Association for Information Systems

AIS Electronic Library (AISeL)

AMCIS 2020 Proceedings

Healthcare Informatics & Health Information Tech (SIGHealth)

Aug 10th, 12:00 AM

Opioid Use Disorder: Studying Quality of Life with IT-based Interventions

Upkar Varshney
GSU, uvarshney@gsu.edu

Neetu Singh
University of Illinois - Springfield, nsing2@uis.edu

Opioid Use Disorder: Studying Quality of Life with IT-based Interventions

Completed Research

Upkar Varshney
Georgia State University
uvarshney@gsu.edu

Neetu Singh
University of Illinois at Springfield
nsing2@uis.edu

Abstract

Opioid Use Disorder (OUD) has become a major public health challenge. There have been several interventions, including those based on health-IT, proposed recently. There is a major need to study these interventions. We are interested in exploring how different IT-based interventions impact opioid related Quality of Life. We developed a model using Markov chain for three different states in OUD. The model and results can lead to better decision making by healthcare professionals, patients and insurance companies. More specifically, the proposed model and results can help in (a) whether to prescribe opioids to different types of patients, (b) what IT-based interventions are suitable with an opioid prescription, and (c) how patients and healthcare professionals can select an intervention out of multiple available interventions.

Keywords

IT-based interventions, opioid use disorder, Markov model, evaluation.

Introduction

Opioid Use Disorder (OUD) is a pattern of opioid consumption that causes significant problems for the patients including impairment and distress (Schatman and Ziegler 2017). OUD is also defined as any intentional use of opioids not following a physician's prescription for a specific medical condition (Finley et al. 2017; Sinha et al. 2017). OUD is a national public health crisis that can lead to an increase in healthcare costs and serious harm to patients (Blendon and Benson 2018). With 2 million people suffering from OUD in the US, the total cost is reaching to $100B/year (NIH 2019). Further, about 50% of the drug overdose deaths in the US are due to opioids (NIH 2019). OUD has become a major challenge for patients and family members, healthcare professionals, employers, regulators, and society. The vulnerability to OUD is related to the history, genetic makeup, current environment and stressors, medical condition (co-morbidities) and type of opioid prescribed. This could lead to mild, moderate, or severe form of OUD (Association 2013), all of which are considered and treated as chronic diseases. Once there, the OUD patients, with or without overdose events, will require expensive inpatient treatment (Chintha et al. 2018; Ivanov and Tacheva 2018) followed by a long-term outpatient treatment in remission.

In this paper, we want to explore what role IT-based interventions can play in OUD. To start, OUD can be expressed as three states for patients (prevention, addiction, and remission). Figure 1 shows the states and possible IT-based interventions for OUD. IT-based interventions can be implemented using both simple and sophisticated mobile apps, sensors, mobile devices, and smart medication boxes (Singh and Varshney 2019; Varshney 2013). This could proactively stop patients from becoming dependent on prescription opioids or developing OUD. This brings our research question: To what extent the IT-based interventions are useful for patients with Opioid Use Disorder (OUD)?

