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Discovering Barriers to Opioid Addiction Treatment from Social Media: A Similarity Network-Based Deep Learning Approach

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Completed Research Paper

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Abstract

Opioid use disorder (OUD) refers to the physical and psychological reliance on opioids. OUD costs the US healthcare systems $504 billion annually and poses significant mortality risk for patients. Understanding and mitigating the barriers to OUD treatment is a high-priority area. Current OUD treatment studies rely on surveys with low response rate because of social stigma. In this paper, we explore social media as a new data source to study OUD treatments. We develop the SImilarity Network-based DEep Learning (SINDEL) to discover barriers to OUD treatment from the patient narratives and address the challenge of morphs. SINDEL reaches an F1 score of 76.79%. Thirteen types of OUD treatment barriers were identified and verified by domain experts. This study contributes to IS literature by proposing a novel deep-learning-based analytical approach with impactful implications for health practitioners.

Keywords: Deep learning, text mining, opioid addiction, data science

Introduction

The misuse of and addiction to opioids, involving nonmedical use, misuse, or abuse of opioid medications (e.g., pain relievers), and use of illicit opioids (e.g., heroin), are epidemic and have become a serious public health crisis in the United States (NIH 2018a). It was estimated that in 2016, 11.8 million Americans misused prescription opioids or used illicit opioids (SAMHSA 2017). Among them, 2.1 million suffered from opioid addiction. This growing crisis devastates millions of Americans with opioid use disorder (OUD). OUD causes serious medical and financial consequences for patients and healthcare systems. In 2017, the number of overdose deaths involving opioids was six times higher than that in 1999 (CDC 2018). On average, 130 Americans die every day from opioid overdose (NIH 2018b). The ramifications of OUD go well beyond the healthcare realm. The Council of Economic Advisors at the White House estimated that in 2015, the cost of OUD was $504 billion, or 2.8 percent of the GDP that year (White House 2017).

In response to the growing burden of OUD, society needs to work together to improve the access to treatment. Although many medical studies show that OUD treatments are effective and could prevent further ramifications, only 17.5% of patients with OUD receive treatment (NIDA 2018). In 2018, the US

Surgeon General stressed the urgency of understanding and removing the barriers to OUD treatment (Office of the Surgeon General 2018). Understanding these barriers forms the premise to decrease overdose mortality, reduce the transmission of infectious diseases, and lower healthcare expenditure (Robeznieks 2018). In this study, we define the barriers to OUD treatment as patient self-described factors leading to the absence of OUD treatment. Our research objective is to propose and evaluate an innovative computational approach to understand the barriers to OUD treatment.

Existing studies employed surveys to understand the barriers to OUD treatment (Hassamal et al. 2017; McKenna 2017; Stumbo et al. 2017). These survey studies are challenged by the narrow patient population, as individuals struggling with OUD often are difficult to reach if they are not actively under treatment. Social media can bridge this gap. In drug forums, in particular, patients share their experiences of taking prescription and illicit opioids. Due to the anonymous nature of these forums, patients are willing to elaborate on their real decision-making on OUD treatments (e.g., Figure 1). This large-scale patient self-reported information creates an unprecedented potential to study the barriers to OUD treatment from the patient decision-making standpoint and facilitate analyses on heterogeneous patient groups in real time. To our best knowledge, no social media approach has been taken in OUD treatment research.

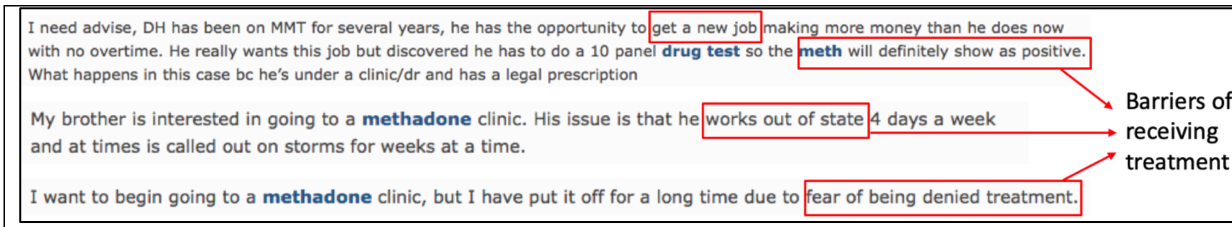

Figure 1. Examples of Patient Narratives about OUD Treatment

Significant challenges still exist to understand patient perspectives in drug forums despite their enormous potential. First, the barriers to OUD treatment are sensitive to real-time events, causing them to vary over time. To facilitate effective and real-time surveillance for OUD treatment barriers, proactive and fine-grained automated models are required. Second, patients prefer to use a wide variety of morphs (fake alternative names) to describe drugs and treatment options in order to avoid censorship and surveillance, entertain readers, or use personal writing styles.

