Monitoring Open-Source Textual Information for Anticipating Emerging Drug Trends through Federated Learning

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1 ABSTRACT

This study addresses the global challenge of drug trafficking by harnessing open-source data from Reddit discussions to identify emerging drug trends, employing sentiment analysis and federated learning to enhance privacy and data security. By analyzing drug-related comments for sentiment distribution and slang terminology, patterns are uncovered in drug use across various regions. The methodology includes data collection from drug-related subreddits, data cleaning, and processing with a focus on privacy-preserving techniques like federated learning, where a global model is trained across distributed datasets without sharing raw data. The research utilizes RoBERTa-base for sentiment analysis and develops a Streamlit interface for visualizing trends and analysis results. Feedback from user experience validation, including interactions with law enforcement, confirms the interface's effectiveness. The findings reveal distinct sentiment distributions among different drug trends, highlighting the study's practical implications for combating the illicit drug trade. This project not only contributes to academic discussions on drug trends but also demonstrates the potential of federated learning in sensitive data analysis, setting a precedent for future research in this area.

2 INTRODUCTION

In our interconnected world, illegal drug trafficking poses a significant global challenge, involving the complex process of production, distribution, and sale of ilicit substances . This ongoing issue constantly challenges legal and medical systems. Law enforcement and policymakers struggle to effectively combat these dynamic markets with existing legislation[26].

The dynamic between humans and information has transformed in our digitally connected world, resulting in a wealth of readily available information on the Internet, encompassing illicit drugs. Actors in the illicit drug market, including manufacturers, dealers, and users, are attracted to the anonymity and global reach provided by online platforms, allowing them to evade legal repercussions [31]. This technological shift also impacts the illicit drug trade, influencing communication among individuals using drugs. Online discussion boards related to drugs play a crucial role in understanding and reaching the population of drug users, offering insights into drug use behaviors, harm reduction messages, and valuable information for shaping drug policies [11].

Furthermore, the increased use of digital platforms has given rise to a market for selling psychoactive substances [2]. Monitoring these digital spaces presents an opportunity to comprehend the dynamics of the market for these substances.

A previous research proposed the use of online open-source drug data, specifically from users reporting on www.pillreport.net, as a source for generating drug intelligence [25]. The understanding of trafficking networks and physical characteristics of drugs played a crucial role to address ilicit drug markets effectively. A dataset of ectasy pills was used to conduct a spatiotemporal analysis, demonstrating the potential of open-source information for monitoring ilicit substances. Employing AI-powered web scraping, the study collected data from the Pill Reports website, analyzing variables like location, logo, shape, color, and listing date to gain insights into drug distribution patterns and trends. The insights align with other data sources, underscoring the potential of open-source intelligence (OSINT) as a cost-effective, real-time monitoring solution for understanding and addressing drug trends.

Another research showcased innovative approaches to software-automated data mining of the digital environment [13]: (i) an e-shop finder detecting platforms offering new psychoactive substances, (ii) scraping forum data for monitoring emerging trends, and (iii) automated sentiment analysis of online discussions. The findings suggest that these methods offer opportunities for timely and granular insights into drug-use phenomena, allowing for ad hoc risk assessments and longitudinal monitoring.

While these automated tools hold promise for drug epidemiology and research, there are still challenges to be addressed in monitoring this vast and growing digital space. One of the main concerns are the ethical considerations such as consent and data protection. There is a need for regular review, ethical standards, and human research input to ensure these tools remain effective additions to epidemiological studies, rather than replacement.

To combat the ethical concerns, federated learning is introduced. Federated learning is an emerging machine learning paradigm designed to address challenges related to data silos and privacy concerns [22]. It involves multiple clients, such as mobile devices or organizations, coordinating with central servers for decentralized machine learning. Initially proposed by Google in 2016, federated learning allows devices to collaboratively train a model without sharing raw data. The process typically involves downloading a global

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model to local devices, updating it with local data in an encrypted manner, aggregating these updates in the cloud, and redistributing the improved model. Federated learning is particularly suitable for privacy-sensitive applications, such as healthcare or mobile devices, where data cannot be aggregated centrally due to legal concerns.

2.1 Objectives

This research is conducted in collaboration with the Police Academy. The project goal is to explore the potential of leveraging open-source information to detect emerging trends in criminality, specifically related to drugs. This research paper aims to answer the following questions:

- **Research question:** How effective is leveraging open-source information from Reddit for detecting emerging trends in drug-related criminality?
  - **Subquestion 1:** How do the sentiments expressed in drug-related comments on Reddit vary across different drugs?
  - **Subquestion 2:** What are the key challenges and limitations encountered in utilizing open-source information from Reddit for detecting emerging trends in drug-related criminality?

Furthermore, since the project's goal involves creating a specialized tool for the Police Academy, it is crucial to discover a method for presenting all discoveries to police officers in a user-friendly manner:

- – **Subquestion 3:** How can a data systems tool assist in comprehending the trends of emerging drugs?
  - **Subquestion 4:** How do users perceive the usefulness and practicality of the developed dashboard prototype for law enforcement purposes?

Following these research questions, this report represent current related work and the methodology for addressing these questions is explained. Subsequently, the findings are demonstrated. Furthermore, the detailed description of the development of the final output and a dashboard tool is provided, along with explanations of its visualizations. The concluding section of the paper is devoted to discussion and suggestions for future work to enhance the tool.

3 RELATED WORK

3.1 Predictive Policing

Predictive policing is a method used by law enforcement that involves analyzing historical crime data to predict where and when crimes are likely to occur. The development of predictive policing has seen a transition from traditional approaches to more sophisticated, data-driven methods [28]. Traditional methods have limitations like reliance on historical data and necessitated extensive manual analysis, which is time-consuming and resource-intensive. Incorporating data from online platforms enables real-time monitoring of criminal activity and allows for a broader array of factors associated with crime. This data can uncover emerging trends and patterns not evident from traditional crime data alone, demonstrating the effectiveness of predictive policing in prior research [33].