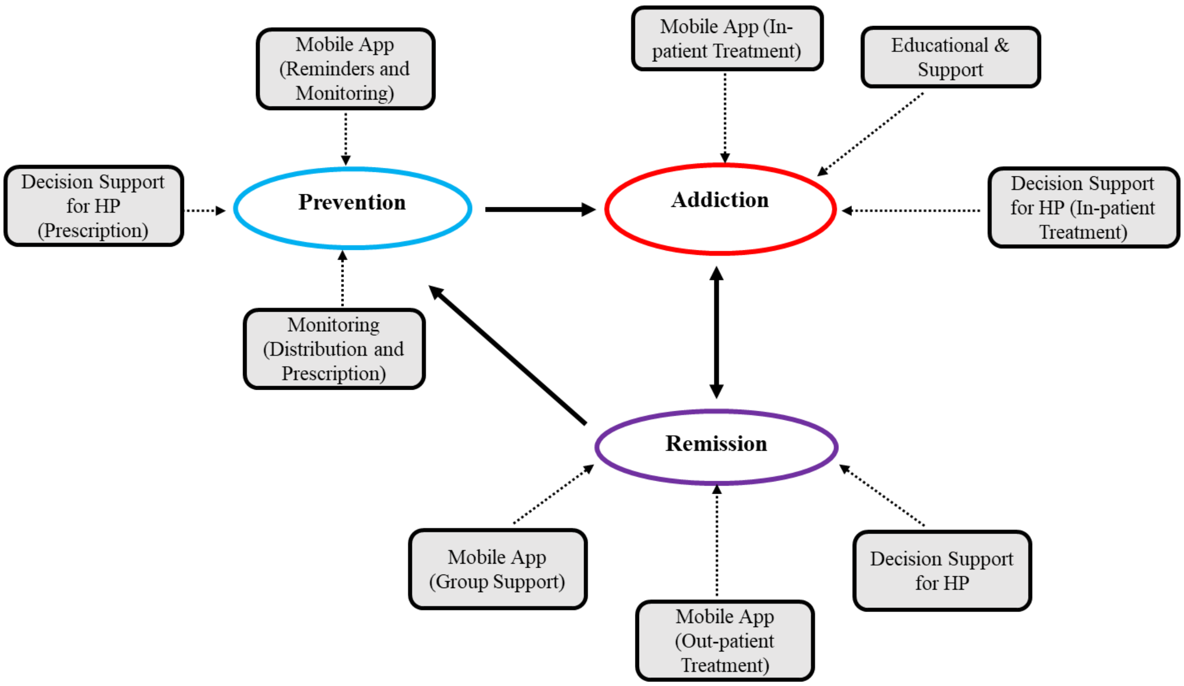

Figure 1. IT-based Interventions at Different Opioid States

To answer our research question, we explored various metrics to measure the impact of IT-based interventions. We observed that Quality of Life (Diener and Suh 1997) is a multi-faceted attribute used in numerous studies in healthcare (Carlsson and Walden 2018; Chen et al. 2014; Mansingh et al. 2013; WHOQOL-BREF 1998; WHOQOL 1995). QOL can measure physical health, psychological, social relationships and environment (WHOQOL-BREF 1998; WHOQOL 1995). These factors are somewhat and very broadly related to people with OUD. Further, another metric for QOL is healthcare related (HRQOL) that measures mobility, self-care, main activity, social relationships, pain, and mood (EuroQol 1990). HRQOL is used both for generic health and specific diseases (Guyatt et al. 1993). However, we felt that QOL and HRQOL are too broad for our study to measure the impact of IT-interventions for Opioid Use Disorder. Therefore, we propose and use a new metric, termed opioid related QOL (ORQOL) that can measure risk score, current condition, prevention, addiction, and remission.

Markov models have been used in numerous healthcare studies (Ayabakan et al. 2016; Kwon et al. 2017; Lam et al. 2018; Luo et al. 2019). In our exploration, we discovered that the quality of life for OUD patients and the impact of IT-based interventions can be studied using Markov models. Therefore, we utilize a Markov chain, a special type of Markov model, for different states of OUD when the system is observable and autonomous (Sonnenberg and Beck 1993). We model prevention, addiction, remission, related treatments, and IT-based interventions for OUD. The model includes decision scenarios for both single and polypharmacy of opioid prescriptions. To the best of our knowledge, this is the first study that uses the Markov chain for studying opioids.

Our model and results can be very helpful for decision making in (a) whether to prescribe opioids to different types of patients, (b) what IT-based interventions are suitable with an opioid prescription, and (c) how patients and healthcare professionals can select an intervention out of multiple available interventions. Several factors are likely to affect these decisions and are addressed in this study.

In the next section, we present the Markov chain for OUD states for patients. We show how the model is developed and solved for different scenarios of decision making. The results from the model are presented and discussed next. Finally, the discussion and conclusion are presented.

The Model for Opioid Use Disorder (OUD)

Markov Chain and QOL

Markov models are useful when a decision problem involves a risk that is continuous over time (meaning the risk is ongoing), when the timing of events is important, and when important events may happen more than once (Sonnenberg and Beck 1993). Markov models have been used in numerous studies when the system is observable and autonomous. We use it to model the patient's opioid states, where the patient moves from one state to the other based on a different set of actions. Since transition probabilities among states are constant over time, we use the Markov chain. More specifically, it is a 3-states model including Prevention, Addiction, and Remission. For example, a patient moves from Prevention to Addiction based on his/her current condition, history, and access to opioid prescriptions. The Prevention state indicates that the patient is vulnerable as he/she has some condition for addiction or is taking prescription opioids. The Addiction state indicates that the patient has developed an addiction and is getting an in-patient treatment (detoxification). After successful treatment, the patient moves to the Remission state and can stay there or move back to Addiction state, or after successful remission, can move to the Prevention state. Because of the Markovian assumption (Sonnenberg and Beck 1993), the current state has no memory for time spent in earlier states, so when the patient is in Addiction state, it does not matter how much time he/she had spent in Prevention state. In practice, the Markovian assumption is not followed strictly in medical problems (Sonnenberg and Beck 1993). However, the assumption is necessary to model the opioid behavior with a finite number of states. The use of Markov models has the potential to permit the development of decision models that more faithfully represent healthcare problems (Sonnenberg and Beck 1993).

