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Smart Interventions for Opioid Abuse:
Design and Evaluation

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ABSTRACT

The number of people in the US with opioid abuse exceeds two million, and the total cost is approximately $100B per year. There is a need for smart interventions that can lead to better outcomes for patients and reduce the need for healthcare resources. In this study, the authors present three smart interventions for patients: (a) mobile reminders, (b) electronic monitoring, and (c) composite intervention. More specifically, the authors present a design approach for smart interventions and operationalize the interventions. They have developed an analytical model for evaluating interventions. Interventions are cost-effective for higher values of intervention effectiveness, hospital, and emergency room cost. However, with quality-of-life (QoL) improvement, cost-effectiveness improves significantly. The authors also explored the use of financial incentives for increasing the adoption of interventions. These results will help patients, healthcare professionals, decision-makers, and family members to choose the most suitable intervention to address opioid abuse.

KEYWORDS

analytical model, evaluation, Opioid abuse, patient level, smart interventions

INTRODUCTION

Prescription opioid abuse is any intentional use of opioids outside of a physician's prescription for a bona fide medical condition (Finley et al., 2017; Lossio-Ventura, Song, Sainlaire, Dykes, & Hernandez-Boussard, 2022; Sarker, DeRoos, & Perrone, 2020; Sinha, Jensen, Mullin, & Elkin, 2017). It can lead to addiction, higher healthcare costs, and serious harm to patients (Azadfard, Huecker, & Leaming, 2022; Blendon & Benson, 2018). This abuse requires detoxification and hospitalization very similar to a chronic condition. The number of people in the US with opioid abuse exceeds 2 million and the total cost is approximately $100B per year (NIH, 2019). According to NIH, about half of the drug overdose deaths in the US are due to opioids (NIH, 2019) and resulted in 80,816 deaths in 2021 (CDC, 2022). Opioid abuse is a major challenge for patients and family members, healthcare professionals, employers, regulators, and society. There is a need for smart interventions at multiple levels before patients develop opioid addiction and require major treatment (Singh & Varshney, 2019a,

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2020; Varshney & Singh, 2020b, 2020c). These smart interventions can lead to better outcomes for patients and reduce the need for healthcare resources.

Each patient has a certain chance of abusing opioids (single vs multiple prescriptions) based on their history, genetic makeup, current environment, medical condition, and type of opioid prescribed. Some of the patients will have low, some moderate and some will have a high level of opioid abuse. This is also time-dependent, and patients can change from low to moderate to high or high to moderate. This has some chance of leading to addiction, which will require expensive inpatient treatment. This abuse should be considered a chronic disease and different patients will require outpatient treatment for different durations of time. A different set of actions will be needed (a) at the source (for healthcare professionals) managing the prescriptions, (b) patient-level during consumption of opioids, and (c) after the patient has developed an addiction. In this paper, we focus on patient-level interventions, which are proactive and with some probabilities will be effective for some patients in preventing them from developing an opioid addiction. To design smart interventions, we present a design approach. Using multiple constraints and considering the environmental context, we have developed three smart interventions. The interventions are (a) mobile reminders (Voelker, 2019), (b) electronic monitoring of opioids (Jungquist et al., 2019), and (c) composite intervention (monitoring, reminders and support from other patients) (Schuman-Olivier et al., 2018; Varshney, 2015). The mobile reminders will be sent to the patient to provide educational and motivational support to avoid overconsumption of opioids. Electronic monitoring will keep track of the prescribed opioids. This involves designing wireless monitoring systems for collecting and analyzing opioid consumption data. The composite intervention will include reminder, monitoring and motivational support from other patients. This intervention can reduce the consumption of prescription opioids by monitoring and reminding patients about taking and/or not taking certain doses within certain windows of time. The interventions can be implemented using both simple and sophisticated mobile apps, sensors, mobile devices, and smart medication boxes. This could proactively stop patients from becoming dependent on opioids or developing an addiction.

Using prescription opioid abuse and intervention data, we derive the healthcare cost of opioid abuse along with the cost of three interventions. Using an analytical model and ROI (Return on Investment) as a metric for the cost-effectiveness of interventions, we derive several results for all three interventions and various levels of effectiveness. We found that ROI is lower than 1 for low and medium values of our parameters, while it is much more favorable when the values of the parameters are set to high. When the value due to a potential improvement in Quality-of-Life (QoL) was included, the ROI significantly improved for all three interventions. Further, we wanted to explore if the use of financial incentives will be suitable to improve the adoption of three interventions. For this, we computed the maximum allowed financial incentives that can be offered to the patients while still meeting the cost-effectiveness goal for the interventions.

The paper is formatted as follows. The design approach is presented in the next section followed by interventions design and operations. Further, the analytical model is developed to evaluate the smart interventions and is followed by results. Finally, the discussion and conclusion including the future work is presented at the end.

DESIGN APPROACH

The design of technological intervention starts with the identification of the environmental factors, patient's condition, and medical history followed by possible solutions. These include communication with and notification to patients, observing consumption behavior, providing individual/group education and support, analyzing patterns of opioid consumption, and providing cognitive behavior therapy. To make these interventions more effective we add context-awareness and refer to these as smart interventions (Singh & Varshney, 2019b). The interventions can be in the form of a mobile app implementing reminders, monitoring, and support functions. These interventions can be single or composite (using two or more interventions). The composite intervention can include group support. All interventions can include analytics to study the effectiveness of interventions. The interventions can be personalized to improve suitability to different patients and reduce the overall cost. If an intervention is not leading to desirable outcomes, it can be changed to a more suitable intervention.