3.2 Drug Trends on Reddit

Previous studies have highlighted the effectiveness of analyzing data from social media platforms to gain insights into trends related to drug use [12] [30]. A recent investigation analyzed the content of over 67 subreddits and examined how online discussions about drugs relate to toxic exposures or overdoses in the USA [1]. Collectively, these studies suggest that utilizing data scraping methods on online drug forums can be a valuable tool for predicting new trends in drug substances. Another study also affirmed the utility of monitoring forums to supplement existing drug substances surveillance systems, potentially providing predictive insights into emerging trends in the drug substances market that have not yet been identified [32]. One study reveals a significant increase in fentanyl-related content across various drug-related subreddits from 2012 to 2021, with the fastest rate of change observed in multi-substance and stimulant subreddits [3]. Our research aims to explore trends by substance-specific categories of subreddit. While understanding how trends may vary by substance is useful, there is a disadvantage due to selection bias on Reddit. Users are expressing their opinions on Reddit and are likely more open about their drug use. Since this may not be indicative of all drug users, the results may not be generalizable to the larger population [24]. Nonetheless, understanding emerging drug trends is crucial for authorities and healthcare professionals to stay ahead of evolving patterns of drug use and potential harms [19]. Additionally, substance-specific trend analysis informs policy decisions on drug regulation strategies and ensures effective allocation of resources to address pressing issues within each drug category.

3.3 Sentiment Analysis

Sentiment analysis (SA) examines opinions on diverse entities and is a branch of machine learning, data mining, natural language processing, and computational linguistics, incorporating aspects of sociology and psychology [35]. In recent years, there has been a surge in the exploration and advancement of sentiment analysis (SA) techniques, driven by various factors such as the proliferation of datasets derived from user-generated web reviews, the integration of machine learning methods into natural language processing (NLP), and a growing interest in automating opinion analysis [5] The primary objective of polarity classification is to ascertain the subjective orientation (positive, neutral, negative) of a document, sentence or feature, along with quantifying the extend of expressed sentiment. User opinions can yield valuable insights for aiding decision-making processes. Furthermore, patient feedback on drugs can aid physicians in their prescribing decision by considering patient experiences with the medication. SA is crucial for discerning drug trends as it enables the analysis of public sentiments and opinions surrounding various drugs, providing insights into their popularity, perception, and potential risks. By leveraging SA, authorities and healthcare professionals can proactively monitor emerging drug trends, identify patterns of usage, and devise effective interventions to address public health concerns.

3.4 Data systems in law enforcement

Law enforcement agencies worldwide are consistently striving to optimize the utilization of technology in policing and law enforcement. Efforts are underway to address existing technological, legal, and organizational hurdles, creating opportunities for the adoption of promising technologies, both existing and emerging. In a previous research among 46 police forces and law enforcement agencies across 11 countries, their needs and obstacles are conducted [6]. The respondents experienced legal and technological obstacles. The absence of a proper legal basis for using specific technologies was the most commonly cited legal obstacle, followed by lack of clarity on legal allowances and personal data handling. Other issues included inadequate user-friendliness of software and limited results of technology in policing. Our research attempts to overcome these obstacles through the use of federated learning and by creating a streamlit interface.

4 MATERIAL AND METHODS

4.1 Data collection

4.1.1 Reddit. Reddit is chosen as the primary data source due to its extensive user community, boasting approximately 1.8 billion monthly visits. As of April 2018, Reddit boasted over 330 million active users and hosted approximately 130 thousand active subreddits, making it a vast and diverse platform for online discourse [15]. Reddit is an internet platform where users can find a wide array of discussion threads organized into groups called "subreddits," each dedicated to a specific topic. Users, known as "Redditors," can subscribe to these subreddits based on their interests and contribute by posting content, which can then be upvoted or downvoted by other users.

Specific subreddits related to drugs were identified for their high levels of activity, non-satiric content, and engaged communities. The list of chosen subreddits can be found in table 1. R/opiates and r/drugs are known to be major drug-related subreddits [24]. Furthermore, these subreddits facilitate discussions on a diverse range of drugs, in addition to maintaining sufficient user engagement and posting activity.

From these subreddits, posts from September 2023 were meticulously selected to constitute the dataset [34]. Following the data filtering and preprocessing explained in the subsequent sections the dataset included approximately 60 thousand posts. This amount is chosen due to limited computing capacity. Handling larger volumes of data would strain available resources. More posts would lead to performance limitations of the tools used for the dashboard.

Subreddit
r/drugs
r/trees
r/DrugsOver30
r/opiates
r/AskDrugs
r/Drugs_Info
r/RealDrugs
r/DrugNerds
r/researchchemicals
r/addiction

Table 1. List of Subreddits

4.1.2 Drug dictionary. The drug dictionary utilized in this research is a self-made resource intended for identifying drugs mentioned in Reddit posts. Constructed based on the most common slang terms for drugs provided by the Drug Enforcement Administration [7], this dictionary consists of keys representing various slang terms related to drugs and corresponding values representing the actual drug names. Details on the 10 selected drugs, along with examples of accompanying slang terms, can be found in table 2. The selection of these drugs was based on their prevalence and significance in drug-related discussions on Reddit, ensuring broad coverage by considering widespread use, potential for misuse, and relevance to current drug discourse. A drug dictionary proves essential due to the diverse language on platforms like Reddit, where users frequently employ slang, abbreviations, or euphemisms for drugs. This complexity makes accurate identification and categorization challenging based solely on explicit drug names. Hence, a comprehensive drug dictionary facilitates precise extraction and analysis of drug-related information from Reddit posts.

Drug Name	**Slang Terms**
amphetamine	b-bombs, diamonds, footballs
cocaine	cheyenne, cookie, designer jeans
fentanyl	china town, friend, shoes
heroin	bonita, chocolate, dirt
ketamine	green, honey oil, vitamine k
lsd	animal, flash, newspapers
marijuana	garden, love nuggets, spliff
mdma	bean, vitamine e, xtc
methamphetamine	chicken, gifts, yellow kind
mushrooms	alice, pizza toppings, tweezes

Table 2. List of Drugs and Slang Terms

4.2 Data cleaning

4.2.1 Text Processing. To prepare the Reddit data for analysis, several text processing steps were applied. The following transformations to each comment in the Reddit posts are applied: text conversion to lowercase, removal of new lines, elimination of links, multiple occurrences of letters, special characters and numbers. Additionally, posts with fewer than 4 words or more than 40 words are filtered out. This filtering helps ensure that the text input provides sufficient context for sentiment analysis while avoiding tokenization issues for neural networks, which typically have a maximum token limit of 128 tokens. Posts with fewer than 4 words may not provide enough context for meaningful analysis, while posts with more than 40 words could lead to tokenization problems due to the potential expansion of each word into multiple tokens.