Our goal is to estimate the probability of a patient in a given state and then translate that to ORQOL (Opioid Related Quality of Life), a new metric for measuring Quality of Life for patients taking prescription opioids. The use of a specific measure, with normalized values (0 to 1), allows us to study the impact of different IT-based interventions. We find that different interventions at different opioid states have an impact on ORQOL. The change in ORQOL is used to compare and decide which intervention to use when and where. This can help in improved decision making, resulting in more efficient resource allocation in healthcare.

Assumptions

Several assumptions were made to keep the model tractable and reasonably accurate (Tedeschi 2006). The assumptions are (1) the patients are adults and living independently and can make rational decisions, (2) the patients can take opioids as prescribed, (3) the patients are willing to try interventions and, (4) for Markov chain, state-transition probabilities are constant over time. These assumptions could be relaxed in future work. We decided to keep the model at reasonable complexity leading to approximated results. For more accurate results, significant details must be added in the model and much more complex analysis must be carried out.

Model Description

The Markov chain is shown in Figure 2 with three different opioid states for patients and seven transition probabilities. Two transition probabilities are zero as patients cannot move to (a) Prevention state from Addiction state and to (b) Remission state from Prevention state directly. Different transition probabilities, impacted by the absence or presence of different interventions, are defined as follows: P_{PP} indicates that the patient does not get a prescription or has a prescription and is managing it well, P_{PA} indicates that the patient is moving from Prevention to Addiction state, P_{AA} indicates that patient remains in Addicted state, while P_{AR} indicates moving from Addiction to Remission state. P_{RA} shows moving back from Remission to Addiction state, P_{RR} indicates that the patient remains in the Remission state, and P_{RP} indicates that the patient has completed remission and is moving to the Prevention state.

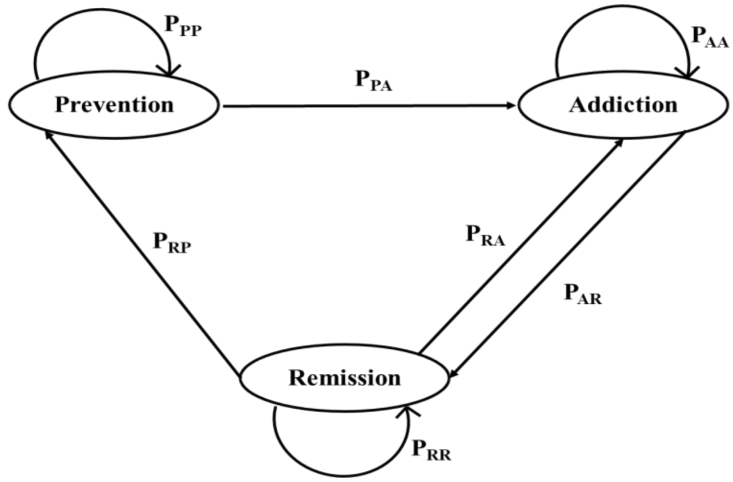

Figure 2. Markov Model for Evaluating the Impact of Different Interventions

Solving the above chain (Figure 2), we obtain the following sets of equations for different actions and transition probabilities that will lead to the development of the model for analyzing ORQOL.

The steady-state probability of being in Prevention state (P_P) is given as

$$P_P = \frac{\frac{P_{RP}}{1-P_{PP}}}{1+\left(\frac{P_{RP}}{1-P_{PP}}\right)+\left(\frac{1-P_{RR}}{P_{AR}}\right)} \quad \textbf{(1)}$$

The steady-state probability of being in Addiction state (P_A) is given by

$$P_A = \frac{\frac{1-P_{RR}}{P_{AR}}}{1+\left(\frac{P_{RP}}{1-P_{PP}}\right)+\left(\frac{1-P_{RR}}{P_{AR}}\right)} \quad \textbf{(2)}$$

Probability of being in Remission state (P_R) is given by

$$P_R = \frac{1}{1+\left(\frac{P_{RP}}{1-P_{PP}}\right)+\left(\frac{1-P_{RR}}{P_{AR}}\right)} \quad \textbf{(3)}$$

For Prevention state,

$P_{PP} = 1 - P_{PA}$

Where, P_{PA} can be expressed as a product of Risk Score and Prescription Probability, as shown in equation 4.