The literal meanings of the morphs are distant from their contextual meanings. The drift between the literal and contextual meanings of morphs poses a significant challenge for researchers, practitioners, and patients to understand the discussion. Motivated by the critical need for fine-grained and automated techniques to understand OUD treatment barriers in drug forums, we propose a novel computational method – SImilarity Network-based DEep Learning (SINDEL).

SINDEL extends the state-of-the-art text mining model with a similarity network-based component and deep learning architecture. The similarity network-based component bridges the literal and contextual semantics of morphs and detects OUD treatment barriers accurately. The deep learning architecture enhances the learning performance on sparse OUD-related narratives through a recurrent and parallel hierarchical structure.

Our study makes the following contributions to information systems literature, data analytical methodology, and healthcare practice. First, we develop a deep learning framework (SINDEL) to extract OUD treatment barriers from drug forums. SINDEL can be generalized to extract information from many other text genres containing specialized morphs, such as hacker forums, health social media, and product reviews.

Second, our study falls into the category of computational design science research that aims to design analytical solutions to problems with social impact (Rai 2017). We develop an information system to address the opioid addiction problem and provide an automated framework to understand patient decision-making.

Third, our empirical findings complement current behavioral health science research on OUD treatments with comprehensive patient experience data. We discover 13 types of OUD treatment barriers. Many of the OUD treatment barriers that we discover have not been noted by prior survey studies, such as side effects of treatment, concerns about buprenorphine or methadone addiction, poor patient-physician relationship, and depressed mental status. We provide valuable implications for medical professionals and policymakers to understand individual opioid-taking behavior and the real treatment barriers faced by patients. Tailored intervention measures can be taken accordingly to prevent medical and financial ramifications, improve OUD management, and reverse the opioid crisis.

Literature Review

OUD Treatments Barriers and Social Media Analytics

Surveys or interviews are commonly used to investigate the barriers to OUD treatment. The barriers to OUD treatment identified in these studies can be categorized into three categories: 1) System-related: the factors related to healthcare systems and regulations, such as government and insurance policies (Oliva et al. 2011) and funding barriers (Knudsen et al. 2011); 2) Provider-related: the factors related to health providers, such as lack of DEA waiver (Andrilla et al. 2017), lack of institutional support (Hutchinson et al. 2014), lack of resources (Wolfe et al. 2010), and geographic constraints (Sharma et al. 2017); 3) Patient-related: patient-specific factors, such as the fear of pain (Stumbo et al. 2017) and lack of information on treatments (Hassamal et al. 2017).

Current studies investigated the barriers to OUD treatment via surveys and interviews, which offer only cursory descriptions of some well-known and hypothesized barriers, lacking depth and comprehensiveness (Larochelle et al. 2016). The surveys only capture a snapshot of barriers. In reality, many patient-level barriers are complicated by patient characteristics and policy changes, causing them to vary over time. The time-invariant analyses in surveys are unlikely to offer a comprehensive understanding of treatment barriers. Furthermore, patients are reluctant to disclose their issues with OUD treatments, especially illicit drug users.

Health big data from social media platforms makes innovative projects possible and opens opportunities for investigations that can yield insights into and understanding of issues such as patient decision-making, human motivation, and social phenomena (Baesens et al. 2014). Because of the anonymous nature of social media, many patients, including illicit drug users, actively share their drug-taking experience with their peers. This patient self-reported experience not only provides real-time and dynamic information but also covers an unprecedent scale of the patient population with heterogeneous characteristics. Yet, no social media approach has been taken in OUD treatment studies.

Despite the enormous potential of social media, significant challenges still exist. When describing OUD treatments, patients use many morphs (fake alternative names) to represent drugs and treatment options. This is because users attempt to avoid censorship and surveillance or use them as idiomatic expressions. For instance, heroin can be described as H, hero, and China white by different users. Conventional text mining methods are not capable of interpreting the real semantics of the morphs.

Morphology and Deep Learning

Morphology is the study of words, how they are formed, and their relationship to other words in a language. Similar to the drug morphs and patient idiomatic expressions in drug forums, morphology studies tackle internet slang (Huang et al. 2017; Sha et al. 2017), synonyms (He et al. 2016; Qu et al. 2017), and semantically similar terms (Yao et al. 2018; Zhang et al. 2016). The main body of literature in morphology utilizes distributed representation and deep learning methods, such as word embedding and BLSTM, to interpret the semantics of morphs.

Word embedding is a vector-based representation of words commonly used in deep learning models for natural language processing. Skip-gram and CBOW are the most common word embedding models (Levy and Goldberg 2014). They learn the neighboring words of a focal word within a window size across the corpus and predict its most likely neighbors.