4.2.2 Named Entity Recognition. Identifying drug names within the comments is crucial for the analysis. Leveraging the drug dictionary, Named Entity Recognition (NER) is conducted to locate instances of drug references. For each comment, occurrences of drug names were identified and labeled either as B-drug (beginning of drug entity) or O (no entity), providing a structured format for subsequent analysis.

4.2.3 Sentiment Analysis. For sentiment analysis, the RoBERTa-base model, acquired from Hugging Face [4] [23] and fine-tuned with the TweetEval benchmark , is selected due to several key advantages it offers. RoBERTa-base benefits from extensive pretraining on a vast corpus of Twitter data spanning from January 2018 to December 2021, making it adept at understanding the nuances of language commonly used in social media discussions, including Reddit comments related to drugs. This model effectively interprets the sentiment in Reddit comments related to drugs, providing scores ranging from 0 to 1 and labeling them as either negative, neutral or positive. Moreover, RoBERTa-base exhibits robustness to noise commonly encountered in social media data, such as slang, misspellings, and informal language. Its extensive training on diverse Twitter data equips it to effectively handle variations in language, contributing to its reliability in detecting sentiment in the Reddit comments.

4.3 Model

4.3.1 BERT. BERT (Bidirectional Encoder Representation from Transformers) is selected as the primary model architecture for the analysis task. The pretrained BERT model is acquired through the Hugging Face Model Hub [9] , specifically using the 'bert-base-uncased' variant. This decision was made based on the effectiveness of BERT in natural language processing tasks, particularly in capturing contextual information bidirectionally [8]. By training in both directions, BERT can better grasp the meaning of text without being constrained by a specific direction, enabling it to learn the contextual meaning of words effectively. BERT can also efficiently perform aspect-based sentiment categorization [17].

To fine-tune BERT for the token classification task of named entity recognition, several hyperparameters were adjusted. These include the learning rate (initialized at 2e-4), the number of training epochs (set to 10), and the batch size (set to 32). Additionally, a weight decay rate of 0.01 was applied to prevent overfitting during training. The optimization process utilized an Adam optimizer with no warm-up steps.

The dataset used for training, validation, and testing consists of approximately 60.000 posts, with 70% allocated for training, 15% for validation, and 15% for testing purposes.

4.3.2 Federated Learning framework. The federated learning framework involves multiple rounds of communication and aggregation. Initially, a global model is initialized and shared with participating parties (eg. Police academies). Each party trains the model locally using their own data, generating local updates. These local updates are then encrypted and aggregated to create a global model update. The updated global model is then distributed back to the participants, and the process iterates until convergence is achieved. The essence of our approach lies in the encryption and subsequent aggregation of these local updates, enhancing the global model without compromising data privacy.

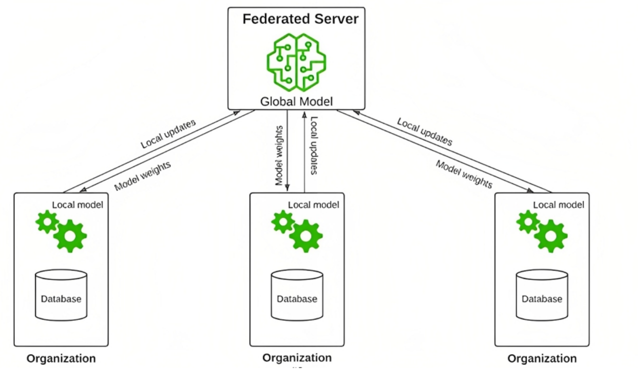

Fig. 1. Federated Learning System Architecture

4.3.3 Federated Learning implementation and challenges. Managing data heterogeneity is crucial within our federated learning framework to guarantee efficient training of the model across varied datasets. Given that local models receive different data, which can significantly influence the accuracy of outcomes due to data diversity, it's essential to address this variability. This challenge underscores the need for careful consideration in how data is prepared and utilized in the federated learning process, ensuring that discrepancies among datasets do not adversely affect the model's performance.By implementing techniques such as data normalization, the challenges posed by the variability of data across our Reddit dataset and future contributors are mitigated. This measure reinforces the integrity and efficiency of our federated learning framework, highlighting our commitment to addressing the multifaceted challenges inherent in collaborative machine learning endeavors.

4.4 Interface

The interface is developed using Streamlit, a powerful Python library for building interactive web applications [21]. By leveraging Streamlit's simplicity, flexibility, and powerful features, the interface offers a user-friendly and interactive platform for exploring drug-related data, performing sentiment analysis, visualizing geographic distributions, and training custom models. Users can seamlessly interact with the interface to gain valuable insights and make informed decisions in the domain of drug analysis and research. Details on this interface can be found in the results section.

4.5 Quantitative user-experience validation

In order to gain feedback on the user-experience on the prototype interface, an A/B testing was conducted. This testing aimed to assess the interface's performance and user satisfaction using metrics derived from the Google HEART Framework, which includes Happiness (User Satisfaction), Engagement, Adoption, Retention, and Task Success. This evaluation metric was chosen over other UX surveys, due to its conciseness and more related questioning.

4.5.1 Validation metrics. First, user satisfaction was emphasized as critical to the interface's long-term adoption and success. User satisfaction was deemed critical, as a satisfied user was more likely to interact with the platform on a regular basis and recommend it to others. The measurement of user satisfaction was highlighted as a method for determining how well the interface met the needs and expectations of police stakeholders. Positive feedback indicated that the prototype was effective in monitoring drug trends.

Second, the importance of high engagement as a measure of the interface's value to users and their active use of it to complete tasks was emphasized. It was emphasized as a reliable indicator of the prototype's utility and effectiveness. The importance of continuous attention and interaction with the interface in monitoring drug trends was emphasized, with high engagement metrics indicating that users were actively exploring the different tools the prototype had to offer.