$$P_{PA} = \mathrm{Risk_{Score}} \times \mathrm{P_{PRESC}} \quad \textbf{(4)}$$

Further, Risk Score is presented as follows:

$$\mathrm{Risk_{Score}} = \mathrm{Risk_{Weight1}} \times \mathrm{Past_{History}} + \mathrm{Risk_{Weight2}} \times \mathrm{Specific_{Condition}} + \mathrm{Risk_{Weight3}} \times \mathrm{Health_{Comorbidities}} + \mathrm{Risk_{Weight4}} \times \mathrm{Risk_{ReqMed}} \quad \textbf{(5)}$$

For three different scenarios, Prescription Probability is given as shown in equations 6, 7, and 8.

$$\mathrm{P_{PRESC.Scenario1}} = \mathrm{Current_{Condition}} \quad \textbf{(6)}$$

$$\mathrm{P_{PRESC.Scenario2}} = 1 - \mathrm{Risk_{Score}} \quad \textbf{(7)}$$

$$\mathrm{P_{PRESC.Scenario3}} = \mathrm{Weight1} \times (1 - \mathrm{Risk_{Score}}) + \mathrm{Weight2} \times \mathrm{Current_{Condition}} \quad \textbf{(8)}$$

Prescription probability with doctor shopping or polypharmacy can be expressed for N doctors as follows:

$$PP_{Poly} = \sum_{R=1}^{N} \binom{N}{R} (P_{Presc})^{R} (1 - P_{Presc})^{N-R} \quad \textbf{(9)}$$

For Addiction state, $P_{AA} = 1 - P_{AR}$

Where, $P_{AR} = (P_{TreatmentResources} \times P_{Treatment} \times P_{TreatmentEffective})$ **(10)**

For Remission state, the transition probabilities are shown in equations 11, 12, and 13.

$$P_{RA} = 1 - P_{PostOUDTreatmentNotEffective} \quad \textbf{(11)}$$

$$P_{RP} = P_{PostOUDTreatmentEffective} \times P_{CompletedReqDur} \quad \textbf{(12)}$$

$$P_{RR} = P_{PostOUDTreatmentEffective} \times P_{NotCompletedReqDur} \quad \textbf{(13)}$$

Finally, the Opioid Related Quality of Life (ORQOL) can be expressed as a function of probability of being in different states and the corresponding QOLs.

$$ORQOL = \sum_{I=1}^{M} P_I \times QOL_I \quad \textbf{(14)}$$

Results

We wanted to explore the role of IT-based prescription decisions and incentives. Using the above model, we derived ORQOL for three different scenarios of opioid prescriptions where information is collected from EHR, sensors, mobile apps and PDMP (Prescription Drug Monitoring Program). The first uses patient's current condition only, while the second scenario considered both risk score (computed by an algorithm using multiple factors) and patient's current condition (0.25 & 0.75, 0.5 & 0.5, 0.75 & 0.25), and the third scenario focused on risk score only. The detailed results including the intermediate analysis are shown in Table 1. The results visualizing the ORQOL for various risk score/current condition are shown in Figure 3.

Decision Scenario	Risk Score	Prescription Probability	P_V	P_A	P_R	ORQOL
Scenario 1: W1 = 0 and W2 = 1.0 (no weight for risk score)	0.0	0.75	1.0	0.0	0.0	1.0
	0.25	0.75	0.348	0.391	0.261	0.479
	0.5	0.75	0.211	0.474	0.316	0.369
	0.75	0.75	0.151	0.509	0.340	0.321
	1.0	0.75	0.118	0.529	0.353	0.295
Scenario 2: W1 = 0.25 and W2 = 0.75 (some weight for risk score)	0.0	0.813	1.0	0.0	0.0	1.0
	0.25	0.75	0.348	0.391	0.261	0.479
	0.5	0.688	0.225	0.465	0.310	0.380
	0.75	0.625	0.176	0.495	0.329	0.341
	1.0	0.563	0.151	0.510	0.339	0.321
Scenario 2: W1= 0.5 and W2= 0.5 (average weight for risk score)	0.0	0.875	1.0	0.0	0.0	1.0
	0.25	0.75	0.348	0.391	0.261	0.479
	0.5	0.625	0.243	0.454	0.303	0.395
	0.75	0.5	0.211	0.474	0.316	0.369
	1.0	0.375	0.211	0.474	0.316	0.369
Scenario 2:	0.0	0.938	1.0	0.0	0.0	1.0

