Understanding Cross-Platform Referral Traffic for Illicit Drug Promotion

Mingming Zha
mzha@iu.edu
Indiana University Bloomington
Bloomington, Indiana, USA

Zilong Lin
zillin@indiana.edu
Indiana University Bloomington
Bloomington, Indiana, USA

Siyuan Tang
tangsi@iu.edu
Indiana University Bloomington
Bloomington, Indiana, USA

Xiaojing Liao
xliao@indiana.edu
Indiana University Bloomington
Bloomington, Indiana, USA

Yuhong Nan
nanyh@mail.sysu.edu.cn
Sun Yat-sen University
Zhuhai, Guangdong, China

XiaoFeng Wang
xw7@indiana.edu
Indiana University Bloomington
Bloomington, Indiana, USA

Abstract

The promotion of illegal drugs has become increasingly prevalent on popular social media platforms such as TikTok, Instagram, and YouTube. Within this ecosystem, miscreants utilize cross-platform referral traffic to advertise and promote illicit drugs. They start by posting illicit drug-promoting comments on upstream social media platforms, attracting potential drug buyers, and then redirecting these buyers to downstream platforms where the actual drug sales take place. To the best of our knowledge, little has been done so far to understand this cross-platform referral traffic for illicit drug promotion and selling on social media platforms, not to mention any effort to systematically identify such referral traffic on social media platforms. In this paper, we designed an automated pipeline for detecting illicit referral traffic and identified 154,753 drug-referral comments and 3,253 drug sellers. Based upon the dataset, we presented the first systematic study on the ecosystem of such cross-platform illicit drug promotion and selling businesses, which sheds light on the strategies and campaigns of illicit drug promotion. These findings provide valuable insights into the broader impact of illicit drug trading activities and highlight the need for increased attention to addressing the associated security concerns in social media platforms.

CCS Concepts

• **Security and privacy** → **Social network security and privacy**; **Web application security**.

Keywords

Referral traffic; Social media; Illicit drug promotion; Cybercrime

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1 Introduction

Drug overdoses in the United States surpass both traffic deaths and suicides in terms of fatalities. According to the National Center for Health Statistics (NCHS) [11], the year 2021 witnessed a tragic loss of over 106,000 lives in the U.S. due to drug-related overdoses, encompassing both illicit substances and prescription opioids. The underground supports for the illicit drug trading business constitute a well-established and continuously evolving cybercrime ecosystem. This ecosystem engages in various steps of such cybercriminal activities, including illicit drug promotion and trading business hosting. For illicit drug promotion, miscreants utilize different channels and various promotion infection techniques to advertise their drug businesses. For illicit drug business hosting, miscreants host their businesses in a manner that persists despite takedown attempts and complaints about illicit activities, among other issues.

The illicit drug trading ecosystem has long been a subject of interest for the cybercrime research community [39, 40, 71]. Prior research has revealed various illicit drug promotion techniques, such as email spam [36, 39], forum abuse [35], search result poisoning [44, 71], as well as illicit drug hosting services, including illicit online pharmacies [51] and underground marketplaces [42, 63]. With the fast growth of social networks and video sharing platforms today, the illicit drug trading ecosystem is extending its reach to these platforms. Emerging reports and anecdotal evidence [48, 77] indicate that drug dealers have begun employing aggressive marketing tactics to promote and sell illegal drugs through social media platforms, with a particular focus on young customers. This trend highlights a pressing need to understand the ecosystem of illicit drug promotion and hosting on social media.

