Exploring Drug Switching in Patients: A Deep Learning-based Approach to Extract Drug Changes and Reasons from Social Media

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Abstract

Social media (SM) can provide valuable information about patients' experiences with multiple drugs during treatments. Although information extraction from SM has been well-studied, drug switches detection and reasons behind these switches from SM have not been studied yet. Therefore, in this paper, we present a new SM listening approach for analyzing online patient conversations that contain information about drug switching, drug effectiveness, side effects, and adverse drug reactions. We describe a deep learning-based approach for identifying instances of drug switching in SM posts, as well as a method for extracting the reasons behind these switches. To train and test our models, we used annotated SM data from internal dataset which is automatically created using a rule-based method. We evaluated our models using Text-to-Text Transfer Transformer (T5) and found that our SM listening approach can extract medication change information and reasons with high accuracy, achieving an F1-score of 98% and a ROUGE-1 score of 93%, respectively. Overall, our results suggest that our SM listening approach has the potential to provide valuable insights into patients' experiences with drug treatments, which can be used to improve patient outcomes and the effectiveness of drug treatments.

1 Introduction

SM platforms (e.g., Twitter, Facebook, forums) have been widely used for health-related purposes, to share and exchange experiences about drugs, treatments and diagnosis or to interact with other patients with similar health conditions in online communities. They provide a unique opportunity to observe patient experiences with medication in real-world settings (Colón-Ruiz and Segura-Bedmar, 2020; Garg, 2021; Ali et al., 2021).

Detecting drug switches and reasons, where patients switch from one medication to another one, can provide valuable insights into medication efficacy, adverse drug reactions, side effects, and patient preferences. A drug switch refers to the substitution of a prescribed medication with a similar drug (Glerum et al., 2020). By monitoring medication switches, researchers and drug companies can gain a deeper understanding of patient experiences with medications and make more informed decisions about treatments. While real-world claims data (e.g., IQVIA claims data) gives medication switch information, it does not provide the reasons of the drug switches. To make use of this amount of user-generated data, it is essential to extract structured data from unstructured information (Badieh Habib Morgan and van Keulen, 2014). Information extraction (IE) is the research domain dedicated to achieve this goal, enabling the use of such a vast amount of unstructured information in a structured and organized manner (Sarrouti et al., 2021a, 2022). While there have been numerous studies examining IE from SM platforms (Liu and Chen, 2013; Denecke and Denecke, 2015; Jenhani et al., 2019; Nemes and Kiss, 2021; Wu et al., 2021; Tu et al., 2022), to the best of our knowledge, there is no study that investigates drug switching in patients and the underlying reasons for such changes through SM analysis. Therefore, our study aims to fill this knowledge gap by providing insights for healthcare professionals and decision-makers to better understand the factors that drive drug switching behaviors among patients. To achieve this, we present an SM listening approach which aims at (1) determining whether a medication switch has occurred based on two drug names mentioned in an SM post, and (2) extract and classify the reasons (e.g., the effectiveness of the drug, adverse reactions, etc.) for the medication change. Our experiments showed that fine-tuning T5 on rule-based annotations achieved good performance (an F1-score of 98% for drug switch detection, and a ROUGE-1 score of 93% for IE and classification).

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2 Related work

Over the last two decades, there has been a growing interest in extracting information from health-related SM posts using natural language processing (NLP), largely due to the widespread use and popularity of SM platforms. Chen et al. (2018) have shown that combining named-entity recognition with signal detection and topic modeling can be effective in extracting valuable insights from SM data related to health. In particular, they demonstrated that this approach was successful in detecting potential signals and gaining a better understanding of patients' behaviors toward drugs, including instances of misuse. Lee et al. (2021) demonstrated that SM, in addition to traditional pharmacovigilance methods, can be utilized to identify potential signals related to new black box warnings, labeling modifications, or drug withdrawals. Although there are still some challenges to be addressed, the authors showed that SM can be a valuable tool for detecting signals associated with commonly mentioned drugs in specialized healthcare social networks and forums. To further advance the field, the authors suggested that additional research is necessary to improve NLP and effectively mine real-world data from SM platforms. Glerum et al. (2020) conducted a study to examine the occurrence of drug switches for certain active substances in the Netherlands. The goal was to gain insight into the use of generic drugs and the process of drug switching in the Netherlands, as well as the factors that influence it. To obtain information on drug switches, the author used in the claims database of the National Health Care Institute in the Netherlands (ZIN), which contains data on prescribed drugs that are dispensed by pharmacists or dispensing general practitioners.

