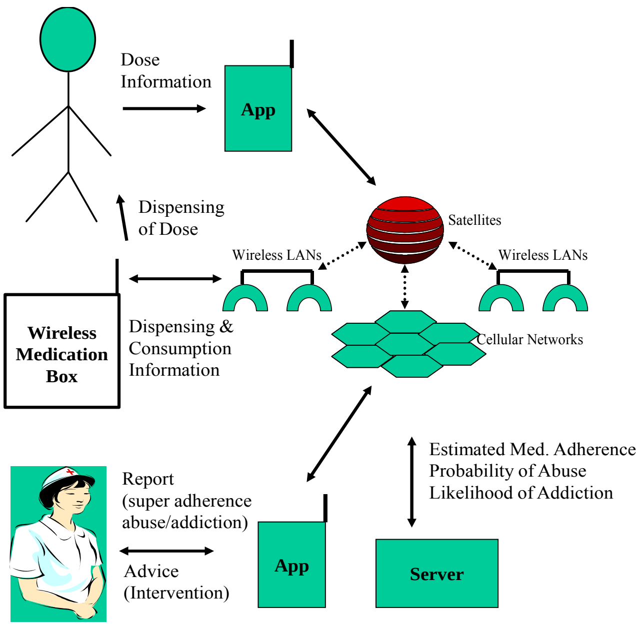
Smart medication systems include monitoring and dispensing of doses, reminders to patients, and communications with healthcare professionals. The examples are Magic Medicine Cabinet (MMC) [29], Smart Medicine Cabinet [19], Smart Medication Management System [27], and Smart Medication Dispenser [24]. These systems monitor medication consumption of patients by using some combination of sensors and wireless technologies. Smart medication systems and/or mobile applications [4, 17, 20 and 21] can be expanded to process medication consumption information and detect undesirable patterns. One such system is shown in Figure 2(a), where information on medication consumption is collected from multiple sources. There are potentially multiple implementations based on (i) the type of wireless networks used (ii) the ways to collect information on medication consumption and (iii) the processing algorithm used for processing and pattern analysis of consumption data. Figure 2(a) also includes various steps in monitoring and analysis of consumption information, and the roles of patient, healthcare professional, and system components are also shown.

2.4 Abuse Monitoring and Decision Support

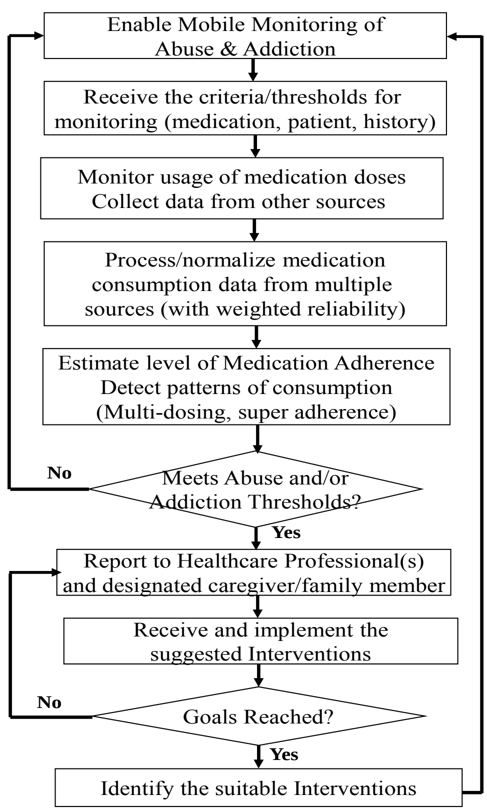
Medication consumption data is analyzed to match various known patterns for both current abuse and potential for near-future addiction based on thresholds and criteria supplied by healthcare professionals as shown in Figure 2(b). This can include thresholds for abuse monitoring and detection, such as >=V doses within N hours or >100 adherence over M days.

With medication consumption information, the system can process how doses are consumed by the patient. Specifically, it can look at the number of doses taken at a time and the inter-dose time between doses and how many times the minimum and maximum limits have been crossed. These can then be processed for any undesirable patterns of medication consumption, which are then reported to healthcare professionals, who in turn will decide on suitable interventions such as changing the medications to less-addictive versions, discontinuing the medications, or treating the patient in a substance-abuse clinic.

There are numerous challenges in implementing and using systems based on these ideas. Some of these challenges include (a) difficulty in getting reliable data on medication consumption, (b) complexity and accuracy of prediction, (c) the cost of intervention when prediction is not accurate (false positive) and (d) personalization and usability of monitoring and prediction system. In addition, privacy, regulatory and legal challenges must be addressed in future.