Referral traffic for illicit drug promotion. Imagine that while watching a video on YouTube, you decide to express your gratitude to the creator by leaving a comment: "Thank you for sharing." Shortly after, an unknown user replies to your comment with the following comment: *"Hey i can refer you to this legit plug i got hooked with he's got top quality MDMA for good rates an also ship's all kinda percs an psychedelics discreetly,"* followed by *"@*[redacted]***i7*** <–" and

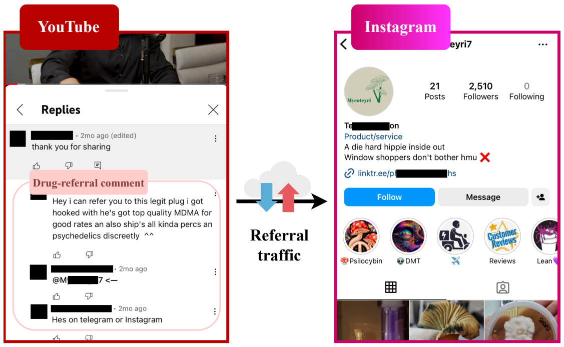

Figure 1: An example of illicit drug referral traffic on YouTube. The drug advertiser account leaves drug-referral comments and redirects potential buyers to Instagram.

"Hes on telegram or Instagram," as illustrated in Figure 1. This comment serves as a promotion for illicit drugs and aims to drive or direct traffic from YouTube to an illicit drug-selling account on Instagram (which we call *drug-referral* comment). Such comments leverage the popularity of social media platforms, utilizing them as a means to generate greater exposure for illegal drug businesses. Although social media platforms often have community guidelines in place to prohibit content related to illegal activities [67], it is observed that both illicit drug-referral comments and drug seller accounts manage to persist for extended periods (as discussed in Section 5). Our research indicates that miscreants exploit social media platforms with high traffic volumes for promotion and redirect traffic to platforms with less-restrictive content moderation.

The referral traffic generated by illicit drug promotions presents an opportunity to establish connections between the advertiser accounts (involved in illicit drug promotion) and the seller accounts (involved in illicit drug business hosting) on social media platforms. This connection allows us to investigate and analyze the illicit drug trading ecosystem, from drug promotion to business hosting on social media platforms, so as to gain an in-depth understanding of the dynamics and mechanisms at play within the illicit drug trading ecosystem in the context of social media platforms.

Our study. In this paper, we report the first systematic study on referral traffic to understand the illicit drug promotion and selling businesses across social media platforms (e.g., YouTube, TikTok, and Instagram). We refer to such malicious activities as *illicit drug referral traffic* (iDRT). More specifically, iDRT lures drug buyers into the ecosystem via illicit drug-referral comments on upstream social media platforms to attract traffic to illicit drug selling business on downstream social media platforms. Our research sheds light on the abusive exploitation of the referral traffic to facilitate this illicit business. Notably, little is known about the real-world impacts of iDRT, and our investigation aims to fill this gap in the literature.

To this end, we developed a pipeline for detecting and tracing iDRTs on social media platforms. Our approach first identified iDRTs from comments under a small set of known polluted illicit drug-related hashtags (e.g., "# mushroom"). Our approach is motivated by the observation that drug advertiser accounts frequently posted promotional ads on upstream platforms by commenting on targeted posts containing drug-related hashtags. These promotional ads typically include contact information for the seller accounts selling illicit drugs on the downstream social media platforms, enabling us to hunt down illegal drug advertiser accounts and illicit drug seller accounts. To collect such hashtags, our pipeline employed a "snow-balling" strategy, from a small set of known illicit drug-related hashtags to discover new ones under related videos. Then we followed the connections between illicit drug-related hashtags and iDRTs to find a set of illicit drug referral traffic. Our results show that this approach is highly effective, achieving an accuracy of 99.92% a precision of 94.59% and a recall of 99.06%.

Findings and discoveries. Our research has unveiled several important trends in the illicit drug referral ecosystem, in terms of scale, promotion strategies, and campaigns. By utilizing our pipeline, we uncovered 154,753 drug-referral comments originating from 6,122 advertiser accounts, which were connected to 3,253 drug-selling accounts. Additionally, we identified 1,646 unique videos that were impacted by these comments, accumulating a collective viewership of over 2.8 billion as of our data collection. Based upon our distinctive dataset, we reported a series of security findings on the emerging drug referral traffic ecosystem. For example, we observed that while the video platform terminated certain illicit advertising accounts, drug-referral comments associated with them persisted, indicating a content moderation gap.