The existing SM listening approaches do not detect drug switches and reasons behind these switches from SM. Therefore, we propose a deep learning-based approach to extract drug switches and different reasons behind these switches. Our approach uses rule-based annotations to train deep learning models. The deep learning model can extract more accurate information than rule-based annotations which are not scalable.

3 Our social media listening approach

Figure 1 presents the flowchart of our SM listening approach which consists of two main components (1) drug switch detection, and (2) IE.

Classification	Definition
PSMT	Positive sentiment
NSMT	Negative sentiment
DEFF	Drug is effective
DNEFF	Drug is not effective
DIL	Drug is liked
DNL	Drug is not liked
ADR	Adverse reactions with drug
NADR	No ADR with drug
DSE	Drug side effects
DALG	Drug allergy
DSW	Drug switch

Table 1: Classification classes and definition.

3.1 Drug switch detection

Given an input SM post SMP consisting of n tokens, i.e., $SMP = \{w_1, w_2, ..., w_n\}$ and a pair of drug names $(drug\_a, drug\_b)$ where $drug\_a \in SMP$ and $drug\_b \in SMP$, the drug switch detection model is tasked with predicting the maximum probable label $\hat{y}$ from the set of labels in annotated data, $y \in \{dsw, no\_dsw\}$. "dsw" indicates a medication switch from Drug A to Drug B, and "no_dsw" indicates no medication change from Drug A to Drug B. The drug switch detection component is based on T5 (Raffel et al., 2020). The input sequence is "drug_a: [D1] drug_b: [D2] SM post: [SMP] relation: [r]". We fine-tuned T5 to generate "dsw", "no_dsw" tokens.

3.2 IE

Given an input SM post SMP consisting of n tokens, i.e., $SMP = \{w_1, w_2, ..., w_n\}$ and a drug name $(drug\_a)$ where $drug\_a \in SMP$, the IE model is tasked with generating spans and their classification classes listed in Table 1. The IE component is also based on T5. The input sequence for the IE task is "drug_a: [D1] SM post: [SMP] classes and their spans: [CLASS: TEXT SPAN]". We fine-tuned T5 to generate classification classes and text spans for each class listed in Table 1. Figure 2 shows an example of both the input and output of our model.

4 Experiments

4.1 Datasets and processing

We used internal datasets which contained SM posts that were automatically annotated using hand-written rules (e.g., the pattern $\{DrugName > 5\ (negation\_pos > 2\ lemma\_work)\}$, a drug name followed by a text span of 5 words or less away that includes a negation part-of-speech two words away or less from a lemma of the word "work" for extracting the text span of DEFF). The