Third, adoption measures the number of users who actively use the interface. A higher adoption rate was thought to indicate greater acceptance and usage among police stakeholders, which was critical to the prototype's success and impact. The prototype's relevance and usefulness to police stakeholders in their day-to-day operations were noted, and it was adopted accordingly. A high adoption rate was suggested as evidence that the interface met their needs and provided useful insights into drug trends.

Fourth, retention measured how well the interface retained users over time. It was interpreted as an indication of the interface's ability to sustain user interest and maintain engagement beyond the initial interaction. Monitoring drug trends is an ongoing task for law enforcement agencies. High retention rates would suggest that the interface continued to provide value and remains relevant to police stakeholders over time, encouraging them to return and use it regularly.

Finally, the measure of task success, defined as the interface's effectiveness in assisting users in meeting their objectives, was discussed. A high goal completion rate was cited as evidence of the interface's intuitiveness, efficiency, and ability to assist users in accomplishing their tasks effectively. The interface was relied on by police stakeholders to monitor drug trends accurately and efficiently, with a high goal completion rate indicating that users could easily navigate the interface, access relevant information, and analyze drug data to make informed decisions.

4.5.2 Participants. A non-random convenience sampling method was employed to recruit participants for the evaluation. A total of 22 participants were selected based on recommendations from previous studies [14][16][20], which emphasized balancing statistical power with practical feasibility. These participants were approached by the authors of this report, and had both Dutch (13) and international (9) origin.

4.5.3 Experiment execution. Participants were presented with specific tasks to complete within the prototype interface:

- Task 1: Participants were tasked with identifying the third most popular drug type using the DrugWatch feature.
- Task 2: Participants were instructed to find a list of street names associated with mushrooms.
- Task 3: Participants were asked to determine whether discussions about ketamine were predominantly positive or negative.
- Task 4: Participants were challenged to locate the most upvoted comment on September 28, 2023.

Completion time per task were measured, in order to give insight into how time consuming each task was, giving an indication as to how easy the interface was to navigate around. Upon completing these tasks, participants provided their responses via a designated form. Subsequently, a survey was administered to gather feedback on validation metrics using a five-point Likert scale. See appendix A for the full survey form.

The survey was conducted using Qualtrics, A simple to use software that allowed for easy retrieval of results. The survey responses were exported as a CSV file and then analyzed using the Python Pandas library.

4.6 Qualitative end-user validation

To gain further insights into the human experience, a qualitative research was chosen to delve deeper into the end-users' nuanced perspectives and experiences, specifically among police stakeholders. The decision to conduct qualitative research alongside existing quantitative methods was motivated by the desire to collect rich, contextual insights that quantitative data alone may not provide. Furthermore, qualitative research allows for the exploration of subjective viewpoints, preferences, and potential areas for improvement that quantitative metrics may overlook.

The primary data collection method used was a semi-structured interview with the ms. Span, chief of police for external security at Schiphol Airport (BBS). The interviewee was selected using convenience sampling, and the interview was conducted over the phone. Several factors influenced the decision to select this person as the ideal interviewee for the study. First and foremost, her firsthand experience in law enforcement provides valuable insights into the prototype interface's practical usability and relevance in real-world policing scenarios. Furthermore, her role in directing colleagues demonstrates a level of authority and expertise within the police force, making her perspective especially valuable for informing potential interface improvements.

The semi-structured nature of the interview allowed for a mix of structured, closed-ended questions and open-ended inquiries. This approach was strategically chosen to kick off the discussion with specific questions aimed at gathering targeted feedback on the prototype's features and functionalities. The interview then progressed to broader, open-ended questions to elicit the interviewee's overall impressions, preferences, and potential unmet needs regarding drug trend monitoring.

A reverse funnel technique was used to allow for a more in-depth analysis of the interviewee's responses and insights [27]. This technique involved starting the interview with narrower, closed-ended questions about the interviewee, their job and past experiences with similar topics, and specific aspects of the prototype interface. As the interview progressed, the questions became more broad and open-ended, allowing for a thorough exploration of the interviewee's perspectives and experiences. Probing questions were asked throughout the interview to elicit additional clarification, examples, or elaboration on specific points raised by the interviewee. For a summarized version of the interview, please refer to appendix B.

4.7 Team management

DrugWatch's success was due in large part to effective team management. Despite communication challenges inherent in the course's dynamic nature, effective task delegation allowed for simultaneous progress across multiple aspects of the project.

Tasks were split strategically among team members to capitalize on their individual strengths and expertise. This approach allowed for parallel work streams, with team members focusing on different components such as coding the machine learning model, designing and implementing the prototype's functionality, developing natural language processing algorithms, and writing the corresponding report.

Clear responsibilities enabled efficient workflow management, allowing team members to work autonomously while remaining on track with project goals and timelines. Regular check-ins and status updates helped to reduce communication barriers and ensure that any emerging issues or dependencies were addressed right away.

Despite the challenges posed by the course's dynamic environment, effective team management promoted cohesion and synergy, resulting in the successful development and completion of the prototype interface.

All details pertaining to this project, including data sourcing, methodology, and analysis, are accessible via a public GitHub repository [29]. The dashboard associated with this project can also be accessed publicly [10].

5 RESULTS

5.1 BERT Model

The training metrics for the BERT model are presented in table 3. Remarkably, the model exhibits impressive performance metrics, achieving high precision, recall, F1 score, and accuracy across multiple epochs of training. Notably, after just the first epoch, the model demonstrates exceptional performance, suggesting rapid convergence and effective learning. While the binary token classification task for the drug dictionary might not challenge general NER tasks, the focus extends beyond just model performance to include the broader framework of federated learning. This allows for customized adaptations to different contexts. Validation of this approach and pipeline effectiveness would benefit from real-world drug market data integration.