The entire design approach is shown in Figure 1 which includes requirement generation and evaluation. We utilize multiple theories (such as social cognitive theory, health promotion model, theory of planned, cognitive load theory) to support the design of smart intervention for opioid abuse. Additional theories can be added to improve the smart intervention for personalization. The insights from the evaluation will lead to further enriching the existing theories and improving the smart intervention by integrating the contextual information.

INTERVENTIONS

In this study, we designed three interventions for managing opioid abuse using the design approach for smart interventions (Figure 1). These interventions are based on specific functions supported by (a) mobile reminders, (b) electronic monitoring, and (c) combined reminders and group support from other patients. The interventions, termed INTV1, INTV2, and INTV3, are shown in Figure 2. INTV1 is based on reminders and can be supported by a mobile application or specialized software on a mobile device. INTV2 is based on communication with a smart medication box that keeps track of doses and timing. INTV3 can be supported by a website that allows patients to interact with one another and to receive educational information related to their specific conditions.

Intervention 1 (INTV1) is shown in Figure 3. The process includes collecting information on the prescription opioid and deriving when and how to generate opioid reminders. After collecting consumption information, a decision must be made on if the dose has been taken or not. The smart reminder will only be generated if the dose has not been taken and it is still safe to consume the dose. If the patient is not responsive to a smart reminder, a notification will be sent to healthcare professionals after a certain number of reminders have been sent to the patient. Figure 4 shows the operationalization of intervention 1. This includes sending a reminder to the patient at the prescribed time if the patient has not taken the dose already. As shown in Figure 4, the reminder app (Rem-App) sends a message to the patient to take the opioid dose within the time-window. The app also tells the patient to wait for the next dose until the next reminder. Finally, the Rem-App detects the

Figure 1. The design approach for smart interventions

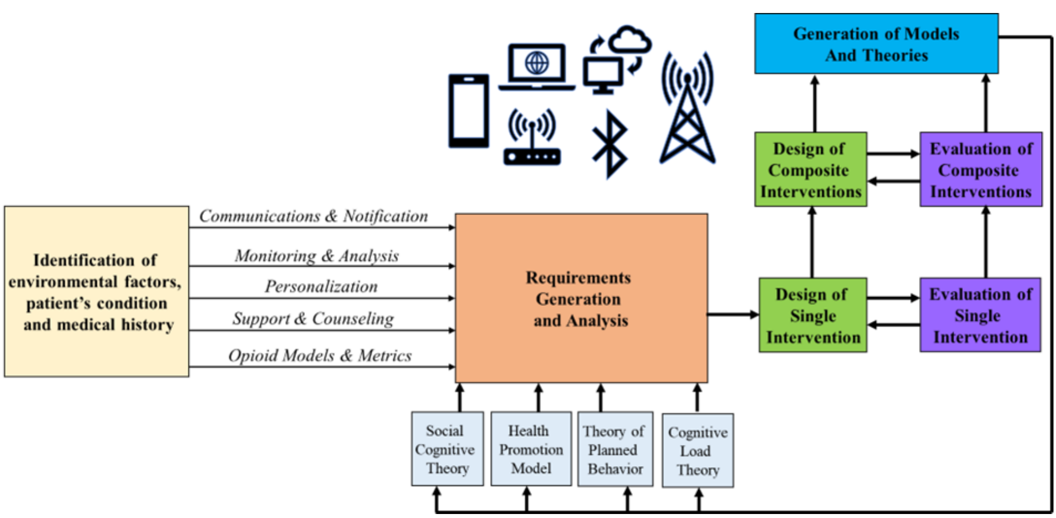
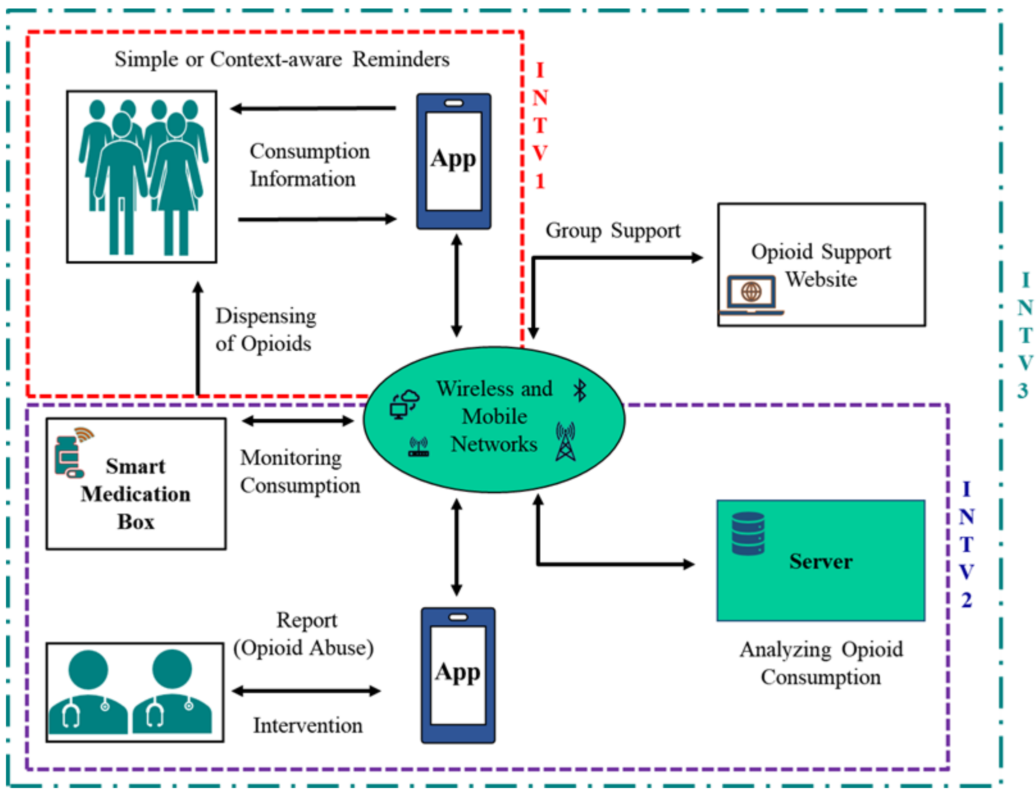