The state-of-the-art deep learning models to process text data are recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM). An RNN contains a self-connected recurrent unit. At each time step, an RNN takes both the last hidden state and the current input to compute the current hidden state. LSTMs are a variant of RNNs. An LSTM contains an input gate, a forget gate, an output gate, a memory cell, and a hidden state.

Standard deep learning is still challenging for tackling morphology, which is exacerbated by online social media platforms and the nature of OUD discussions. The morphs of drugs and treatment options are often used in OUD discussions. Usually, the literal meaning of these morphs is distant from their contextual meaning. Morphs for drugs in the same class are semantically closer than those across drug classes. Each opioid class has a unique effect, regimen, and instruction, leading to varying semantic context in OUD discussions. Oxycodone is a semi-synthetic opioid, the morphs of which include oxy, O.C., oxycet, oxycontin, and more. The morphs of heroin include H, China white, and more. Oxy and O.C. are not simply morphs of opioid drugs, but they represent the same drug class (oxycodone) as well. Therefore, oxy and O.C. are more closely related than oxy and China white. Although standard deep learning could capture the semantic meaning of the words, the interconnected relationships within the same opioid class are neglected.

The vector representation of words enables deep learning methods to demonstrate outstanding performance in various natural language understanding tasks. It models the semantic context of words using the neighboring words of the focal word. However, in addition to the semantic relatedness to local neighboring words, key entities of interest, such as drug names and treatment effects, are related due to the medical context. Therefore, we are motivated to propose a new deep learning architecture that incorporates the vector representation of words and semantic similarity in a network to extract OUD treatment barriers from drug forums.

Research Method

The OUD treatment barrier mining problem has two objectives: barrier extraction and barrier clustering. Barrier extraction identifies patient self-described OUD treatment barriers. Since patients use different expressions to describe the same type of barrier, barrier clustering groups the identified OUD treatment barriers based on their semantic meaning. The process of the OUD treatment barrier mining is shown in Figure 2. The novelty of our approach is highlighted in red.

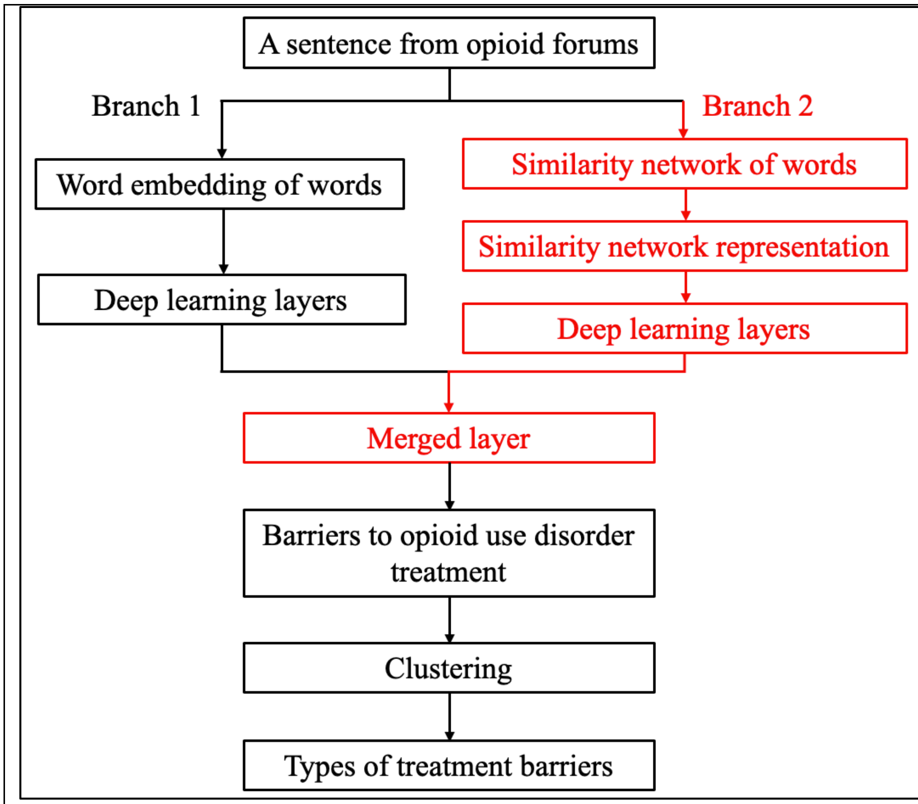

Figure 2. The OUD Treatment Barrier Mining Framework

The proposed OUD treatment barrier mining approach receives a sentence from drug forums as the input. Two parallel representation models represent the sentence with two vectors. Branch 1 utilizes word embedding to generate semantic vectors for each word. Branch 2 creates a similarity network of words and generates a network representation for each word. The two representations are concatenated in the hidden layers which further recognize the OUD treatment barriers in the sentence. A clustering model is utilized to cluster the extracted barriers into meaningful categories of OUD treatment barriers.