Table 3. BERT Model Training Metrics

Loss	Validation Loss	Precision	Recall	F1	Accuracy
0.0097	0.0026	0.9966	0.9976	0.9971	0.9996
0.0015	0.0011	0.9996	0.9997	0.9996	0.9999
1.6109e-04	7.4520e-04	0.9998	0.9999	0.9998	1.000

5.2 Sentiments per Drug

The sentiment analysis conducted on Reddit posts concerning various drugs shows a range of opinions as seen in table 4. Some drugs, like LSD and marijuana, generally get neutral or positive comments, while other, like fentanyl and heroin, often get negative ones. In some cases, users have conflicting feelings about certain drugs. The sentiments distribution across all drugs leans predominantly neutral, followed by negative sentiments, with positive sentiments being the least common, as illustrated in figure 2. Not every drugs occurs as often as seen in figure 3. Marijuna emerges as the most frequently mentioned drug, with an occurrence of nearly 18.000 mentions, followed by methamphetamine and heroin. Conversely, amphetamine, ketamine and mushrooms are the least mentioned drugs, with the latter having around 1000 mentions. These findings emphasize the necessity of nuanced understanding in interpreting online discussions related to drug usage, thereby informing strategic decision-making processes in law enforcement.

Table 4. Drug Sentiment Counts

Drug	Sentiment	Count
amphetamine	neutral	857
	negative	580
	positive	340
cocaine	neutral	2612
	negative	2485
	positive	1068
fentanyl	negative	2575
	neutral	1738
	positive	979
heroin	neutral	3216
	negative	3121
	positive	1751
ketamine	neutral	614
	negative	420
	positive	253
lsd	neutral	1916
	negative	1239
	positive	1109
marijuana	neutral	8307
	negative	6526
	positive	3069
mdma	neutral	1845
	negative	1389
	positive	801
methamphetamine	neutral	4133
	negative	3735
	positive	2172
mushrooms	neutral	433
	negative	347
	positive	311

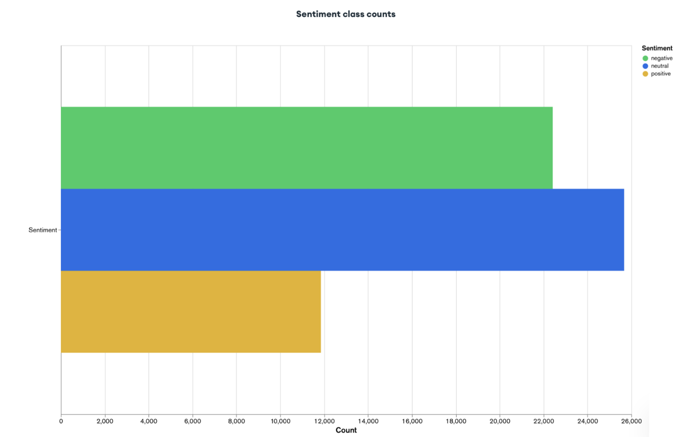

Fig. 2. Sentiment Distribution

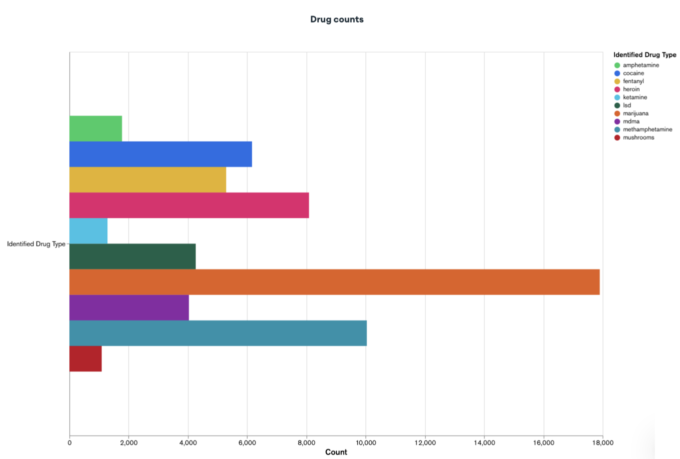

Fig. 3. Drug Counts

Figure 4 shows the distribution of reddit comments over dates. The plot illustrates a peak in activity around the 19th of the months, followed by a decline around the 25th, with the lowest number of comments occurring towards the end of the month. A possible reason for this peak in activity around the 19th could be related to payday cycles. Many individuals receive their salaries around this time, which may lead to increased spending on drugs or heightened social activities, thereby resulting in more discussions and comments on Reddit.

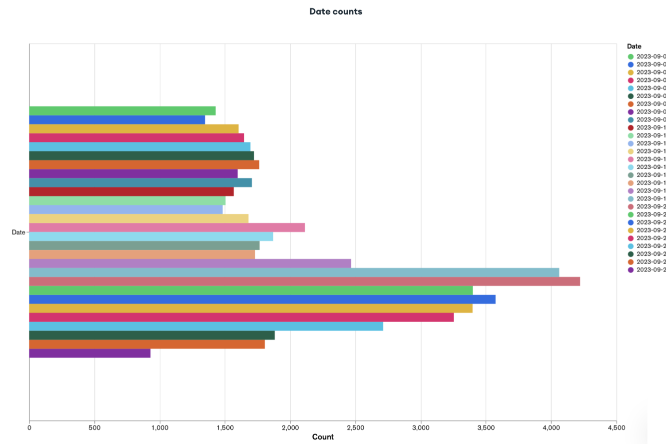

Fig. 4. Distribution of Reddit Comments Over Dates

5.3 Dashboard

The end result is a dashboard designed for use by the police academy. A key goal of the project was to develop a functional prototype of a tool for mapping and visually presenting data in an innovative way. This tool should adhere to fundamental principles of visual and interaction design, enabling analysts to explore and interact with the data to investigate the outcomes of their research inquiries. The decision was made to create a prototype dashboard. This dashboard allows analysts to view visual representations of processed data and interact with the interface to filter and compare data, revealing interesting patterns and trends in drug popularity. Additional details regarding the dashboard's appearance, functionality, and interaction are provided in the attached screenshots.

5.3.1 Drug Encyclopedia. Users can explore detailed information about different drugs by selecting them from a drop-down menu as seen in figure 5. Each drug entry provides a description of the drug, allowing users to gain insights into its properties and effects, as illustrated in figure 6. Note that these descriptions are GPT generated.