Figure 2. Three interventions for preventing prescription opioid abuse



patient's mood for its context-aware operation. It asks healthcare professionals (HP) to intervene if doses are taken too closely or more frequently or more doses at a time than prescribed (analysis of consumption patterns).

Intervention 2 (INTV2) is shown in Figure 5. This involves enabling the prescription opioid monitoring and receiving the various thresholds for monitoring. The monitoring process involves data from smart medication box, consumption data from multiple sources with weighted reliability, and identifying the patterns of consumption. Based on the monitoring observations, the notifications will be processed to report to the healthcare professional. This will include tracking of how many times pressure has been applied to "forced" open the smart medication box. Figure 6 shows the operationalization of intervention 2. The prescription opioid app (PO-App) retrieves dosing consumption data from the smart medication box. The consumption history is analyzed by the PO-App and if any abnormal patterns or behaviors are found then the healthcare professionals are contacted for a suitable intervention.

Intervention 3 (INTV 3) is shown in Figure 7. This integrates functions from INTV1 and INTV2 and incorporates group support from friends, family, and counselors. Figure 8 shows the operationalization of intervention 3. The support app (SUP-App) provides group support resources including contacting, scheduling, and counseling. These are highly personalized to the current need of the patients.

The proposed interventions are compared in Table 1, based on their functions, potential strengths, and limitations. INTV1 will collect opioid consumption information from the patient and send the reminder to avoid overconsumption. The potential problems include recall bias of the patient, user interface challenges, and any reliability and access problems. INTV2 will monitor and analyze opioid

Figure 3. Intervention one: Reminder

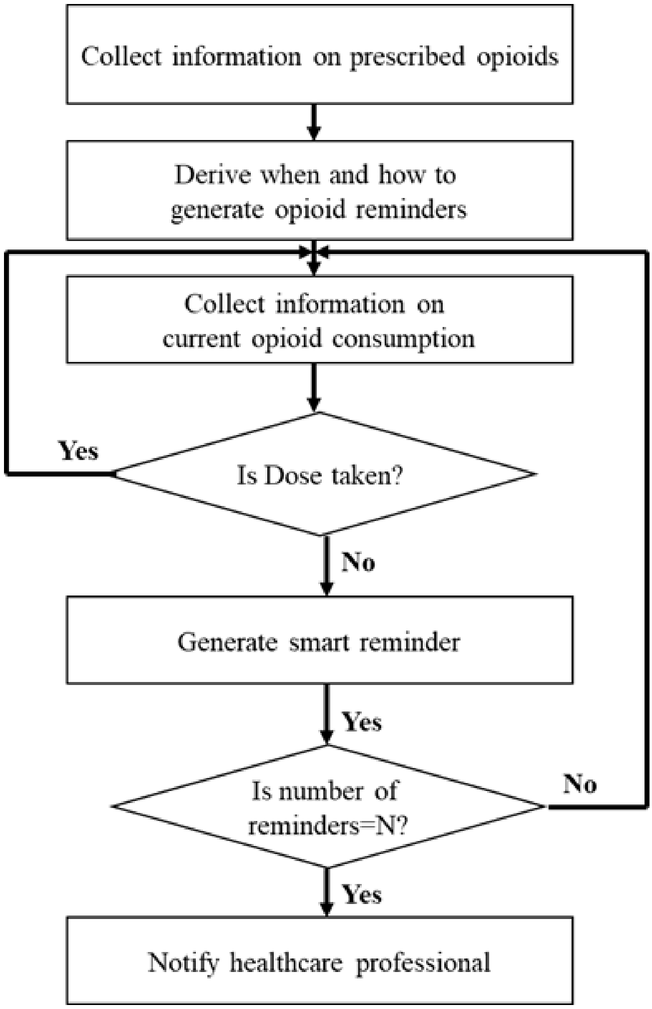


Figure 4. Operationalization of intervention one (Context-aware reminders)