Furthermore, our measurement revealed new promotion strategies employed by advertiser and seller accounts. First, we identified a promotional tactic involving the use of multiple drug advertiser accounts to generate hot threads, thereby amplifying the visibility of illicit drug-referral comments. Specifically, we found 6,018 instances of initiator-advertiser conversations, where two advertiser accounts collaborated to create trending discussions, enhancing the exposure of their promotions. Second, we discovered that illicit drug advertiser accounts strategically selected videos featuring drug-related hashtags to post advertisements and actively engaged with potential buyers through comments, facilitating targeted promotion towards prospective customers. For instance, 22.62% of drug-referral comments were in response to parent comments where audiences displayed an interest in drugs. Additionally, we observed that 92.2% of advertiser accounts replied to popular comments (those with high replies or high likes) under a video, aiming to increase the public visibility of the drug-referral comments. This implied that these advertiser accounts exploited the video comment ranking system to promote illegal drugs. Interestingly, we noted that 154 seller accounts publicly disclosed shipping information or shared customer feedback to establish the authenticity and credibility of their drug sales.

Moreover, our analysis unveiled a complicated drug promotion network, involving 1,948 *drug promotion campaigns*, which were established based on the relationship between advertiser and seller accounts. Among these campaigns, 16.84% involved multiple seller accounts, and one instance stood out with 87 advertiser accounts and 16 seller accounts. Additionally, we discovered that 83 drug promotion campaigns were active on multiple video platforms, including YouTube and TikTok. These findings provide the first evidence of cross-platform drug promotion campaigns, suggesting that such activities are likely operated as a service catering to various drug seller accounts.

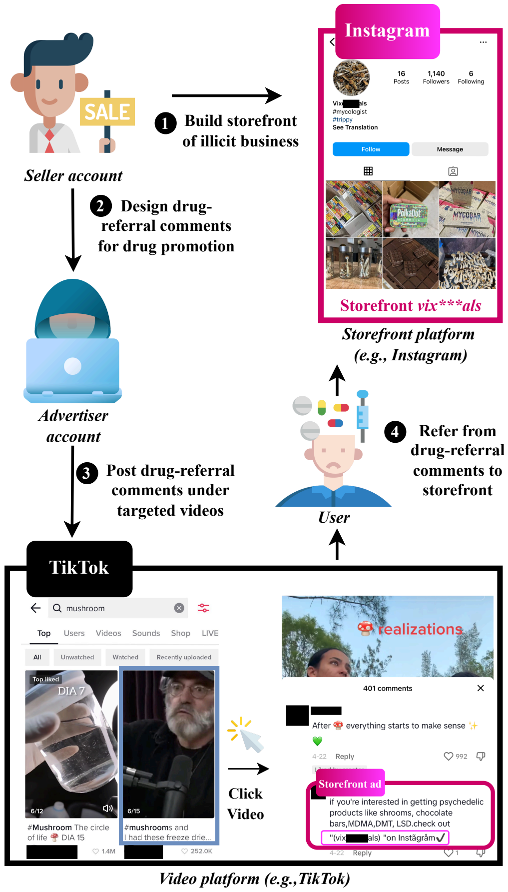

Figure 2: An example of referral traffic ecosystem.

Contributions. The contributions of the paper are outlined as follows:

• We present the first systematic study on the ecosystem of referral traffic for illicit drug promotion and selling businesses operating on popular social media platforms.

• We design and develop an automated pipeline for identifying illicit drug referral traffic as well as the associated advertiser and seller accounts involved in these activities.

• Our study unveils important trends of illicit drug-referral traffic, in terms of scale, promotion strategies, and campaigns. These findings shed light on the broader impact of illicit drug trading activities and reveal the security risks of related parties.