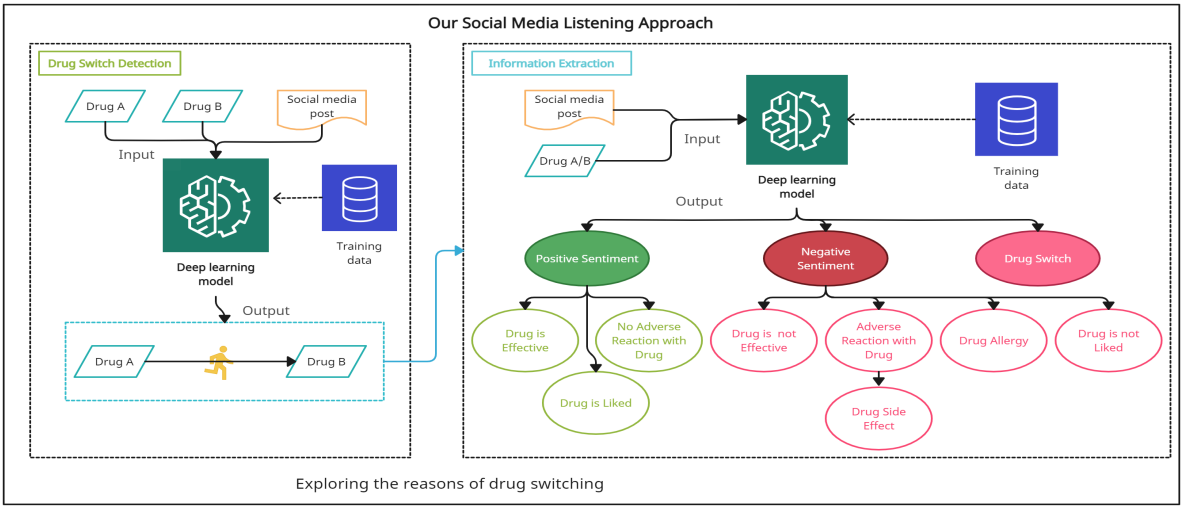

Figure 1: Overview of our social media listening approach

SM POST: *Hi there, I hope you feel better soon. I did not have any problems when I was taking drug_a. But my friend had asthma and his doctor put him on drug_a, and within a month he started having some worst side effects such as muscle aches, difficulty in breathing and pain or tenderness around my eyes and cheekbones. With all these problems, the doctor switched him over to drug_b and he still having shortness of breath or troubled breathing.*
MODEL OUTPUT **PSMT:** *did not have any problems when I was taking drug_a*, **NSMT:** *drug_a, and within a month he started having some worst side effects such as muscle aches, difficulty in breathing and pain or tenderness around my eyes and cheekbones.*, **DSW:** *put him on drug_a, and within a month he started having some worst side effects such as muscle aches, difficulty in breathing and pain or tenderness around my eyes and cheekbones. With all these problems, the doctor switched him over to drug_b*, **DSE:** *drug_a, and within a month he started having some worst side effects such as muscle aches, difficulty in breathing and pain or tenderness around my eyes and cheekbones.*, **ADR:** *drug_a, and within a month he started having some worst side effects such as muscle aches, difficulty in breathing and pain or tenderness around my eyes and cheekbones.*, and **NADR:** *did not have any problems when I was taking drug_a*

Figure 2: SM post and model output.

rules are based on distance of tokens, entities, and linguistic features such as lemma and POS tags. The datasets, which include SM posts from Facebook and forums, contain rule-based annotations such as text span and classification classes listed in Table 1. Figure 3 presents an example of pseudo SM post and rule-based annotations.

In order to detect drug switches, we used examples in our internal datasets as positive instances and automatically generated negative examples using predefined rules. This is because the datasets do not include negative examples. For negative examples, we applied the following criteria: (1) if an SM post mentions two drug names, $drug\_a$ and $drug\_b$, but no drug switch occurs, then $drug\_a + drug\_b + SMP$ is considered a negative example, and (2) if an SM post mentions $drug\_a$ and $drug\_b$ and there is a drug switch from $drug\_a$ to $drug\_b$ but not from $drug\_b$ to $drug\_a$, then $drug\_b + drug\_a + SMP$ is considered a negative example. These negative examples are created to consider the directionality in drug switching. The training, development and testing sets consist of 107,793, 11,977 and 13,308 annotated SM posts, respectively.

SM POST:
See the SM post presented in Figure 2.
RULE-BASED ANNOTATIONS:
Drug name: drug_a
Classification classes and text span: PSMT: *did not have any problems when I was taking drug_a.*
DSW: *put him on drug_a, and within a month he started having some worst side effects such as muscle aches, difficulty in breathing and pain or tenderness around my eyes and cheekbones. With all these problems, the doctor switched him over to drug_b*, **NADR:** *did not have any problems when I was taking drug_a.*

Figure 3: Example of rule-based annotations

Recall	Precision	F1-score
0.99	0.98	0.98

Table 2: Drug switch detection results

For IE, we used examples of SM posts, which included classes and text span (as listed in Table 1), as our training and testing instances. The training, development and testing sets consist of 426,361, 10,659 and 14,109 annotated SM examples, respectively.