W1= 0.75 and W2= 0.25 (high weight for risk score)	0.25	0.75	0.348	0.391	0.261	0.479
	0.5	0.563	0.262	0.443	0.295	0.410
	0.75	0.375	0.262	0.443	0.295	0.410
	1.0	0.188	0.348	0.391	0.261	0.479
Scenario 3: W1 = 1.0 and W2 = 0.0 (complete weight for risk score)	0.0	1.0	1.0	0.0	0.0	1.0
	0.25	0.75	0.348	0.391	0.261	0.479
	0.5	0.5	0.286	0.429	0.286	0.429
	0.75	0.25	0.348	0.391	0.261	0.479
	1.0	0.0	1.0	0.0	0.0	1.0

Table 1. The Role of Prescription decisions on ORQOL

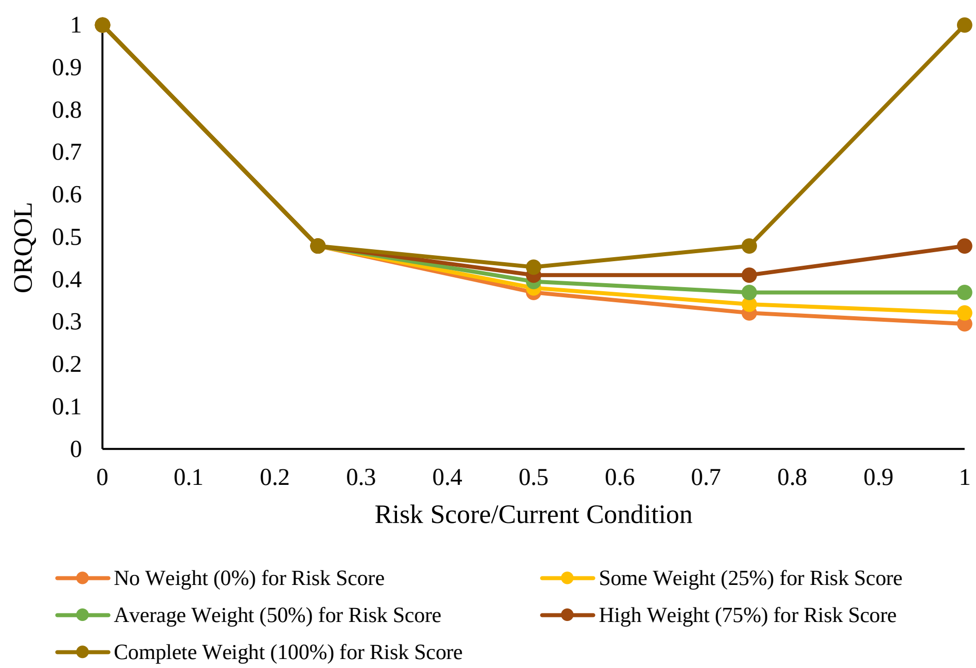

Figure 3. ORQOL for Rewarding Healthcare Professionals for Improved Prescriptions

The next set of results is obtained to show the role of polypharmacy where patients approach multiple healthcare professionals to obtain one or more opioid prescriptions. This is normally done across multiple states in the US, as state level monitoring (Prescription Drug Monitoring Programs) keeps track of opioid prescriptions in an individual state. As expected, the ORQOL becomes worse with an increased level of polypharmacy as shown in detailed results in Table 2 and as a pattern in Figure 4.

Polypharmacy level	Risk Score	Prescription Probability	P_P	P_A	P_R	ORQOL
1	0.0	0.875	1.0	0.0	0.0	1.0
	0.25	0.75	0.348	0.391	0.261	0.479
	0.5	0.625	0.243	0.454	0.303	0.395

	0.75	0.5	0.211	0.474	0.316	0.369
	1.0	0.375	0.211	0.474	0.316	0.369
2	0.0	0.984	1.0	0.0	0.0	1.0
	0.25	0.938	0.299	0.420	0.280	0.439
	0.5	0.859	0.189	0.487	0.324	0.351
	0.75	0.750	0.151	0.509	0.340	0.321
	1.0	0.609	0.141	0.515	0.344	0.313
3	0.0	0.997	1.0	0.0	0.0	1.0
	0.25	0.984	0.289	0.427	0.284	0.431
	0.5	0.947	0.175	0.495	0.330	0.340
	0.75	0.875	0.132	0.521	0.347	0.301
	1.0	0.756	0.117	0.530	0.353	0.294