2 Motivation and Research Scope

Motivating example. To understand the workings of iDRT on social media, we explore the ecosystem of this emerging illicit promotion approach. Figure 2 illustrates the workflow of the cross-platform referral traffic used to promote the illicit drug trade. First, seller accounts begin their illicit operations on less strictly-vetted social media platforms, which we refer to as the *storefront platforms* (❶). Subsequently, advertiser accounts leverage the contact details and product information from seller accounts to formulate drug-referral comments (❷). Advertiser accounts then post these crafted drug-referral comments on popular video-sharing social media platforms (*video platforms*), directing users to the seller accounts' businesses (❸). When unsuspecting users encounter these drug-referral comments and follow their instructions, the resultant referral traffic guides them to the online storefronts of these clandestine operations (❹). This referral traffic increases the visibility and traffic to the seller accounts' storefronts, allowing them to expand their operations. For instance, consider an illicit drug seller account, termed "vix[redacted]als," which established its presence on a storefront platform like Instagram. To promote illicit drug products of this seller account, advertiser accounts designed drug-referral comments like "*if you're interested in getting psychedelic products like shrooms, chocolate bars, MDMA, DMT, LSD. check out '(vix[redacted]als)' on Instagram.*" Then, advertiser accounts strategically posted drug-referral comments under TikTok videos tagged with drug-related hashtags (e.g., "#mushroom"), aiming to lure users to the specified seller account's storefront. Based on the information provided in these comments, users were attracted to the storefront, resulting to a surge in referral traffic and greater exposure for the seller account's profile.

Research scope. Referral traffic on social media platforms has become a crucial channel for the promotion of illicit drugs, capitalizing on its wide reach and vulnerability to manipulation. In this study, our objective is to shed light on this emerging threat by understanding the strategies employed in the promotion and sale of illicit drugs through referral traffic, particularly on platforms such as YouTube and TikTok. These platforms were selected for our investigation due to their prominence as popular video-sharing platforms with a large user base [59, 69]. While our data acquisition from YouTube and TikTok may not capture the entirety of drug-related referral traffic, the insights derived from our analysis have broader implications for the overall landscape of referral traffic.

Our research focuses on analyzing the content related to drug-related video hashtags and their associated comments. In contrast to previous studies that primarily examine popular videos or posts on these platforms [14], we observed that drug-related video hashtags are more likely to be contaminated by advertiser accounts for drug promotion. To illustrate, when searching for videos using the top 100 most popular hashtags and 5 drug-related hashtags, we found that only 2.12% of videos with popular hashtags exhibited referral traffic for illegal drug sales, whereas a significant majority of 92.38% of videos tagged with drug-related hashtags contained referral traffic associated with illicit drug businesses. Moreover, drug-related hashtags have been observed as a prevalent practice for drug dealers to engage social media users for drug trafficking [29, 41]. The underlying reason for this trend is the enhancement of product visibility through these hashtags. As referred in [19], well-known hashtags possess a substantial following and are extensively utilized by social media users, thereby amplifying the reach and exposure of the promoted substances.

3 Hunting Drug-referral Traffic

In this section, we elaborate on our pipeline for hunting drug-referral comments on popular video platforms. We also discuss the ethical considerations associated with our research.

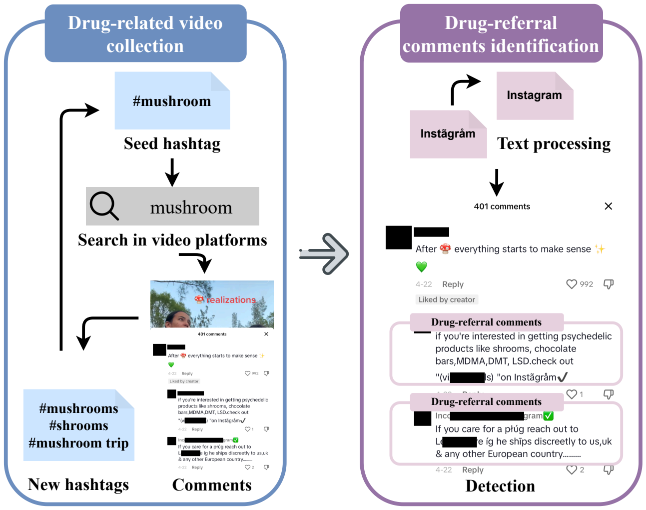

Figure 3: Pipeline for detecting illicit drug-referral traffic and related parties.