Initial drug	New drug	SM post
Drug_a	Drug_b	I was on Drug_b. I had switched from Drug_a to Drug_b. **Gold label:** DSW **Predicted label:** NO_DSW
Drug_b	Drug_c	I was on Drug_b. I had switched from Drug_a to Drug_b. I know nothing about Drug_c. **Gold label:** NO_DSW **Predicted label:** NO_DSW
Drug_a	Drug_c	I was on Drug_b. I had switched from Drug_a to Drug_b. I know nothing about Drug_c. **Gold label:** NO_DSW **Predicted label:** NO_DSW
Drug_e	Drug_f	I take Ativan. My son tried Drug_f, switched to Drug_e and loves it. **Gold label:** NO_DSW **Predicted label:** NO_DSW
Drug_f	Drug_e	I take Ativan. My son tried Drug_f, switched to Drug_e and loves it. **Gold label:** DSW **Predicted label:** DSW
Drug_a	Drug_b	I was on Drug_a which is better than Drug_b but got switched to Drug_d. **Gold label:** NO_DSW **Predicted label:** NO_DSW
Drug_b	Drug_d	I was on Drug_a which is better than Drug_b but got switched to Drug_d. **Gold label:** DSW **Predicted label:** DSW
Drug_a	Drug_d	I was on Drug_a which is better than Drug_b but got switched to Drug_d. **Gold label:** DSW **Predicted label:** DSW

Table 3: Examples of drug switches.

ROUGE-1			ROUGE-2			ROUGE-L		
R	**P**	**F1**	**R**	**P**	**F1**	**R**	**P**	**F1**
94.4	93.9	93.0	91.4	91.0	90.2	94.2	93.8	92.9

Table 4: Information extraction results

4.2 Results

To assess the effectiveness of the drug switch detection model within our SM listening approach, we used standard evaluation metrics such as precision, recall, and F1-score. Our results, as presented in Table 2 using T5, demonstrate that our model performs well in accurately identifying instances of drug switching in SM posts with an F1-score of 98%. Furthermore, Table 3 presents examples of drug switches, along with the corresponding posts we created and the model's predictions. These examples show that our model is capable of detecting the directionality of drug switching, which is a valuable feature for understanding patient behavior.

On the other hand, to evaluate the effectiveness of our text span extraction model, we used the standard ROUGE metric (Lin, 2004) and reported the ROUGE-1, ROUGE-2, and ROUGE-L scores. The results, as presented in Table 4, show that our model is capable of accurately extracting the reasons behind medication changes in SM posts (a ROUGE-1 of 93%). Figure 2 shows an example of SM post and our model results. In this work, we only evaluated T5 for its effectiveness in various natural language processing tasks such as question answering (Sarrouti et al., 2021b) and text summarization (Yadav et al., 2021), etc. Models evaluation goes beyond the scope of the paper, which is introducing drug switch detection and extracting reasons behind the drug switches from SM.

On the other hand, we conducted some tests with ChatGPT (Brown et al., 2020) and shared the results of an SM post along with two questions as shown in Figure 4. Our assessment showed that ChatGPT could manage both tasks. But, it might be expensive to apply it on a large amount of SM posts. It can also take time to process high-volume requests.

SM POST: My doctor switched me over to drug_b since drug_a leaves you unfertile and has many side effects such as no appetite, mood swings, and depression.
QUESTION Is there a medication change from drug_b to drug_a based on the SM post, answer with yes or no and without explanation?
CHATGPT: No.
Question: Extract the medication change information in a structured way from the the SM post
CHATGPT:
Initial Medication: drug_a, **New Medication:** drug_b
Reason for Medication Change: side effects of drug_a (including loss of fertility, no appetite, mood swings, and depression)

Figure 4: ChatGPT evaluation on drug switch detection and IE.

Overall, our SM listening approach provides an effective way to identify drug switches from SM posts, and valuable insights into patient behavior and treatment preferences by extracting the reasons of drug switches. Our approach thus represents a significant contribution to the field of SM listening and healthcare research.

4.3 Error analysis

We conducted a manual analysis of our test sets and compared the performance of our deep learning-based approach to rule-based annotations. Table 5 presents some examples.