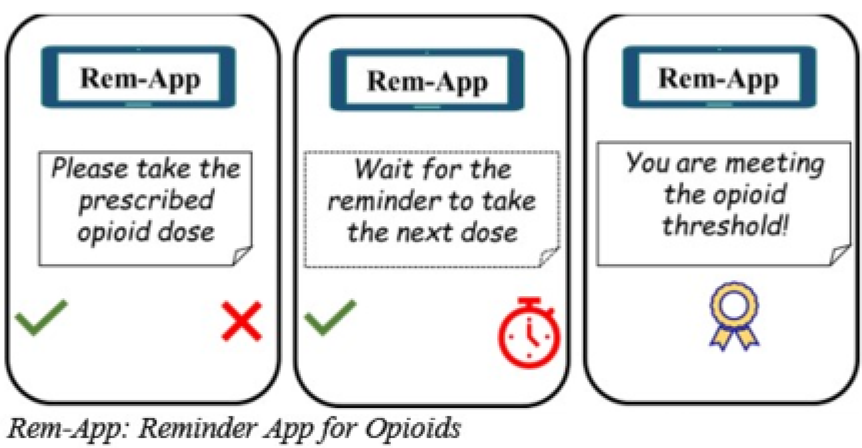


Figure 5. Intervention two: Monitoring

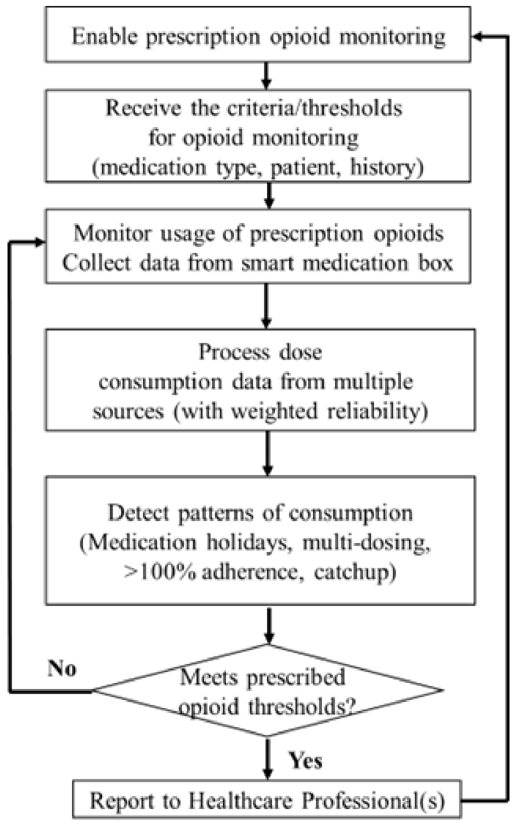
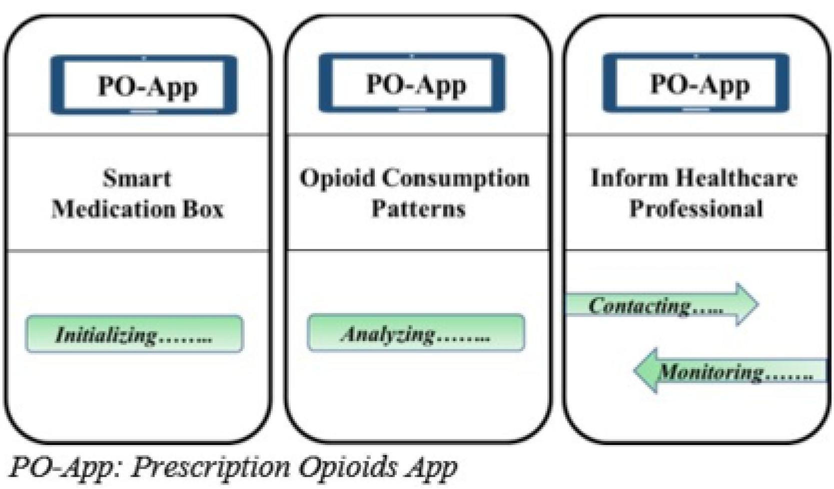


Figure 6. Operationalization of intervention two (Monitoring)



consumption information from a smart medication box. The potential problems include the operation of smart medication box and network access. INTV3 requires a sophisticated website and highly personalized support for the patient and can be fairly complex.