Table 1: Collection of videos and comments.

Platform	Collection Period	# Videos	# Hashtags	# Comments
YouTube	01/03/2023 - 01/10/2023 06/01/2023 - 06/07/2023	30,660	6,307	11,847,301
TikTok	11/01/2022 - 04/01/2023	1,653	6,264	606,276

3.1 Overview

Figure 3 illustrates an overview of our analysis pipeline. The process initiates with the collection of potential videos and comments using drug-related hashtags (Section 3.2). After that, we employ natural language processing (NLP) techniques to filter out comments that specifically promote cross-platform drug products, referred to as drug-referral comments (Section 3.3). Additionally, we extract referral details, such as references to storefront platforms and contact accounts, from drug-referral comments (Section 3.4). Lastly, we perform searches for the identified contact accounts on the storefront platforms to verify the presence of illicit drug sales (Section 3.4).

3.2 Drug-related Video Collection

As outlined in Section 2, we observed that advertiser accounts exploit drug-related hashtags to promote the products of drug dealers. To gather a comprehensive set of drug-related videos, we employed a "snowballing" strategy. Initially, we conducted searches for videos using a predefined set of known drug-related hashtags. This set consists of 69 hashtags from previous research [29] and 31 drug names reported by the National Institute on Drug Abuse (NIDA) and the Drug Enforcement Administration (DEA) [28]. Subsequently, we expanded our hashtag set by including new hashtags identified from the collected videos, following manual review. We iterated this procedure until no further videos were identified.

During our data collection, we focused on two video platforms (YouTube and TikTok), as detailed in Table 1. We collected a total of 32,313 drug-related videos associated with 6,307 drug-related hashtags. Out of these videos, 30,660 were posted on YouTube, while 1,653 originated from TikTok. These collected videos amassed a total of 11,847,301 comments on YouTube and 606,276 comments on TikTok. It is worth noting that among the analyzed hashtags, 43 were banned on TikTok due to their association with illicit drug names [6].

3.3 Drug-referral Comments Identification

Drug-referral comments. Following the collection of 12,453,577 comments from 32,313 drug-related videos, our subsequent step involves filtering out referral comments that promote drug referral traffic. During the comment collection process, we observed that advertiser accounts often employ obfuscation techniques to evade detection. These techniques include the use of homoglyphs or special symbols to conceal sensitive words, such as "müshrōōms" and "i*ĝ." Additionally, advertiser accounts may attach images or usernames containing promotional information, as depicted in Figure 1. Furthermore, leveraging the context of comments, certain advertiser accounts distribute promotional information across a sequence of successive comments, necessitating the aggregation of these comments to decipher their intended meaning.

To remove noise in the comments, we implemented a series of preprocessing techniques. Firstly, we eliminated all special symbols in the comment texts (i.e., transforming "i*ĝ" to "ig"). Additionally, we leveraged Google Translate [1] to translate non-English comment texts into English. Moreover, we identified homoglyphic characters and converted them to English letters using Homomorph Python package [50]. If comments include attached images, we employed the Tesseract OCR tool [66] to extract the text from those images. Furthermore, we consolidated successive comments posted by the same account if they were published within a short time frame (i.e., within 5 minutes).