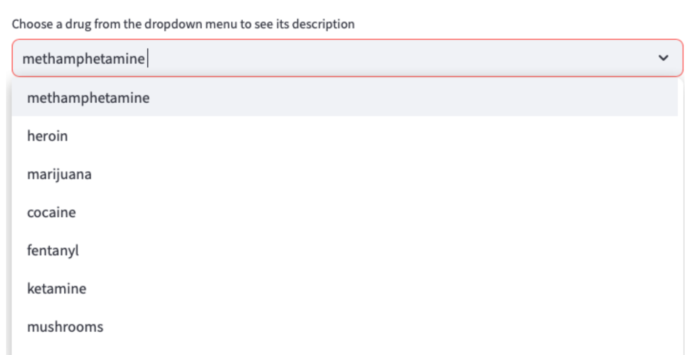

Fig. 5. Drop-down menu

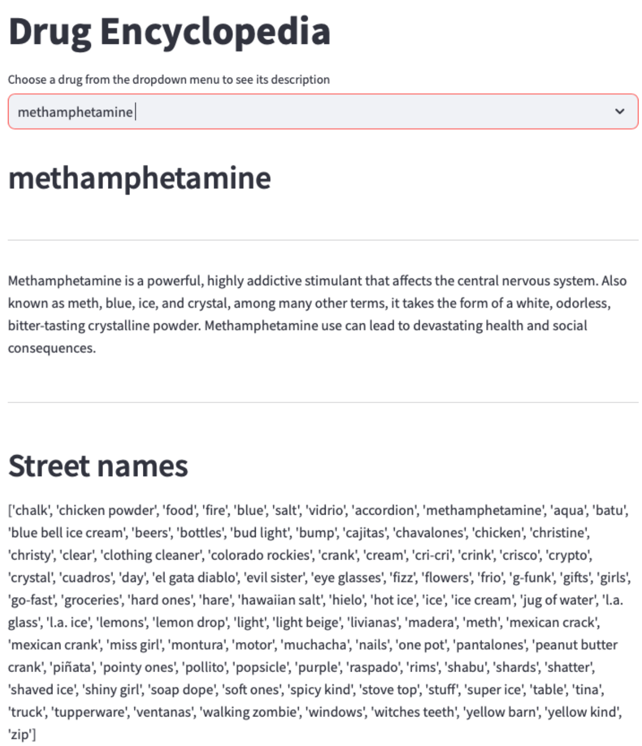

Fig. 6. Drug Encyclopedia

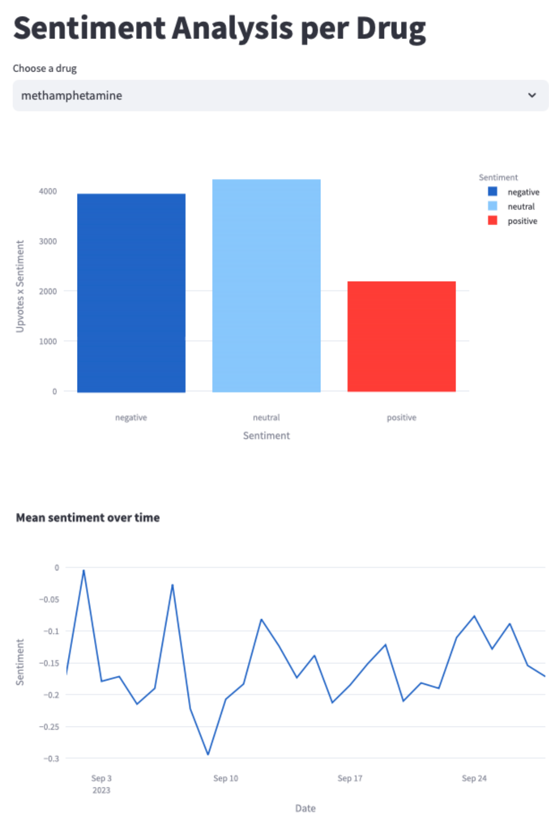

Fig. 7. Sentiment Analysis per Drug

5.3.2 Sentiment Analysis. This section allows users to perform sentiment analysis on drug-related comments. Users can select a specific drug from the drop-down menu, and the interface generates a bar chart showing the sentiment distribution of comments related to that drug, see figure 7. This visualization helps users understand the overall sentiment associated with different drugs.

5.3.3 Map Visualization. The map visualization in figure 8 enables users to visualize the geographic distribution of drug-related comments. The interface displays a map with markers representing the locations where the comments were posted, if metadata is available about the location. This functionality provides insights into the spatial patterns of drug-related discussions.

Fig. 8. Map

5.3.4 Popular Drugs Ranking. Users can explore the popularity of different drugs by examining a ranking of the most mentioned drugs in the dataset. The interface in figure 9 displays a bar chart showing the frequency of mentions for the top 10 drugs, allowing users to identify the most discussed drugs.

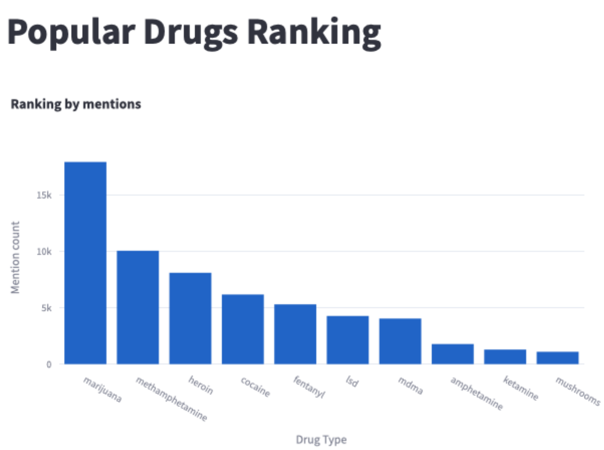

Fig. 9. Popular Drugs Ranking

5.3.5 Train Model. This section in figure 10 allows users to train a model using their own data. Users can upload a file containing labeled sentences for model training. Moreover, there is an option to upload a drug dictionary as seen in figure 11. After uploading the file, users can customize the training process and initiate model training. The interface provides a progress bar to track the training progress in real-time.