Figure 7. Intervention three: Composite

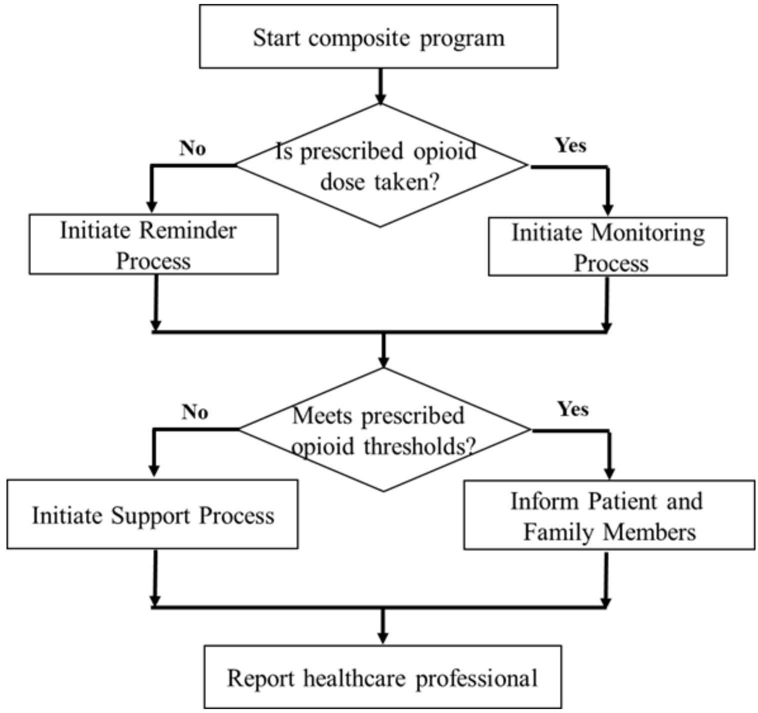
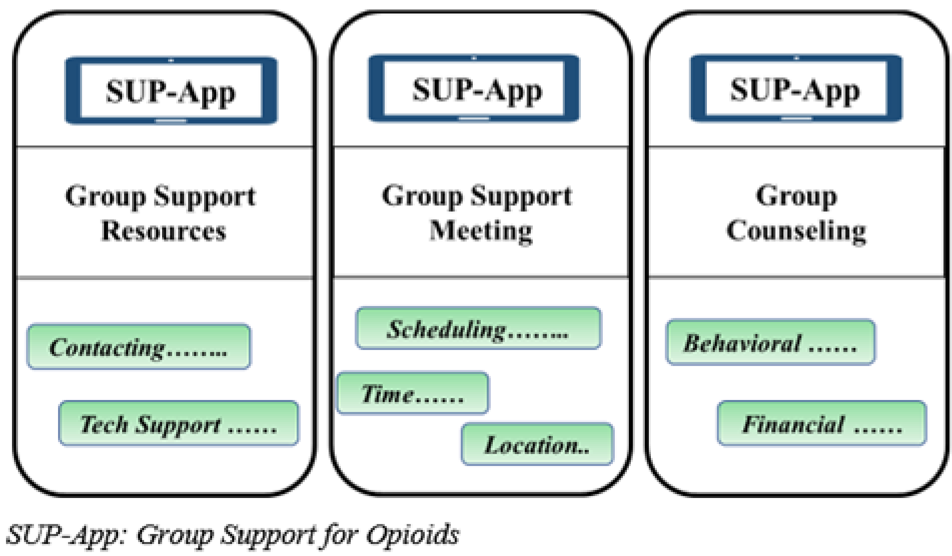


Figure 8. Operationalization of intervention three (Composite)



In this paper, we do not study the medical effectiveness of these three interventions, but rather focus on the cost of these interventions and when these interventions may be suitable. In the future, these interventions can be implemented and tested with real patients for improving opioid consumption behavior.

Table 1. Comparison of proposed interventions

Intervention	Functions	Operation	Potential Strengths	Potential Limitations
INTV1 (Mobile Reminders)	Simple Reminder	If taken do not take the next dose, else if not taken please take it now	Reduce overconsumption	Accuracy and Effectiveness
	Context-aware Reminder	Will only come to maintain the prescribed opioid dose	Personalized	Complexity
INTV2 (Electronic Monitoring)	Electronic Monitoring	Monitoring and analyzing opioid consumption and necessary intervention	Works with Smart Medication Boxes and family members/healthcare professionals	Monitoring and analyzing overhead, trying to reach and use the time of family member and healthcare professionals
INTV3 (Composite)	Composite (group support, educational and reminders)	Integrating the operations of INTV1, INTV2, and technical/behavioral interventions	In addition to potential strengths of reminders and monitoring, effective due to interventions and support from patients	The complexity of group support and composite intervention

ANALYTICAL MODEL

Analytical models are the representations of mechanisms that govern natural phenomena that are not fully recognized, controlled or understood (Tedeschi, 2006). They have become indispensable tools for policy and decision-makers and researchers (Tedeschi, 2006). However, certain techniques must be used to evaluate mathematical models for objectives, scope and assumptions, appropriateness or validation, and limitations. Essentially, the model should be appropriate for its intended purpose under the given conditions. The model is appropriate (Tedeschi, 2006) for studying opioids in chronic illnesses, where multiple opioids are used over an extended period. The interventions and their cost can be approximated by the model. Therefore, the model is valid and sound and does what it is supposed to do (Tedeschi, 2006). Further, the three steps of model validation (Hamilton, 1991): verification of the model, sensitivity analysis, and evaluation of the model, are performed below.

The verification involved step by step checking of the model and debugging where one or more changes in inputs could lead to unacceptable output (Hamilton, 1991; Tedeschi, 2006). Further, the model was calibrated using values from other studies (AHRQ, 2014; Aroke et al., 2018; Mallow, Belk, Topmiller, & Strassels, 2018; NYState, 2018; Schuchat, Houry, & Guy, 2017; Vivolo-Kantor et al., 2018). The model builds upon prior models, and the results obtained from the model are also supported by other studies. The model was validated by testing for many known cases to verify its functioning. Further, the causal relationships of Opioid with pharmacy cost, hospitalization cost, emergency room and outpatient cost, and the intervention cost for multiple chronic conditions were utilized (AHRQ, 2014; Aroke et al., 2018). All relationships in the model were verified and additional relationships were derived by utilizing known relationships.

The sensitivity analysis was performed to test the behavior of every equation in the model (Hamilton, 1991). There are several ways to perform sensitivity analysis for mathematical models (Christopher Frey & Patil, 2002). We focused on the nominal range sensitivity (Varshney & Singh, 2020a). For our model, we broadly defined the ranges of all input values obtained from other studies and expanded even further to cover more extreme cases. The analysis included combining several input values and measuring outputs for these combinations of inputs. The results of this analysis are presented in the next section. This also helps in answering “what-if” questions such as “what if patients lived in a city where hospital costs for opioids were lower” or “what if an opioid intervention stopped working”.