The Similarity Network-Based Representation

The proposed similarity network-based representation contains two parallel representations. The first representation is a word embedding representation to capture the semantic meaning of words, so that morphs can be interpreted as their intended meaning. Let S be a training sequence $[w_1, w_2,\ldots,w_T]$. Variable w_i denotes word i in the sequence. The training objective is to maximize the objective function in Equation 7.

$$L = \frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0}\log p\left(w_{t+j}\middle|w_t\right). \tag{7}$$

Parameter T denotes the number of training words. Parameter c is the window size (the words that appear within a distance of c words). Variables w_{t+j} are the words surrounding w_t.

The second representation aims to construct a network of words in order to capture the interconnected relationships. In this network $G = (V, E)$, each node V is a word, and the edge E is the semantic similarity between words. As such, each word is linked to a set of words that are closely related. For instance, oxy will be linked with O.C. and Oxycet, because they are the most similar morphs. Oxy will not be linked with China white, because they represent different drug classes. This word similarity network is capable of addressing the limitation of word embedding by considering the semantic relationships among entities of interests. Instead of using the representation of the focal word, we use similar words that are connected to the focal word as the second representation for the focal word. Figure 3 shows an example.

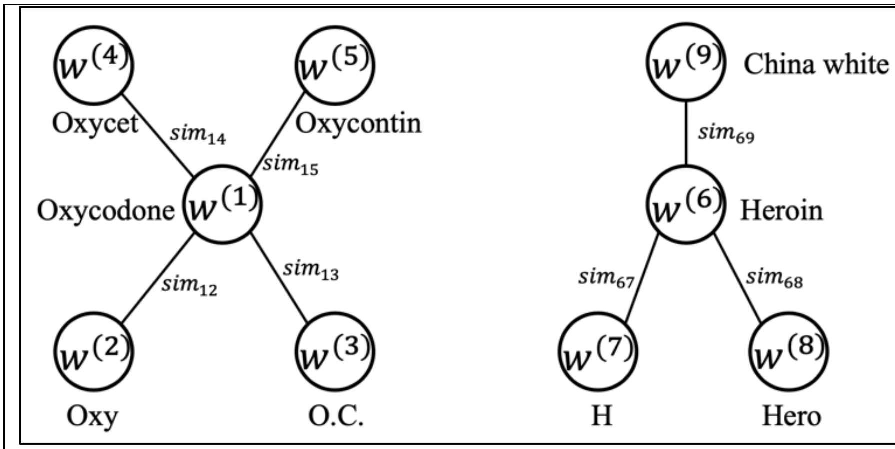

Figure 3. An Example of a Word Similarity Network

In the simple example in Figure 3, Oxycodone ($w^{(1)}$) is linked to oxy, O.C., Oxycet, and Oxycontin, because they belong to the same drug class. We use $w^{(2)}$, $w^{(3)}$, $w^{(4)}$, and $w^{(5)}$ to represent $w^{(1)}$. Likewise, China white, H, and hero are linked to heroin. We use $w^{(7)}$, $w^{(8)}$, and $w^{(9)}$ to represent $w^{(6)}$. In our corpus, we construct a similarity network for all words and compute the similarity between each pair of words. We select a set of most similar words for each word and link them together. The number of similar words is determined in the empirical analyses with the highest performance. Word similarity is computed using the cosine similarity of word embedding as shown in Equation 8.

$$sim_{ij} = \frac{\boldsymbol{x}^{(i)} \cdot \boldsymbol{x}^{(j)}}{\parallel \boldsymbol{x}^{(i)} \parallel \parallel \boldsymbol{x}^{(j)} \parallel}. \tag{8}$$

Variables $\boldsymbol{x}^{(i)}$ and $\boldsymbol{x}^{(j)}$ are the word embedding of word $w^{(i)}$ and $w^{(j)}$. Given word w, let $w^{(1)}, w^{(2)}, \dots, w^{(10)}$ be the top ten words that are the most similar to word w. Let $sim^{(1)}, sim^{(2)}, \dots, sim^{(10)}$ be the similarity between word w and the other ten words. Let $\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \dots, \boldsymbol{x}^{(10)}$ be the word embedding for $w^{(1)}, w^{(2)}, \dots, w^{(10)}$. The similarity network representation of word w is defined in Equation 9.

$$\boldsymbol{x}_s = \sum_{i=1}^{10} sim^{(i)} \boldsymbol{x}^{(i)}. \tag{9}$$

A Deep Learning Architecture

To effectively extract the barriers to OUD treatment, we utilize a bidirectional long short-term memory (BLSTM) architecture. We devise a multi-view BLSTM model that processes the word embedding representation and the similarity network representation in parallel. The multi-view BSLTM model contains two branches. Each branch has independent BLSTM layers that contain LSTM units. Our model is called SImilarity Network-based DEep Learning (SINDEL).