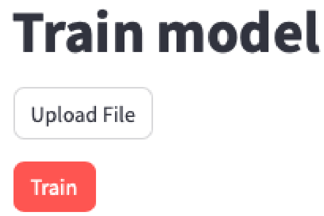

Fig. 10. Train Model

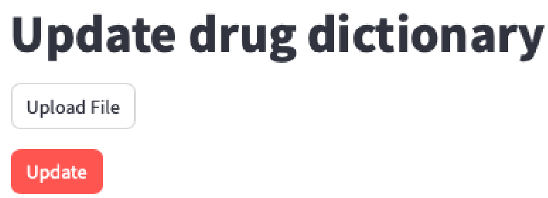

Fig. 11. Update drug dictionary

5.3.6 Inspect Data. Users can inspect the raw data used in the analysis through the section in figure 12. The interface provides options to filter the dataset based on specific criteria, such as date range, categorical values, numeric ranges, or text substrings as seen in figure 13. This functionality enables users to explore and analyze the dataset in detail.

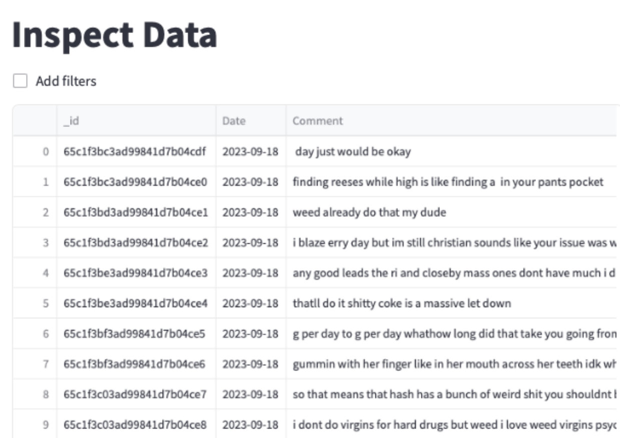

Fig. 12. Inspect Data

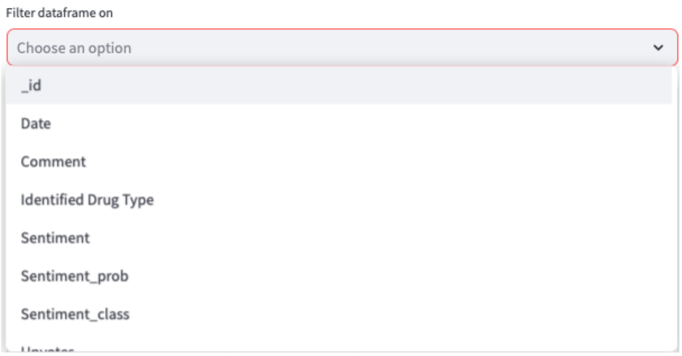

Fig. 13. Filter data

5.4 Validation

The evaluation of the DrugWatch interface yielded results across various metrics, which are showcased in the tables below.

5.4.1 User-experience survey. Based on the output from the survey, the proportion of the maximum possible score for each survey question was calculated. These numbers give an indication of the levels of user satisfaction and engagement in regards to the prototype. The results can be seen in table 5.

Table 5. User-experience survey score proportion

Question	Proportion of maximum possible score
Question 1	0.866
Question 2	0.755
Question 3	0.773
Question 4	0.836
Question 5	0.973

The completion time per task has been averaged over all of the respondents and is showcased in table 6. This table provides insights into participants' efficiency in completing assigned tasks within the interface, offering an indication of task complexity and user proficiency.

Table 6. User-experience survey score proportion

Task	Average completion time (s)
Task 1	15
Task 2	22
Task 3	38
Task 4	98

5.4.2 End-user interview. The interview conducted provided deeper understanding and context regarding users' experiences and perspectives on the prototype. From this interview, key themes emerged, highlighting the following points:

- **Prototype Usability:** The biggest point of critique that arose during the interview was the lack of any real usability. "*While the prototype has some interesting information to show, none of it is of any real use to us.*" The interviewee stated that the actual useful information lies between what there is now. "*What we are truly looking for is the ability to predict drug trends.*" For DrugWatch to become an actual strong tool, it needs to be able to predict drug usage and trafficking. Taking into consideration not only chat logs, but also identifying suspicious behaviours, transactions, and communication patterns. "*Predicting drug trafficking routes is the ultimate goal, as it is more effective to fight distribution, instead of on the usage.*"
- **Interface Navigation:** The interviewee expressed overall satisfaction with the interface's intuitiveness. Despite overall satisfaction with usability, she did express minor frustrations with specific aspects of interface navigation. "*The prototype is often slow to respond, and not all information is intuitive to find.*" Because of this, the interviewee suggested that optimizing the interface's responsiveness and refining the organization of information could significantly enhance the user experience. Additionally, she emphasized the importance of streamlining navigation pathways to improve efficiency and reduce user frustration.
- **Feature Utility:** While the interviewee found most features valuable and essential to the case, she found the information redundant. Most information shown, mainly found in the drug encyclopedia, is already known amongst the police force and has no need to take up space in the prototype. Furthermore, the interviewee found a lack of predictive trends made the prototype mostly lacking any actual useful features. "*Although the sentiment analysis is nice, potentially combining it with the popularity ranking of a drug could prove to be significantly more insightful.*"
- **Impact on Decision-Making Processes:** While the interviewee highlighted the interface's potential to inform decision-making processes within the police force, she expressed reservations about its reliance on data accuracy and relevance. Concerns were raised regarding the necessity for data validation processes to ensure the integrity of insights derived from the interface, emphasizing the importance of data quality in supporting effective decision-making.
- **Model integration:** One topic the interviewee was pleased with, was the application of federated learning into the prototype. "*It is a topic we have been looking into for a while now, as it has many useful applications. Seeing you make use of it is something I am very pleased about.* She stated how federated learning brings many benefits, such as data privacy and a potential increase in collaboration between other stakeholders. Additionally, having a data feedback loop is something she was very adamant about. However, she also stated that using such as model brings its own challenges and limitations. Despite her lack of understanding in regards to these more technical topics, she found it a step in the right direction.

6 CONCLUSION

The research employed a multi-faceted approach to assess the effectiveness of leveraging open-source information from Reddit for detecting emerging trends in drug-related criminality. Data collection involved scraping drug-related comments from specific subreddits and utilizing a custom drug dictionary for named entity recognition. Text processing techniques were applied for data cleaning, including text normalization and filtering. Sentiment analysis was conducted using the RoBERTa-base model, fine-tuned for social media data. The BERT model was employed for named entity recognition, with hyperparameters adjusted for optimal performance.