The evaluation of the model was done to test the adequacy (or robustness) of the model based on the precision and accuracy of results (Hamilton, 1991; Tedeschi, 2006). The model is precise as it produces values that are close to one another in multiple iterations. The model accuracy is based on (a) known relationships and (b) calibration of results for decision making. To measure accuracy further, we tested our model on input data and results from (AHRQ, 2014; Aroke et al., 2018; Mallow et al., 2018; NYState, 2018; Schuchat et al., 2017; Vivolo-Kantor et al., 2018). We further evaluated our model by computing the ROI for all three interventions for low, medium, and high range of input parameters. These values are in close agreement, so our results on opioid abuse and healthcare cost are validated using published data, while other results on cost of interventions are extrapolated based on known relationships and available data from multiple studies. Several assumptions were made to keep the analytical model tractable and reasonably accurate (Tedeschi, 2006). The assumptions are:

Assumption 1: The patients are adults and living independently.
Assumption 2: The patients can take opioids as prescribed.
Assumption 3: The patients are willing to try one or more interventions.
Assumption 4: It is possible to amortize the cost over multiple patients.

These assumptions could be relaxed in future work. To improve the readability of the analytical model, the notations used are shown in Table 3.

To develop the model, we focused on healthcare savings which can be derived using the cost of healthcare without intervention and cost of healthcare with intervention as shown in equation 1:

Table 2. Input parameters, key values, and sources

Input Parameters	Average for opioid abuse	Source
The hospitalization rate	.08 per person/year (0.05 - 1)	(NYState, 2018; Schuchat et al., 2017)
The duration of hospital stays	4.35 days (2-10 days)	(Mallow et al., 2018)
The daily cost of hospital stays	$1884 per day ($1000 - $3000)	(Mallow et al., 2018)
The rate of emergency room visits	0.086 person/year (0.05 - 1)	(Vivolo-Kantor et al., 2018)
The cost of emergency room visits	2150 ($1000 - $5000)	(AHRQ, 2014)
The outpatient visit rate	12 times a year	Assumption once a month
The cost of outpatient visits	$458 ($200 - $700)	(Mallow et al., 2018)
The annual cost of brand name medication/polypharmacy	$7078 ($4000 - $10000)	(Aroke et al., 2018)
The annual cost of generic medication	$692 ($120 - $1000)	(Aroke et al., 2018)
Probability of brand name prescription	6% (0-20%)	(Aroke et al., 2018)
Probability of generic prescription	94% (80-100%)	(Aroke et al., 2018)

Table 3. Notations used in analytical model

Notation	Meaning
$Accurate_{INTV}$	Intervention is accurate
C_{MIN}	The cost per minute of cellphone calls
$CF_{HOUR\text{-}J}$	The cost of j^{th} hour for a family member (salary and benefits)
$Cost_{FIX}$	The fixed cost of intervention
$Cost_{VAR}$	Variable cost of intervention per year
$CP_{HOUR\text{-}I}$	The cost of i^{th} hour for healthcare professionals (salary and benefits)
CS_{II+1}	The cost of switching from I^{th} to $I+1^{st}$ intervention
$Doctor_{PrescOpioid}$	Finding a doctor to prescribe opioids
$Doctor_{WillingPresc}$	Doctor willing to prescribe
FI_{MAX}	Maximum allowed financial incentive for adoption of an intervention
$HC_{Savings}$	Healthcare Savings
$HC_{CostwithoutINTV}$	Cost of healthcare without intervention
$HC_{CostwithINTV}$	Cost of healthcare with intervention
$INTV_{CostperYear}$	Cost of intervention per year
K	The duration to study the benefits of reducing opioid abuse
$N_{MIN\text{-}K}$	The number of phone minutes used in the k^{th} day
NP	Number of patients
$NYRINTV$	Number of years intervention will be used
$Patient_{Willingness}$	Willingness of patient
$Patient_{Suitability}$	Suitability to a patient
$P_{Addiction}$	Probability of addiction
$P_{EffectiveINTV}$	Probability that intervention is effective
P_{PRESC}	Probability of prescription
QALY	Quality adjusted life years

continued on following page

Table 3. Continued

Notation	Meaning
QoL	Quality-of-Life
$Reliable_{INTV}$	Intervention is reliable
ROI	Return of Investment
TCI	Total Cost of Intervention
TF_{HOUR}	Total time spent by a family member
TP_{HOUR}	Total time spent per year by healthcare professionals
$Total_{Value}$	The total value obtained due to intervention in 1 year

$$HC_{Savings} = HC_{CostwithoutINTV} - HC_{CostwithINTV} \tag{1}$$

As shown in equation 2, the cost of intervention per year can be given as the sum of two ratios: the ratio of fix cost to the number of patients amortized over the number of years intervention will be used and the ratio of variable cost to the number of patients.

$$INTV_{CostperYear} = \left(\frac{Cost_{FIX}}{NP * NYRINTV}\right) + \left(\frac{Cost_{VAR}}{NP}\right) \tag{2}$$

The probability of prescription P_{Presc} is derived as a function of finding a doctor to prescribe opioids $Doctor_{PrescOpioid}$ and doctor willing to prescribe $\left(Doctor_{WillingPresc}\right)$. Further, the probability that intervention is effective is a product of willingness of patient, suitability of intervention to a patient, and whether the intervention is accurate and reliable.