The LSTM units in branch one take the word embedding as the input, and the LSTM units in branch two take the similarity network representation as the input. The computational process for branch two is shown in Equations 10-15. The computational process in the first branch is the same, except that the input at each time step is word embedding $\boldsymbol{x}^{(t)}$ instead of similarity network representation $\boldsymbol{x}_s^{(t)}$.

Similarity network-based input gate: $\boldsymbol{i}_s^{(t)} = \sigma\left(\boldsymbol{W}_{si}\boldsymbol{x}_s^{(t)} + \boldsymbol{U}_{si}\boldsymbol{h}_s^{(t-1)} + \boldsymbol{b}_{si}\right);$ (10)

Similarity network-based forget gate: $\boldsymbol{f}_s^{(t)} = \sigma\left(\boldsymbol{W}_{sf}\boldsymbol{x}_s^{(t)} + \boldsymbol{U}_{sf}\boldsymbol{h}_s^{(t-1)} + \boldsymbol{b}_{sf}\right)$; (11)

Similarity network-based output gate: $\boldsymbol{o}_s^{(t)} = \sigma\left(\boldsymbol{W}_{so}\boldsymbol{x}_s^{(t)} + \boldsymbol{U}_{so}\boldsymbol{h}_s^{(t-1)} + \boldsymbol{b}_{so}\right)$; (12)

Similarity network-based cell state: $\boldsymbol{u}_s^{(t)} = \sigma\left(\boldsymbol{W}_{su}\boldsymbol{x}_s^{(t)} + \boldsymbol{U}_{su}\boldsymbol{h}_s^{(t-1)} + \boldsymbol{b}_{su}\right)$; (13)

Similarity network-based memory cell: $\boldsymbol{c}_s^{(t)} = \boldsymbol{i}_s^{(t)} \circ \boldsymbol{u}_s^{(t)} + \boldsymbol{f}_s^{(t)} \circ \boldsymbol{c}_s^{(t-1)}$; (14)

Similarity network-based hidden state: $\boldsymbol{h}_s^{(t)} = \boldsymbol{o}_s^{(t)} \circ tanh\left(\boldsymbol{c}_s^{(t)}\right)$. (15)

Variable $\boldsymbol{x}_s^{(t)}$ is the current input, and $\boldsymbol{h}_s^{(t-1)}$ is the previous hidden state. Parameters $\boldsymbol{W}$, $\boldsymbol{U}$, and $\boldsymbol{b}$ are weight parameters with values between 0 and 1. Each forward or backward hidden state has 128 dimensions. We condense useful information from the 300-dimensional $\boldsymbol{x}^{(t)}$ to 128 dimensions in the LSTM cell, following prior studies (Chan and Lane 2015; Rao et al. 2015). The learning rate in gradient descent is 0.1. The dropout rate is 0.2.

The above computation is processed independently for the word embedding branch and the similarity network branch. Each branch obtains a hidden state in the last time step. The final hidden states of branch one and two are further concatenated as an integrated model. Figure 4 shows a graphic illustration of the model architecture. The red part indicates the innovation of this study.