(a) Architecture of the Abuse Monitoring System



(b) Process and Decision Support

Figure 2. The Architecture and Decision Support for Abuse Monitoring System

3. MODEL & EVALUATION

Several assumptions are made to keep the analytical model tractable and reasonably accurate. These assumptions, likely to be relaxed in near future, are (a) the addictive medications are similar within a class, and (b) patients are adults who live and work on their own and have either consented to the monitoring of their medications or agreed to provide consumption information to a mobile device. Further, the limitations of the model are that (a) it is based on medication adherence data from patients, which is currently limited and/or unreliable and (b) various parameters are approximated based on limited work in this area. However, with more data in near future, better calibration of the model will result in improved accuracy. Also, being able to populate the model with better parameter values and weights to derive the probabilities will also improve the accuracy of prediction.

3.1 Metrics

Abuse is modeled as more frequent use and/or more doses of medications at a time than recommended. We compute the probability of current abuse based on known patterns of use and then we estimate likelihood of near-future addiction. The following metrics are used in monitoring and analysis:

- Probability of Multi Dosing (P_{MD}): this represents the chance that a patient is taking more doses at the same time or within a short predefined interval with the same effect.
- Probability of Accidental Dosing (P_{AD}): this represents the chance that a patient is taking more doses **accidently** at the same time or within a short predefined interval.
- Probability of Current Abuse (P_{CA}): this represents the chance that a patient is intentionally taking more doses at the same time or within a short predefined interval.
- Likelihood of Addiction (L_{ADD}): this represents the probability of near-future addiction based on current abuse, patient's history and medication-related factors. The adjustments are made to take into account the probability of any random or accidental overdose.

3.2 Analytical Model

The medication adherence during an observed period can be given by

$$MA_{TRUE} = (N_{taken}/N_{pres}) \times 100 \quad (1)$$

Where N_{pres} is the number of prescribed doses and N_{taken} is the number of doses taken by the patient. N_{taken} can be more than N_{pres} as patient may have access to more doses from previous prescriptions and refills, use of poly pharmacy, and prescription and refill sharing with others. Thus the upper bound on the total number of doses available to patient (more than the prescribed) is N_{max}, which is much higher in abuse and addiction cases.

3.2.1 The Estimated Medication Adherence

The basic algorithm receives the consumption data from smart medication boxes and/or mobile device and estimates the level of medication adherence as follows:

$$MA_{EST} = P_S \times P_C \times MA_{TRUE} \quad (2a)$$

Where P_S is the probability that smart medication system is able to detect a dosing event and P_C is the probability that the correct outcome of the dosing event (patient took the dose or not) can be detected.

The context-aware algorithm processes the data by compensating for known problems and estimates the level of medication adherence as follows:

MA_{EST} = Max(P_S x P_C x MA_{TRUE}, P_S x P_C x MA_{TRUE} + (1- P_S x P_C), P_S x P_C x MA_{TRUE} + (1- P_S x P_C)* (0.5 x MA_{TRUE}), $F_{RECALL-ENTRY}$ x MA_{TRUE}) (2b)

The Max-error = $|MA_{EST} - MA_{TRUE}|$

$F_{RECALL-ENTRY}$ is the patient's recall factor related to dosing information. One challenge is the difficulty in estimating $F_{RECALL-ENTRY}$ (how much patient is fudging or under-estimating the number and frequency of doses). In practical terms, this can be initialized based on prior behavior and updated as more information becomes available.

The results for different sensing reliability (80, 90 and 100%) of smart medication systems are shown in Figure 3, where the true medication adherence is varied from 0-500% of the desired level. The estimated medication adherence level more or less follows the true medication adherence with small amount of error.

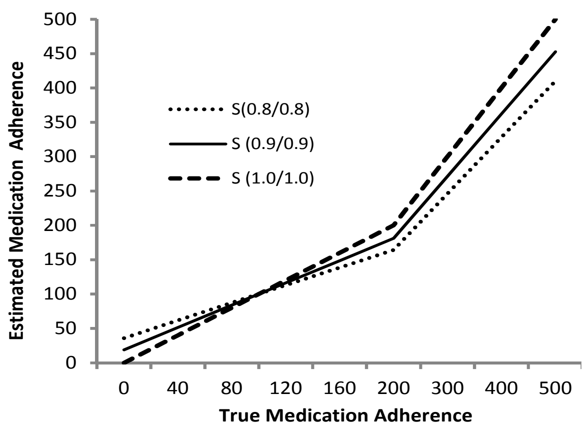


Figure 3. Estimated Medication Adherence vs True Medication Adherence for Three Sensing Reliabilities

3.2.2 The Variation in Medication Consumption

Some patients may take multiple doses to catch-up the missing or delayed doses. The number of times the gap between doses has exceeded the max-interdose-time, or GM, can be given by

$$GM = \sum_{I=1}^{Npres} ((T_{I+1} - T_I) > T_{max}) \quad (3)$$

T_{max} is the maximum allowed time between two doses to remain medically compliant. The value of GM can be used to determine the number of times the patient has skipped or delayed a medication.