The error analysis showed that our method was

	Example
(1)	**Drug name**: drug_a, **SM Post:** *See the SM post presented in Figure 2.* **Rule-based annotations: PSMT:** *did not have any problems when I was taking drug_a*, **DSW:** *put him on drug_a, and within a month he started having some worst side effects such as muscle aches, difficulty in breathing and pain or tenderness around my eyes and cheekbones. With all these problems, the doctor switched him over to drug_b*, **NADR:** *did not have any problems when I was taking drug_a* **Our approach: PSMT:** *did not have any problems when I was taking drug_a*, **NSMT:** *drug_a, and within a month he started having some worst side effects such as muscle aches, difficulty in breathing and pain or tenderness around my eyes and cheekbones.*, **DSW:** *put him on drug_a, and within a month he started having some worst side effects such as muscle aches, difficulty in breathing and pain or tenderness around my eyes and cheekbones. With all these problems, the doctor switched him over to drug_b*, **DSE:** *drug_a, and within a month he started having some worst side effects such as muscle aches, difficulty in breathing and pain or tenderness around my eyes and cheekbones*, **ADR:** *drug_a, and within a month he started having some worst side effects such as muscle aches, difficulty in breathing and pain or tenderness around my eyes and cheekbones*, and **NADR:** *did not have any problems when I was taking drug_a*
(2)	**Drug name**: drug_a, **SM Post:** *Hello, here is my short story: I am taking drug_b for now. Regarding drug_a, I don't take it since I have panic disorder and agoraphobia. Although drug_b worked well for me, I am having mood changes.* **Rule-based annotations: NSMT:** *drug_a, I don't take it since I have panic disorder* **DSE:** *drug_a, I don't take it since I have panic disorder***ADR:** *drug_a, I don't take it since I have panic disorder* **Our approach: NSMT:** *drug_a, I don't take it since I have panic disorder and agoraphobia* **DSE:** *drug_a, I don't take it since I have panic disorder and agoraphobia* **ADR:** *drug_a, I don't take it since I have panic disorder and agoraphobia*
(3)	**Drug name**: drug_a, **SM Post:** *I was on drug_b and drug_a for a long time, and never had hair loss (Male Hair). I started having hair loss with drug_c , I am having some problems like nausea and no appetite. Drug_b did not help me with seizures. But drug_a helped me a lot and was able to control seizures , but did nothing for nausea. On the other hand, drug_c has helped me with clonic seizure.* **Rule-based annotations: NSMT:** *drug_a for a long time, and never had hair loss (Male Hair). I started having hair loss with drug_c , I am having some problems like nausea* **DSE:** *drug_a for a long time, and never had hair loss (Male Hair). I started having hair loss with drug_c , I am having some problems like nausea and no appetite* **DSE:** *drug_a for a long time, and never had hair loss (Male Hair). I started having hair loss with drug_c , I am having some problems like nausea* **DSE:** *drug_a for a long time, and never had hair loss (Male Hair). I started having hair loss* **ADR:** *drug_a for a long time, and never had hair loss (Male Hair). I started having hair loss with drug_c , I am having some problems like nausea and no appetite* **Our approach: NSMT:** *drug_a helped me a lot and was able to control seizures, but did nothing* **DNEFF:** *drug_a helped me a lot and was able to control seizures, but did nothing*

Table 5: Examples of pseudo SM posts, rule-based annotations and our model output.

able to extract more information and identify additional classification classes and spans. For example, in example #1, our model identified six classes (PSMT, NSMT, DSE, DSW, ADR, and NADR) while the rule-based annotations only had three (PSMT, DSW, and NADR). Our model was also able to address conflicting sentiments about the same drug, such as in example #1 where PSMT and NSMT spans about drug_a were correctly identified.

In addition, the error analysis showed that our approach accurately extracted the corresponding spans for each class. For example, in example #2, the rule-based annotations missed the span for "Agoraphobia" due to an incomplete dictionary or distance length restrictions, while our model was able to extract it. Additionally, our model was able to handle the challenge of multiple drugs with different spans within the same SM post and accurately extract the corresponding spans for a given drug name. In example #3, rule-based annotations erroneously added information related to drug_b to drug_a, while our model correctly identified the text span for each drug.

5 Conclusion

In our paper, we presented our SM listening approach to extract valuable insights from patients' conversations and understand the reasons why patients switch drugs during treatment. To achieve this, we developed a drug switch detection model that can determine whether a drug switch has occurred by analyzing mentions of two drug names in an SM post. Furthermore, we described an IE model that can extract the reasons for the medication change, such as adverse reactions, side effects, the effectiveness of the drug, etc. The results showed that our approach achieved good performance in drug switching detection and IE tasks.

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