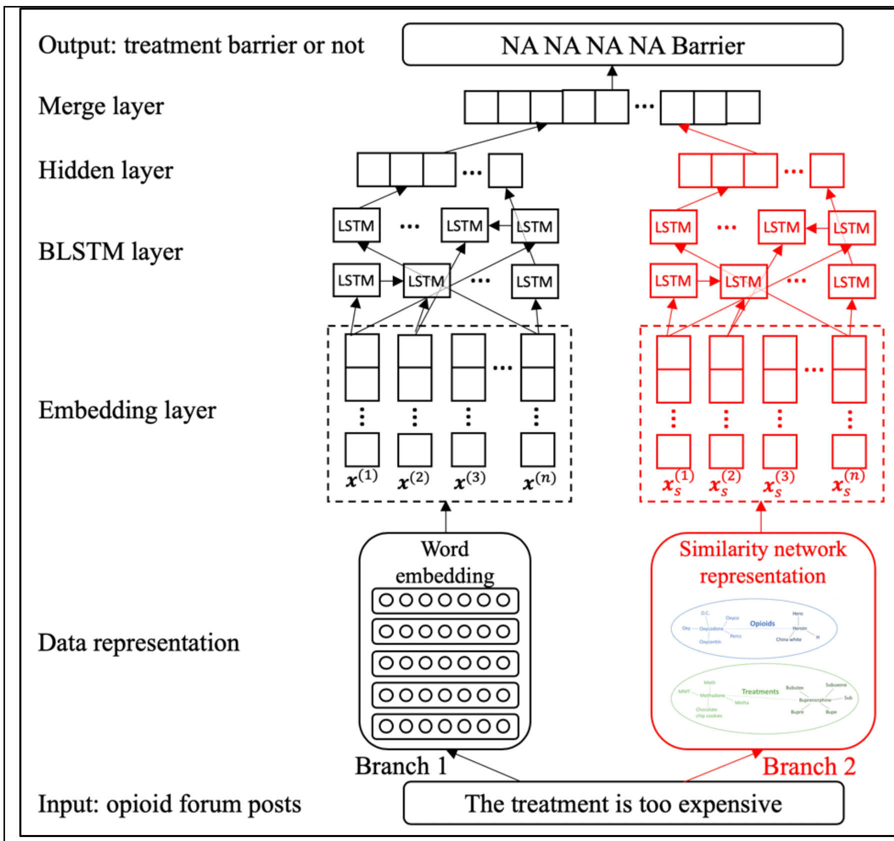

Figure 4. Similarity Network-Based Deep Learning Architecture

The input to the SINDEL model is a sentence from the research corpus. The sentence is represented with word embedding and the similarity network representation. Two BLSTM layers process these two representations in parallel. Finally, a Softmax layer (Equation 16) is stacked on the top to predict the word type (OUD treatment barrier or not).

$$p(y = j|\boldsymbol{x}) = \frac{e^{\boldsymbol{x}^{\mathrm{T}}\boldsymbol{w}_j}}{\sum_{k=1}^{K} e^{\boldsymbol{x}^{\mathrm{T}}\boldsymbol{w}_k}}. \tag{16}$$

Variable y is the predicted word type. Variable $\boldsymbol{x}$ is the input to the Softmax layer. Parameter $\boldsymbol{w}$ is the weight parameter.

Empirical Analyses

Data Preparation

The research testbed comes from a leading health IT platform Drugs-Forum.com, which contains a large collection of patient discussions about drug use and recovery. This platform provides the opportunity for opioid users to interact with peers without being judged. Because of the anonymity and the specificity of the platform, opioid users elaborate on their drug use, addiction, and treatment experience. This platform also allows illicit drug users to share their experience with illicit drugs, such as heroin, cocaine, and fentanyl.

We collected the posts from Drugs-Forum related to drug use from the start of Drugs-Forum to September 1, 2018. The raw dataset encompasses 27,154 posts. We randomly sampled 3,000 posts related to OUD treatment. Four expert annotators read the posts and annotated the OUD treatment barriers for model training purposes. The IOB labeling scheme is adapted to assign tags for each word in a sentence. Each word has a label suggesting if it is inside (I), outside (O), or the beginning (B) of an expression of OUD treatment barriers. Figure 5 shows an example of the annotation.

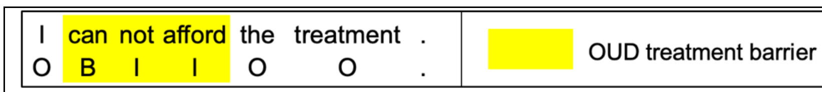

Figure 5. Annotation Example

To test inter-annotator reliability, we leverage Cohen's Kappa. The Kappa value for the OUD treatment barrier annotation is 0.92, indicating excellent reliability. A fifth expert annotator reviewed disagreements and made the final judgment. We further segmented the posts into sentences with the sentence boundary detection package from NLTK. A total of 40,917 sentences were generated. We chose 70% of the annotated data as the training set, 10% as the validation set, and the remaining 20% as the test set.

Evaluation of Extracting OUD Treatment Barriers

As shown in Table 1, our SINDEL model outperforms the conventional machine learning methods (SVM, LR, NB, and CRF) by a very large margin in F1 score and precision. CRF achieves the highest precision (78.46%) among the common baseline methods. SINDEL outperforms CRF in precision by 6.85%. LR has the highest F1 score (50.01%) among the baseline methods. SINDEL still outperforms LR in F1 score by 53.91%. NB achieves the highest recall, because it recognizes most instances as OUD treatment barriers (very low precision), which is not feasible for practical use.

Table 1. Evaluation of SINDEL against the Conventional Machine Learning Methods

Method	Precision	Recall	F1 score
SVM	58.10%	40.09%	47.40%
LR	45.25%	61.15%	50.01%
NB	22.54%	95.50%	36.47%
CRF	78.46%	36.59%	49.90%

SINDEL (Ours)	85.31%	70.14%	76.97%

Table 1. Evaluation of SINDEL against the Conventional Machine Learning Methods

To test the statistical significance of the performance improvement of the SINDEL model, we repeat the training and testing procedures for each model 20 times and conduct *t*-tests to compare the performance of SINDEL against the conventional machine learning baseline models. The *t*-test results summarized in Table 2 indicate that our proposed SINDEL significantly outperforms all the baseline models ($p < 0.001$).