The number of times the gap between doses is less than the minimum-interdose-time, or GL can be given as

$$GL = \sum_{I=1}^{Npres} ((T_{I+1} - T_I) < T_{min}) \quad (4)$$

T_{min} is the minimum allowed time between two doses to remain medically compliant. The value of GL can be used to determine the number of times the patient has overdosed or attempted a catch-up on a medication. Multiple neighboring values of (T_{I+1}-T_I) would indicate some degree of unusual medication taking behavior [9, 14 and 16].

3.2.3 Monitoring Current Abuse and Near-future Addiction

The high levels of medication adherence, or super adherence, can be detected by analyzing any reduced time-gaps between doses (frequent dosing) and/or taking multiple doses at a time (simultaneous dosing). The probability of multi dosing at I doses can be given as

$$P_{MD-I} = (1/ I!).(\lambda t)^I.e^{-\lambda t} \quad (5)$$

Where λ is the estimated dosing rate by the abuse monitoring system and can be expressed as dosing rate scheduled x MA_{EST}/MA_{DES}, and t is the time interval where doses taken have the same effect as taking multiple doses simultaneously. MA_{DES} is the desirable level of medication adherence (<=100%). The probability of multi-dosing, a major component of abuse detection, is shown in Figure 4 for 2, 3, and 4 doses as the medication adherence is increased from 100% to 500%. As the threshold of doses goes up, the probability of multi-dosing goes down.

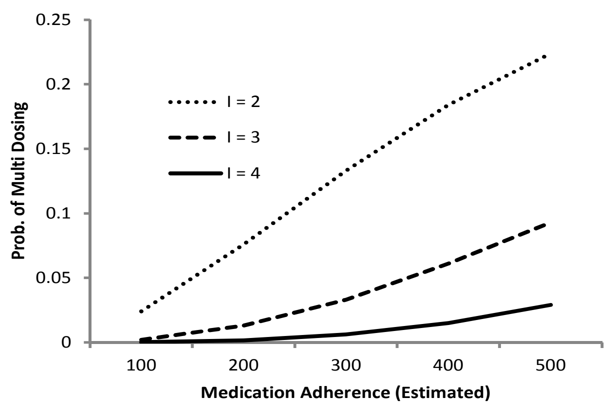


Figure 4. Multi-dosing with Higher Adherence

The Probability of Multi Dosing (P_{MD}) can be expressed as

$$P_{MD} = (1/M) \sum_{I=1}^{M} (I \times P_{MD-I}) \quad (6)$$

P_{MD-I} represents the probability of multi-dosing for I doses, while M is the upper limit on the number of doses a patient can take anytime.

The probability of abuse is given as the difference between weighted multi-dosing probability and probability of accidental dosing (P_{AD}) as follows

$$P_{abuse} = P_{MD} - P_{AD} \quad (7)$$

The probability of accidental dosing can be derived based on the frequency of dosing and past behavior of the patient. The accuracy of these parameters will affect the prediction accuracy of abuse.

For varying levels of estimated medication adherence, the probability of abuse is derived and shown in Figure 5. The probability increases non-linearly with the level of medication adherence. And as expected, the probability of abuse is higher for lower multi-dose thresholds, supplied by healthcare professional after considering the specific characteristics for the medication and, if available, patient's past history of medication abuse.