$$P_{EffectiveINTV} = \left(Patient_{Willingness} Patient_{Suitability} \times Accurate_{INTV} Reliable_{INTV}\right) \tag{3}$$

The cost of interventions includes the cost of training, the ongoing time cost of healthcare professionals or family members involved, and the cost of communications. The patient's time is not included as suggested by (Windsor et al., 1990). However, minutes used for cell phone calls are included in the total cost of the intervention. Thus, the general equation for the total cost of the intervention (TCI) can be given as:

$$TCI = \sum_{I=1}^{TP_{HOUR}} \mathrm{CP}_{\mathrm{HOUR-I}} + \sum_{J=1}^{TF_{HOUR}} \mathrm{CP}_{\mathrm{HOUR-J}} + \sum_{K=1}^{DiY} \mathrm{N}_{\mathrm{MIN-K}} \times C_{MIN} + INTV_{CostperYear} \tag{4}$$

where, TP_{HOUR} is the total time spent per year by healthcare professionals and CP_{HOUR-I} is the cost of i^{th} hour for healthcare professionals including salary and benefits. TF_{HOUR} and CF_{HOUR-J} represent the same factors for a family member. N_{MIN-K} is the number of phone minutes used in the k^{th} day and

C_{MIN} is the cost per minute of a phone call. DiY represents the number of days in a year. C_{FIX} is the fixed cost of intervention, such as the development cost, and is amortized over intervention duration and the number of patients covered. C_{VAR} is the variable cost and can include maintenance cost of the intervention (such as website/servers) amortized over the number of patients. Not all interventions will have every cost component, but the above equation can be used to derive total cost of interventions for all three interventions. If the selected intervention is not effective, then the total cost of intervention also includes the switching cost as follows:

$$TCI = \sum_{I=1}^{N-1} (\mathrm{TCI}_{\mathrm{I}} + CS_{II+1} + TCI_{II+1}) \tag{5}$$

where, CS_{II+1} is the cost of switching from Ith to I+1st intervention.

For an intervention to be cost-effective, the savings must be more than the total cost of interventions (or $HC_{Savings}$ >= TCI). To quantify savings to different costs of interventions, we define Return on Investment (ROI) as the ratio of the product of the probability of prescription, probability of addiction, healthcare savings for addicted patient, and probability that intervention is effective to the cost of intervention:

$$ROI = (P_{Presc} \times P_{Addiction} \times HC_{Savings} \times P_{EffectiveINTV}) \,/\, TCI \tag{6}$$

Assuming non-negative quality of improvement values, the total QALY (Quality-adjusted Life Years) gained can be expressed as the sum of two improvements, one due to additional years obtained and another due to Quality-of-Life improvement in the existing years. However, we can focus on 1-year benefit, so the QALY gained is equal to the Quality-of-Life improvement when the patient does not have opioid abuse. Thus, the total value obtained in 1 year is the product of cost equivalent of one QALY and the number of QALY gained due to the intervention:

$$Total_{Value} = C_{QALY} \times N_{QALY} \tag{7}$$

Now, we explore the use of financial incentives for the adoption of an intervention (not given as cash, but to meet insurance deductible/co-pay/out-of-pocket). The maximum value of this financial incentive over a year can be given as follows:

$$FI_{MAX} = (P_{Presc} \times P_{Addiction} \times HC_{Savings} \times P_{EffectiveINTV}) - TCI \tag{8}$$

We are currently modeling a utility function involving personalized interventions for patients and patient's desirability for the interventions and outcomes. We will also address the optimization of this utility function along with mathematical proofs of lemmas and theorems. This will allow our analytical model to be more generalizable. The QALY gained will be computed using both the utility and predicted life expectancy.

RESULTS

Although multiple interventions are medically suitable in preventing opioid abuse, we want to evaluate the cost of interventions and study when and where these interventions are cost-effective. Next, the cost components of various interventions are shown in Table 4 along with the values used (BLS, 2018;

Page, Horvath, Danilenko, & Williams, 2012; Varshney, 2013). The cost of electronic monitoring is a function of the dosing frequency as additional processing is required from the healthcare professional every time an opioid is consumed or scheduled. Mobile reminders are the simplest intervention while composite intervention is likely to be most effective. The cost of the mobile application varies from zero to ten dollars a month to accommodate different versions (basic, premium, deluxe) of the app.

The ROI for different interventions is shown in Table 5. We included low, medium, and high values of parameters, to cover many different scenarios, in deriving ROI. The ROI is <1 (shown in red) for low and medium values of our input parameters, while it is much more favorable when the values of the parameters are set to high. For the same level of effectiveness, INTV3 is cost-effective only for 100% medical effectiveness and high value of parameters.