Table 2. Pairwise T-tests for SINDEL against the Conventional Machine Learning Methods

Method Pair	Precision	Recall	F1 score
SINDEL vs SVM	< 0.001***	< 0.001***	< 0.001***
SINDEL vs LR	< 0.001***	< 0.001***	< 0.001***
SINDEL vs NB	< 0.001***	< 0.001***	< 0.001***
SINDEL vs CRF	< 0.001***	< 0.001***	< 0.001***

*: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

Table 2. Evaluation of SINDEL against the Conventional Machine Learning Methods

We also compare our SINDEL model with state-of-the-art deep learning methods. The results in Table 3 show that SINDEL outperforms RNN, LSTM, and BLSTM in all three evaluation metrics. BLSTM achieves the best results among the deep learning baseline methods due to the advantages of the bidirectional architecture. SINDEL improves upon BLSTM in precision by 4.15%, recall by 11.96%, and F1 score by 8.44%. In Table 4, the pairwise *t*-tests for SINDEL against the deep learning methods indicate the performance improvement of our SINDEL is statistically significant. The superior performance of SINDEL against all the baseline methods in Table 1 and Table 3 demonstrates the effectiveness of the proposed similarity network-based deep learning in extracting OUD treatment barriers.

Table 3. Evaluation of SINDEL against the Deep Learning Models

Method	Precision	Recall	F1 score
RNN	75.19%	48.49%	58.80%
LSTM	71.90%	54.48%	61.77%
BLSTM	81.91%	62.65%	70.98%
SINDEL (Ours)	85.31%	70.14%	76.97%

Table 3. Evaluation of SINDEL against the Deep Learning Models

Table 4. Pairwise T-tests for SINDEL against the Deep Learning Models

Method Pair	Precision	Recall	F1 score
SINDEL vs RNN	< 0.001***	< 0.001***	< 0.001***
SINDEL vs LSTM	< 0.001***	< 0.001***	< 0.001***
SINDEL vs BLSTM	< 0.001***	< 0.001***	< 0.001***

*: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

Table 4. Pairwise T-tests for SINDEL against the Deep Learning Models

The SINDEL model utilizes word embedding and the similarity network as the representation. We utilize the word2vec model to generate word embedding in the previous analyses. We further test the robustness of our model by using other commonly adapted word embedding models including a locally-trained Skip-gram model and GloVe. Table 5 shows the performance of these embedding models. Table 6 shows the significance of the performance comparison.

Table 5. Evaluation of SINDEL Using Different Word Embeddings

Method	Precision	Recall	F1 score
SINDEL with Skip-gram	80.09%	68.56%	73.87%
SINDEL with GloVe	83.84%	59.14%	69.33%
SINDEL (Ours)	85.31%	70.14%	76.97%

Table 5. Evaluation of SINDEL Using Different Word Embeddings

Table 6. Pairwise T-tests for SINDEL Using Different Word Embeddings

Method Pair	Precision	Recall	F1 score
SINDEL (Ours) vs SINDEL with Skip-gram	< 0.001***	< 0.01**	< 0.001***
SINDEL (Ours) vs SINDEL with GloVe	< 0.05*	< 0.001***	< 0.001***

***: p < 0.05; **: p < 0.01; ***: p < 0.001**

Table 6. Pairwise T-tests for SINDEL Using Different Word Embeddings

The word2vec model reaches the best performance among all word embedding models. The locally-trained Skip-gram achieves lower performance because the word embedding training size is smaller than that of word2vec. GloVe also has lower performance because many of the discussions in the entire dataset drift from OUD treatment. The global representation induces noisy information.

The similarity network representation captures the interconnected relationships among similar morphs, thus identifying more morphs of OUD treatment barriers together with the original term. In Table 7, we show examples of the additional morphs that the similarity network could capture.

Table 7. Examples of Morphs Captured by the Similarity Network Representation

Original Term	Similar Morphs Captured by the Similarity Network
Heroin	Dopesick, H, chinawhite
Ache	Achey, sore, bites
Methadone	Meth, M, MMT

Table 7. Examples of Morphs Captured by the Similarity Network Representation

In addition to heroin, the similarity network could capture dopesick, H, and chinawhite. Therefore, OUD treatment barriers mentioned together with dopesick, H, and chinawhite could be identified as well. Acne is a withdrawal reaction after treatment, which can be a barrier that prevents patients from receiving treatment. Other types of barrier symptoms (achy, sore, bites) are also extracted by the similarity network. Methadone is an OUD treatment medication. Patients may mention it when describing treatment barriers, such as methadone addiction and withdrawal. Morphs of methadone, such as meth, M, and MMT, are extracted together to improve the model performance.