Table 2. Role of Polypharmacy on ORQOL

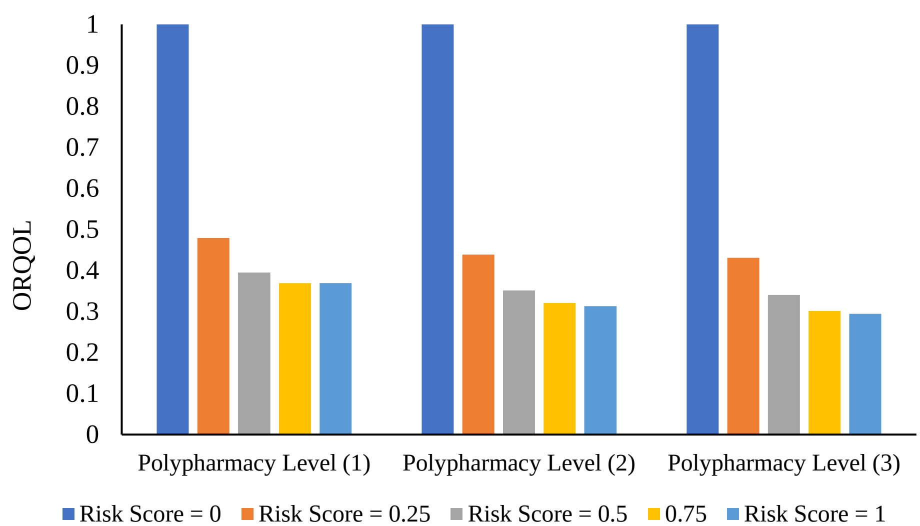

Figure 4. ORQOL for Different Levels of Polypharmacy

Now, we want to explore the impact of IT-interventions, such as a mobile app for patient support and education, in Remission. Using the Markov chain and associated equations, we derive the ORQOL. These results show that the time a patient spends in the Remission state and Addiction state (highly undesirable) reduces with a corresponding increase in the Prevention state (highly desirable). Overall, the ORQOL improves as the effectiveness of IT-interventions increases. The results are shown in Figure 5.

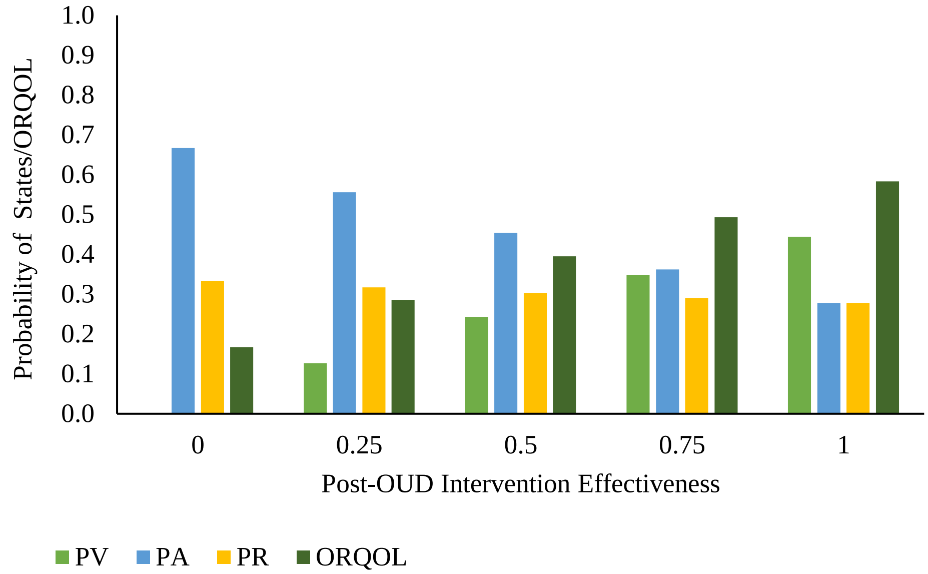

Figure 5. ORQOL for IT-interventions in Remission

Finally, we want to explore how preventive IT-interventions will impact ORQOL. These include educational interventions: (a) discouraging patients from polypharmacy, (b) managing the opioid consumption safely by being adherent, and (c) reducing the risk of addiction. These potentially implemented as mobile or web-based IT-interventions could reduce the risk of addiction. The results are shown in Table 3 and Figure 6. The ORQOL is improved as the effectiveness of preventive IT-intervention increases.