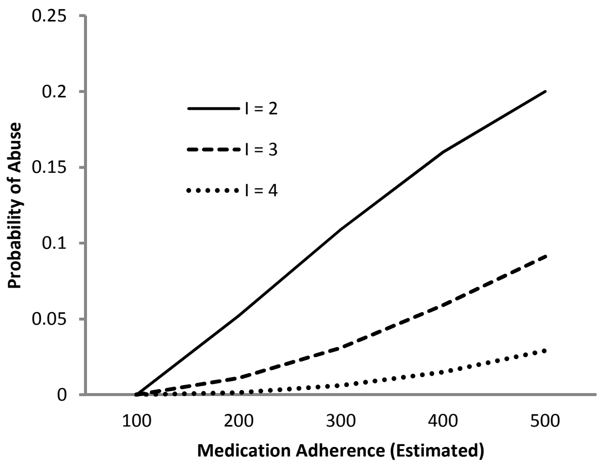


Figure 5. The Probability of Abuse for Different Thresholds

3.2.4 Overall Likelihood of Addiction

The likelihood of addiction can be expressed as follows:

$$L_{ADD} = \alpha \text{ x } P_{pat} + \beta \text{ x } P_{med} + \gamma \text{ x } P_{abuse} \quad (8)$$

P_{pat} includes the patient related factors such as past history, demographics, co-morbidity, known vulnerability towards addiction, family and social influence, among others. P_{med} represents medication related factors including addiction potential of the medication, other medications and access to medications. P_{abuse} represents the patient behavior as monitored by smart medication boxes or mobile applications. The factors α, β, and γ can be initialized to values and then improved/optimized to achieve better personalization of the monitoring and intervention system. The likelihood of addiction is shown in Figure 6 for varying medication adherence. More results will be presented at the conference.

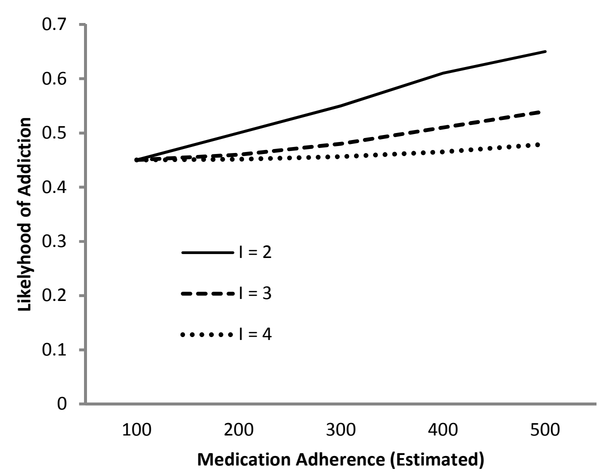


Figure 6. The Likelihood of Addiction for Different Thresholds

From the above results, we observe that (a) smart medication systems can provide a reasonable estimate of actual medication adherence of the monitored patient, especially when used with context-aware algorithm in estimating incomplete dose information, (b) the probability of multi-dosing increases non-linearly with an increase in dose-consumption (or estimated medication adherence), (c) the probability of abuse can be as high as 22% for higher adherence and for 2-dose threshold for abuse, and (d) the likelihood of addiction increases non-linearly with dose-consumption (or estimated medication adherence).

A higher value of likelihood of addiction (based on current consumption pattern) can be used as an alarm for family and/or healthcare professionals to intervene. More research is needed to evaluate the effectiveness of educational, family and medical interventions (less addictive versions or reducing the doses).

4. CONCLUSIONS & FUTURE RESEARCH

Mobile health can play a major role in addressing prescription medication abuse. The patient's medication taking behavior can be monitored anytime anywhere using wireless smart medication systems, specialized sensors or mobile devices where patients enter dose-consumption data. We note that such data is both unreliable and limited. This affects the prediction accuracy of our model. As more data will become available, we expect that better calibration of the model will be possible. This, along with more accurate values of parameters and weights, will improve the prediction accuracy of current abuse and near-future addiction. In this exploratory paper, we addressed medication related challenges, designed a system to monitor and analyze the patterns of medication use to detect current abuse, and presented an analytical model to evaluate the performance. Our results show that it is possible to estimate medication adherence. The probabilities of multi-dosing is observed to be rising non-linearly with super adherence (>>100% medication adherence). The probability of current abuse is utilized to estimate the probability of near-future addiction. More results on the evaluation of various interventions for reducing medication abuse and potential addiction will be presented at the conference. We are aware that additional work, such as field study and/or clinical trials, is needed to improve the accuracy of our model and results.

More research can be conducted in (a) comparison of different algorithms for accuracy of medication adherence estimation, (b) identification of more patterns for abuse and addiction, (c) improving personalization of the medication monitoring and interventions, (d) implementation and user testing of an abuse monitoring system, and (e) comparison of effectiveness of multiple interventions in preventing abuse and/or addiction. We envision that a significant amount of data will be generated by long-term monitoring of health and medication consumption. The work presented here can be utilized in the analysis of such data for healthcare and addiction purposes. We hope that other researchers will address the challenges identified in this paper.

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