6.1 Variation in Sentiment Across Different Drugs

The sentiment analysis conducted on Reddit posts revealed diverse opinions regarding different drugs. Substances like LSD and marijuna generally received neutral or positive comments, others like fentanyl and heroin tended to garner negative sentiments.

6.2 Challenges of Utilizing Reddit Data

Despite its potential, leveraging open-source information from Reddit for detecting emerging trends in drug-related criminality poses challenges. These include handling data heterogeneity, managing the volume of data for efficient processing, and addressing the complexity of language, including slang and abbreviations commonly used in online discussions.

6.3 Role of Data Systems Tools in Understanding Emerging Drug Trends

A data systems tool can assist the police in comprehending emerging drug trends by gathering data from platforms like Reddit, employing text analysis techniques such as NER and SA, and presenting insights through interactive dashboards. By identifying drug mentions, analyzing sentiments, and visualizing trends, such a tool enables law enforcement agencies to monitor the popularity, sentiment, and geographic of emerging drugs, facilitating informed decision-making and strategic responses.

6.4 User Validation

While the current prototype is clear and easy to navigate, it lacks any real usability. The current information it showcases is of no actual use to the stakeholder. In order to make DrugWatch a usable product, the predictive capabilities need to be fleshed out and should change its focus from the end user to the distribution of upcoming drugs.

7 DISCUSSION

7.1 Design Decisions

Reflecting on the project, the design decisions were strategically aligned with the goal of leveraging open-source data to investigate drug trends, with a significant emphasis on privacy through federated learning. This choice showcased the potential of federated learning in sensitive analyses, establishing a foundation for future research in privacy-preserving data analysis. Our findings, indicating varied sentiment distributions among drugs and geographic trends, underscore the nuanced understanding of drug discourse online, aligning with stakeholder needs for insightful drug trend monitoring.

7.2 Design Justification

Our research aligns with the recognized need for systematic approaches to harness social networks for illicit drug content analysis, as highlighted by previous studies[18]. By integrating federated learning, our work not only acknowledges the global challenge of illicit drug use and the pivotal role of social networking sites as surveillance tools but also advances the field by emphasizing data privacy. This novel approach underlines the significance of our findings in supporting the development of efficient, privacy-preserving analysis methods to enhance drug-related policy and law enforcement strategies, thereby responding to the call for more effective prevention programs.

7.3 Limitations

Our study acknowledges additional limitations concerning the data's representativeness, accuracy, and ethical considerations. The reliance on digital environments such as Reddit means our data reflects only internet users' views, potentially excluding key demographic groups. Furthermore, the inherent inaccuracies or incompleteness of digital data could affect our analysis' precision. Ethical concerns, particularly regarding privacy, are paramount when collecting and utilizing online data, necessitating careful consideration and adherence to ethical guidelines. These challenges underscore the importance of cautious interpretation of our findings and highlight the need for comprehensive approaches that incorporate diverse data sources and ethical research practices. These considerations are crucial for advancing the field of drug trend analysis and ensuring the responsible use of technology in public health research.

8 FUTURE WORK

Looking forward, our research paves the way for further exploration into the use of social media analytics in public health surveillance, suggesting avenues for incorporating more sophisticated analytical models and expanding the scope of data sources for a more comprehensive understanding of drug use patterns. These efforts could significantly enhance the capability of health officials and policymakers to respond to evolving drug trends promptly and effectively.

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A SURVEY QUESTIONS

Happiness (User Satisfaction):

Survey Question: How satisfied are you with the overall usability and functionality of the prototype?

Likert Scale Responses:

(1) Very Dissatisfied
(2) Dissatisfied
(3) Neutral
(4) Satisfied
(5) Very Satisfied

Engagement (Events per Session, Time Spent):

Survey Question: How time-consuming was it finding your way around the prototype?

Likert Scale Responses:

(1) Never
(2) Rarely
(3) Occasionally
(4) Frequently
(5) Very Frequently

Adoption:

Survey Question: How likely are you to continue using the drug trend monitoring interface in your work?

Likert Scale Responses:

(1) Very Unlikely
(2) Unlikely
(3) Neutral
(4) Likely
(5) Very Likely

Retention:

Survey Question: How often would you return to use the drug trend monitoring interface?

Likert Scale Responses:

(1) Never
(2) Rarely
(3) Occasionally
(4) Frequently
(5) Very Frequently

Task Success (Goal Completion Rate):

Survey Question: How effectively does the drug trend monitoring interface help you achieve your goals?

Likert Scale Responses:

(1) Not at all effectively
(2) Slightly effectively
(3) Moderately effectively
(4) Very effectively
(5) Extremely effectively

B SUMMARIZED INTERVIEW TRANSCRIPTION

The interview conducted was with ms. Span, the Chief of Police for External Security at Schiphol Airport. In this interview, many facets of the DrugWatch interface's possible use in law enforcement operations were discussed, with a focus on the fight against drug-related offenses. Based on her vast experience in law enforcement, the interviewee offered insightful information about the real-world difficulties and demands that police officers confront when they are assigned to keep the public safe and combat drug trafficking. She used examples from her previous work as a ground officer to emphasize the value of tools like DrugWatch in offering a more targeted and focused approach to dealing with drug-related crimes. Talking about her past, she explained that most information is not shared, and information on drug trends is not known to ground officers. She also underlined the importance of DrugWatch's predictive modeling capabilities, especially in spotting suspicious transactions and behaviors and eventually figuring out drug trafficking routes. This proactive approach, in her opinion, would greatly improve police force interventions by stopping drug smuggling operations before they even reach end users. She gave advice on how using other data than only forum posts would help make the model more useful. Ideally, they would want to apply camera footage in order to monitor certain behaviour, banking transactions, and communication patterns. This last point she mentioned is already achieved with using BERT. The interviewee commended DrugWatch for incorporating a feedback loop mechanism for data, and for incorporating federated learning, acknowledging that these features have the potential to continuously enhance and improve the model's accuracy over time. She did, however, also emphasize the need for additional improvement, especially in regards to developing more predictive modeling components to more accurately identify trafficking routes. She ended and emphasised on the note that the real problem that needs to be taken care of is the ever-increasing amount of drug trafficking. Tackling this problem by its roots, instead of the branches that keep growing from it, is the only way to stop drug crime.