	Risk Score	Actual Risk Reduction	Prescription Probability	P_P	P_A	P_R	ORQOL
No preventive IT-intervention	0.0	0.0	0.875	1.0	0.0	0.0	1
	0.25	0.0	0.75	0.348	0.391	0.261	0.479
	0.5	0.0	0.625	0.243	0.454	0.303	0.395
	0.75	0.0	0.5	0.211	0.474	0.316	0.369
	1.0	0.0	0.375	0.211	0.474	0.316	0.369
IT-intervention for max. risk reduction = 0.25	0.0	0.0	0.875	1.0	0.0	0.0	1
	0.25	0.25	0.875	1.0	0.0	0.0	1
	0.5	0.25	0.75	0.348	0.391	0.261	0.479
	0.75	0.25	0.625	0.243	0.454	0.303	0.395
	1.0	0.25	0.5	0.211	0.474	0.316	0.369
IT-intervention for max. risk reduction = 0.50	0.0	0.0	0.875	1.0	0.0	0.0	1
	0.25	0.25	0.875	1.0	0.0	0.0	1
	0.5	0.5	0.875	1.0	0.0	0.0	1
	0.75	0.5	0.75	0.348	0.391	0.261	0.479
	1.0	0.5	0.625	0.243	0.454	0.303	0.395

IT-intervention for max. risk reduction = 0.75	0.0	0.0	0.875	1.0	0.0	0.0	1
	0.25	0.25	0.875	1.0	0.0	0.0	1
	0.5	0.5	0.875	1.0	0.0	0.0	1
	0.75	0.75	0.875	1.0	0.0	0.0	1
	1.0	0.75	0.75	0.348	0.391	0.261	0.479
IT-intervention for max. risk reduction = 1.0	0.0	0.0	0.875	1.0	0.0	0.0	1
	0.25	0.25	0.875	1.0	0.0	0.0	1
	0.5	0.5	0.875	1.0	0.0	0.0	1
	0.75	0.75	0.875	1.0	0.0	0.0	1
	1.0	1.0	0.875	1.0	0.0	0.0	1

Table 3. Impact of Preventive IT-interventions

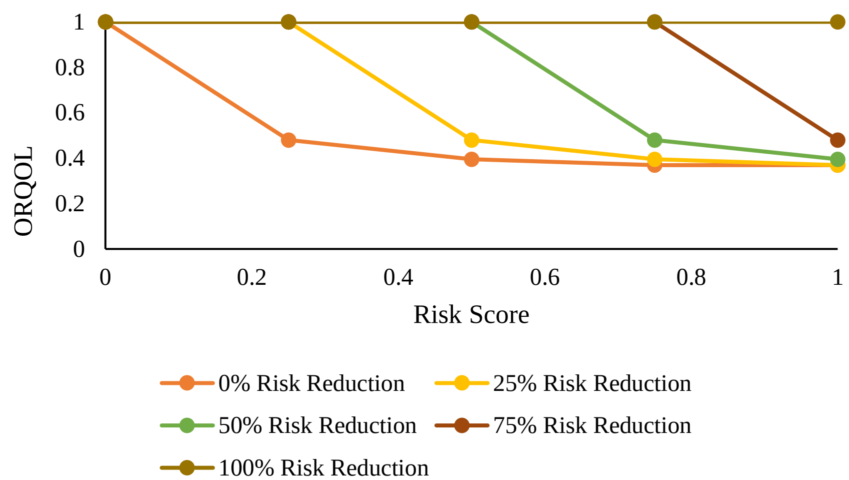

Figure 6. ORQOL for Preventive IT-interventions

Discussion and Conclusion

In this paper, we study how IT-based interventions impact the Quality of Life for OUD patients. IT-based interventions can be implemented using both simple and sophisticated mobile apps, sensors, mobile devices, and smart medication boxes. We explored various metrics to measure the impact of IT-based interventions and decided to use a new metric termed opioid related QOL (ORQOL). We developed a Markov chain model with three states of OUD. Using this, we included prevention, addiction, remission, related treatments, and interventions. The work includes both single and polypharmacy scenarios for opioid prescriptions. To the best of our knowledge, this is the first study that uses the Markov chain for opioids.

We derived several results on the impact of different IT-interventions on decision making, prescription writing, addiction, and remission. This can be very helpful for decision making in (a) whether to prescribe opioids to a different type of patients, (b) what interventions are provided along with an opioid prescription, and (c) how patients can select an intervention out of multiple available interventions.

More work is needed to study QOL/HRQOL using empirical data for OUD. Work is also needed to extend and validate ORQOL to increase its usefulness for multiple opioid studies. The current work can be extended to include a randomized controlled trial (RCT) to evaluate the medical effectiveness of IT-based interventions. The research can be further extended to field studies and empirical work using the Health Promotion Model, Theory of Addiction, Theory of Adaptation, and other theories related to OUD.

References

Association, A. P. 2013. *Diagnostic and Statistical Manual of Mental Disorders (DSM-5®)*. American Psychiatric Pub.

Ayabakan, S., Bardhan, I., and Zheng, E. 2016. "What Drives Patient Readmissions? A New Perspective from the Hidden Markov Model Analysis," *International Conference on Information Systems*.