Clustering OUD Treatment Barriers

The SINDEL model could extract the OUD treatment barriers from the research data. These barriers are the actual expressions that patients used in the drug forums. Many expressions may indicate the same type of treatment barrier. We, therefore, cluster the extracted treatment barriers to identify the general types. We use k-means as the clustering method.

To choose the optimal number of clusters, a medical expert panel, including two biomedical researchers, examined the clusters for medical relevance. Thirteen clusters are identified by the expert panel. Table 8 shows the types of OUD treatment barriers.

Table 8. Types of OUD Treatment Barriers

Type	Description	Percentage[1]	Examples
Lack of motivation	The patient does not have motivation to quit opioids	24.67%	Don't have the time to go to a methadone clinic, CANT stop, doesn't want to quit
Lack of medical literacy	The patient lacks knowledge of consequences of addiction	21.88%	A waste of time, dying of boredom, don't have any desire to be clean
Concerns about social stigma and job opportunities	The patient is concerned about social stigma or afraid of losing jobs	12.67%	Fails a pre employment drug screen, new job training that requires no drug or medication use
Afraid of withdraw reactions	The patient is afraid of the withdrawals after quitting	12.35%	Hate withdrawals, precipitated withdrawals
Side effects of treatment	The patient is concerned about the side effects of treatment	9.13%	Headaches, migraines, insomnia
Reliance because of chronic pain/fatigue	The patient cannot stop opioids because of chronic pain	5.64%	I'm sick in pain, chronic pain flares up
Concerns about buprenorphine/methadone addiction	The patient is concerned about buprenorphine or methadone addiction	3.85%	Methadone addiction
High cost of treatment	The patient cannot afford the treatment or insurance does not cover	2.91%	Expensive, unaffordable
Poor patient-physician relationship	The patient does not have good relationship with the providers	2.19%	Clinic denies me, doc was pissed
Enjoy euphoric feeling of drugs	The patient enjoys the euphoric feeling of opioids and does not want to quit	1.70%	Like dope, craving
Depressed mental status	The patient is depressed and does not want to receive treatment	1.57%	Severe depression
Lack of accessibility	Treatment is not accessible to patients	0.63%	No rehab
Others	Others	0.82%	Can't, good

[1] The percentage of each barrier reflects the situation in drug forums, which may be different from the patient population.

Table 8. Types of OUD Treatment Barriers

The results shed valuable insights to understand patient's decisions about receiving OUD treatment. Lack of motivation is the most common barrier to receiving OUD treatments (24.67%). Although these patients are aware of the consequences of addiction, they postpone visits to health providers. To motivate these patients, social support and family encouragement are essential to help them receive treatment. Lack of medical literacy is also common among patients. These patients do not understand the ramifications of opioid addiction. Thus, they have no intention of being treated. Intervention strategies for this group of patients include patient education and informational support.

In addition to the barriers that confirm prior literature, we also identified new barriers that have not been noted in prior survey studies, such as side effects of treatment, concerns about buprenorphine or methadone addiction, poor patient-physician relationships, and depressed mental status. These barriers have not been identified by survey studies because these barriers are sensitive and involve personal behavior. The patients are willing to share these undisclosed opinions in drug forums because of the anonymity.

Uncovering these new barriers enables a deeper understanding of patients' opioid addiction behavior and facilitates more effective intervention strategies. For instance, poor patient-physician relationship prevents patients from seeking addiction treatment. Overlooking this perspective devastates the efforts of other stakeholders. In order to improve opioid addiction management, health providers need to foster a healthy relationship with their patients. Depressed patients also have little motivation to seek treatments. This new finding provides guidance for caregivers to treat the depression disorder of the patients together with OUD.

Conclusion

Our research objective is to develop a computational approach for understanding the barriers to OUD treatment from the patients' perspective. We designed a novel deep-learning-based approach to collect relevant patient discussions from drug forums, extract the OUD treatment barriers, and analyze the types of barriers. In line with the design science research methodology, we rigorously evaluated our model and compared it with state-of-the-art baseline models. Our SINDEL model outperforms all the baseline models, attributed to the similarity network-based component. The SINDEL model can be generalized in many other information retrieval tasks involving morphs.

The SINDEL model extracted the OUD treatment barriers from drug forums. This is among the first attempt to analyze OUD treatment barriers from large-scale health social media data. The OUD treatment barriers detected in this study have profound implications for the key stakeholders, including physicians, patients, policymakers, pharmaceutical companies, and healthcare systems. These stakeholders could gain rich insights from the patient perspective and understand the real barriers faced by the patients. Being aware of these barriers allows proactive intervention and early preventions to avoid harmful outcomes caused by OUD.

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