Next, we decided to include the value due to a potential improvement in Quality-of-Life (QoL). The ROI for different interventions with QoL included is shown in Table 6. Now, the ROI is <1

Table 4. The cost components of various interventions

The Intervention	Included Components	Time (Total Cost)	Total Cost of Intervention (TCI) (Low, Medium, High)
INTV1: Mobile Reminders	Training of a nurse (one-time initial cost)	2, 3 and 4 hours ($40, $60, $80)	$1099, $1179, $1259
	One phone call per day	5 minutes ($1.67)	
	Rest two calls as recorded messages	2 minutes ($0.67)	
	Mobile App cost per month	0, $5, $10	
INTV2: Electronic Monitoring	Training and installation	2, 3 and 4 hours ($40, $60, $80)	$1199, $1419, $1639
	Messages	2 minutes ($0.67)	
	Message Processing by a Nurse	5 minutes ($1.67)	
	Cost of Monitoring System/Software	$100, $300, $500	
INTV3: Composite	Informational Material Reminder Group Support Specialized Application	$500,000 developmental cost $5000/month maintenance cost	$1080 (1000 patients), $1453 (600 patients), $3320 (200 patients)
	Family/Healthcare professional	30 minutes ($20/hour cost=$10)	

Table 5. ROI for various types and level of intervention effectiveness

Effectiveness	ROI								
	INTV1			INTV2			INTV3		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
25%	0.0005	0.04	0.66	0.0005	0.03	0.51	0.0005	0.03	0.25
50%	0.001	0.08	1.32	0.0015	0.09	1.53	0.001	0.06	0.5
75%	0.0015	0.12	1.98	0.0015	0.09	1.53	0.0015	0.09	0.75
100%	0.002	0.16	2.64	0.002	0.12	2.04	0.002	0.12	1

Low, Medium, and High range for following input parameters:
Hospitalization, Number of days, Cost/day, Emergency visit rate, Emergency cost/visit, Probability of addiction

(shown in red) only for low values of our parameters, while it is much more favorable (shown in green) when the values of the parameters are set to medium or high.

Next, we decided to add a financial incentive (not cash, but payment for insurance deductible, out-of-pocket expenses or co-pay for general healthcare and wellness) to improve the adoption of three interventions by patients. We wanted to compute the maximum allowed financial incentives that can be offered to the patients while still meeting the cost-effectiveness goal for the interventions. Based on the medical effectiveness level of intervention, the range of financial incentives varies from \$165-\$1509 for INTV1 for medium values and \$2066-\$12041 for high values. Similar numbers are \$597-\$1269 for INTV2 for medium values and \$1686-\$11661 for high values. The numbers and range for INTV3 for medium values are \$563-\$1235 and \$5-\$9980 for high values.

DISCUSSION, CONCLUSION, AND FUTURE WORK

Prescription opioid abuse can lead to addiction, higher healthcare costs, and serious harm to patients. This abuse requires detoxification and hospitalization very similar to a chronic condition. One of the major observations from the literature is that only 10% of people with opioid abuse get treatment or help. Therefore, opioid abuse is a major challenge for patients and family members, healthcare professionals, employers, regulators, and society. There is a need for interventions at multiple levels before patients develop opioid addiction and require major treatment. In this paper, we focused on patient-level interventions, which are proactive and with some probabilities will be effective for some patients in preventing them from developing an opioid addiction. The smart interventions are (a) mobile reminders, (b) electronic monitoring of opioids, and (c) composite intervention.

Table 6. ROI for different interventions with quality-of-life improvement

Effectiveness	ROI with QoL								
	INTV1			INTV2			INTV3		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
25%	0.0232	0.57	2.646	0.0214	0.47	2.035	0.0236	0.4601	1.003
50%	0.0464	1.14	5.292	0.0427	0.941	4.071	0.0473	0.9203	2.006
75%	0.0697	1.71	7.938	0.0641	1.411	6.106	0.0709	1.38	3.009
100%	0.0928	2.28	10.584	0.0854	1.882	8.141	0.0946	1.841	4.012

Low, Medium, and High range for following input parameters:
Hospitalization, Number of days, Cost/day, Emergency visit rate, Emergency cost/visit, Probability of addiction, QoL

Table 7. Maximum allowed financial incentives

Effectiveness	Maximum Allowed Financial Incentives/Year with QoL								
	INTV1			INTV2			INTV3		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
25%	0	0	\$2066	0	0	\$1686	0	0	\$5
50%	0	\$165	\$5391	0	0	\$5011	0	0	\$3330
75%	0	\$837	\$8716	0	\$597	\$8336	0	\$563	\$6655
100%	0	\$1509	\$12041	0	\$1269	\$11661	0	\$1235	\$9980

Low, Medium, and High range for following input parameters:
Hospitalization, Number of days, Cost/day, Emergency visit rate, Emergency cost/visit, Probability of addiction, QoL

Using prescription opioid abuse and intervention data, we derived the healthcare cost of opioid abuse along with the cost of three interventions. Using an analytical model and ROI (Return on Investment) as a metric for cost-effectiveness of interventions, we derived several results for all three interventions and various levels of effectiveness. We found that ROI is lower than 1 for low and medium values of our parameters, while it is much more favorable when the values of the parameters are set to high. When the value due to a potential improvement in Quality-of-Life was included, the ROI significantly improved for all three interventions. Further, we wanted to explore if the use of financial incentives will be suitable to improve the adoption of three interventions. For this, we computed the maximum allowed financial incentives that can be offered to the patients while still meeting the cost-effectiveness goal for the interventions.

Future work can include a meta-analysis/contextual analysis of data from multiple sources to further evaluate the model using empirical research or RCT or both. Further, the IT-based interventions can be compared with the non-IT interventions for opioid abuse. A randomized controlled trial (RCT) to evaluate the medical effectiveness of three proposed interventions will be highly desirable. The research can be further extended to field studies using Health Promotion Model, Theory of Addiction, Theory of Adaptation, and other theories on drug abuse.

COMPETING INTERESTS

All authors of this article declare there are no competing interests.

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