Blendon, R. J., and Benson, J. M. 2018. "The Public and the Opioid-Abuse Epidemic," *New England Journal of Medicine* (378:5), pp. 407-411.

Carlsson, C., and Walden, P. 2018. "Digital Wellness Services: Key to Better Quality of Life for Young Elderly," *BLED eConference*, p. 26.

Chen, J.-F., Wu, L.-L., Chou, S.-C., and Chang, C.-H. 2014. "Online Social Support for Weight Control and Improved Quality of Life," *PACIS*, p. 222.

Chintha, K. K., Indic, P., Chapman, B., Boyer, E. W., and Carreiro, S. 2018. "Wearable Biosensors to Evaluate Recurrent Opioid Toxicity after Naloxone Administration: A Hilbert Transform Approach," *Proceedings of the Annual Hawaii International Conference on System Sciences*. NIH Public Access, p. 3247.

Diener, E., and Suh, E. 1997. "Measuring Quality of Life: Economic, Social, and Subjective Indicators," *Social indicators research* (40:1-2), pp. 189-216.

EuroQol, G. 1990. "Euroqol-a New Facility for the Measurement of Health-Related Quality of Life," *Health policy* (16:3), pp. 199-208.

Finley, E. P., Schneegans, S., Tami, C., Pugh, M. J., McGeary, D., Penney, L., and Sharpe Potter, J. 2017. "Implementing Prescription Drug Monitoring and Other Clinical Decision Support for Opioid Risk Mitigation in a Military Health Care Setting: A Qualitative Feasibility Study," *Journal of the American Medical Informatics Association* (25:5), pp. 515-522.

Guyatt, G. H., Feeny, D. H., and Patrick, D. L. 1993. "Measuring Health-Related Quality of Life," *Annals of internal medicine* (118:8), pp. 622-629.

Ivanov, A., and Tacheva, Z. 2018. "Examining the Role of Personality Traits in Fatal Opioid Overdose: Text Mining Approach," in: *International Conference on Information Systems*.

Kwon, H. E., Dewan, S., Oh, W., and Kim, T. 2017. "Efficacy of a Health App for Obesity and Overweight Management: A Hidden Markov Model," *ICIS*.

Lam, M. W., Liu, X., Meng, H. M., and Tsoi, K. K. 2018. "Drawing-Based Automatic Dementia Screening Using Gaussian Process Markov Chains," *Hawaii International Conference on System Sciences 2018 (HICSS-51)*.

Luo, K., Wang, Q.-H., and Teo, H. H. 2019. "The Dynamic Impacts of Online Healthcare Community on Physician Altruism: A Hidden Markov Model," *International Conference of Information Systems*, Munich, Germany.

Mansingh, G., Osei-Bryson, K.-M., and Asnani, M. 2013. "Determinants of Quality of Life of Sickle Cell Patients: A Kddm Process Model Based Exploration," *CONF-IRM*, p. 19.

NIH. 2019. "Opioid Addiction." Retrieved July 19, 2019, from https://ghr.nlm.nih.gov/condition/opioid-addiction

Schatman, M. E., and Ziegler, S. J. 2017. "Pain Management, Prescription Opioid Mortality, and the Cdc: Is the Devil in the Data?," *Journal of pain research* (10), p. 2489.

Singh, N., and Varshney, U. 2019. "Medication Adherence: A Method for Designing Context-Aware Reminders," *International Journal of Medical Informatics*, (132), p. 103980.

Sinha, S., Jensen, M., Mullin, S., and Elkin, P. L. 2017. "Safe Opioid Prescription: A Smart on Fhir Approach to Clinical Decision Support," *Online journal of public health informatics* (9:2).

Sonnenberg, F. A., and Beck, J. R. 1993. "Markov Models in Medical Decision Making: A Practical Guide," *Medical decision making* (13:4), pp. 322-338.

Tedeschi, L. O. 2006. "Assessment of the Adequacy of Mathematical Models," *Agricultural systems* (89:2-3), pp. 225-247.

Varshney, U. 2013. "Smart Medication Management System and Multiple Interventions for Medication Adherence," *Decision Support Systems* (55:2), pp. 538-551.

WHOQOL-BREF, G. 1998. "Development of the World Health Organization Whoqol-Bref Quality of Life Assessment," *Psychological medicine* (28:3), pp. 551-558.

WHOQOL, G. 1995. "The World Health Organization Quality of Life Assessment (Whoqol): Position Paper from the World Health Organization," *Social science & medicine* (41:10), pp. 1403-1409.