Detection. To determine whether a comment is drug-referral, we developed a text classifier utilizing BERT. More specifically, after preprocessing the comment text, we collected a sample of 18,000 comments from 6,638 unique videos and trained the text classifier with BERT. This dataset, referred to as the *ground truth* dataset, consisted of 9,000 unique drug-referral comments (*Badset*) and 9,000 benign comments (*Goodset*). Particularly, to build the *ground truth* dataset, we enlisted the expertise of two experienced security professionals, who devoted approximately two weeks to perform the manual validation, following annotation guidelines [34, 71], e.g., highlighting the cases with the combination of social media names and drug-related terms like drug names, slang terms, and emoji. Throughout the annotation process, the two annotators evaluated 20,150 comments, encountering 968 instances with disagreement, resulting in a Cohen's Kappa coefficient of 0.90. Further details regarding these cases with disagreement are provided in Appendix A.1. We have publicly shared this annotated dataset [13].

To evaluate the effectiveness of our classifier, we created a *test* dataset by randomly selecting 9,000 video comments, excluding those present in the *ground truth* dataset. This dataset was then manually labeled by two security researchers. The manual validation process took approximately one week to complete. Our text classifier achieved an accuracy of 99.92%, a precision of 94.59%, and a recall of 99.06% on the *test* dataset.

Table 2: Abbreviations of social media platforms for cross-platform identification.

Platform Name	Abbreviations	Platform Name	Abbreviations
Instagram	IG, Insta	Facebook	FB
Telegram	TG, TGM, TEL	Twitter	TW
Snapchat	SC, snap, Ghost Emoji	Kik	Kiki
Wickr Me	Wickr	Signal	SIG
WhatsApp	WA, WAPP, Whatapp	Yik Yak	YY

Discussion and evaluation. We utilized a classifier instead of a set of heuristics since the latter could incur large false positives, due to the use of the heuristic features in legitimate activities. To assess the efficacy of our BERT-based classifier, we compared it with a baseline heuristic method. Particularly, the baseline method leverages promotional signals, such as combinations of promotional terms, drug names, slang, or emojis, which have been identified in prior literature as common features of illicit drug promotion [33, 37], to identify drug-referral comments. For instance, a comment containing phrases like "*if you're interested in getting psychedelic products like shrooms, chocolate bars, MDMA, DMT, LSD. check out '(vix[redacted]als)' on Instagram.*" would be flagged due to the presence of drug names (e.g., "shrooms" and "MDMA") and a promotional term (i.e., "check out"). Upon evaluation of these methods on our *test* dataset, the baseline method demonstrated a precision of 15.96% with a recall of 96.23%, while our text classifier achieved a precision of 94.59% and a recall of 99.06%. This result underscores the inadequacy of the heuristic method in capturing drug-referral comments.

Furthermore, we conducted a validation process to ensure data completeness, as depicted in Figure 4. The graph illustrates a consistent upward trend in data collection, indicating robust data integrity. Further details regarding this validation process can be found in Appendix A.2. Additionally, we conducted an additional experiment to assess the coverage of our pipeline. We found that 2.12% of videos with popular hashtags contained referral traffic for illicit drug sales, while 92.38% of videos with drug-related hashtags featured at least one drug-referral comment. These findings confirm that drug advertiser accounts predominantly post drug-referral comments on videos associated with drug-related hashtags, thereby validating the effectiveness of our approach. Additional information regarding this experiment is available in Appendix A.3.

3.4 Cross-platform Drug Seller Extraction

Storefronts and seller accounts. To investigate drug sellers and their storefronts, we extracted referral information, including storefronts and associated seller account names, from identified drug-referral comments. Our analysis revealed a phenomenon where drug dealers predominantly utilize popular social media platforms such as Instagram for hosting their storefronts, in addition to self-built dedicated websites (refer to Section 4.1 for more details). We observed that drug-referral comments frequently contain abbreviations for these platforms, such as "ig" for Instagram [57]. To facilitate our analysis, we compiled a list of popular social media platforms and their corresponding abbreviations, as presented in Table 2. These platforms were identified based on literature and

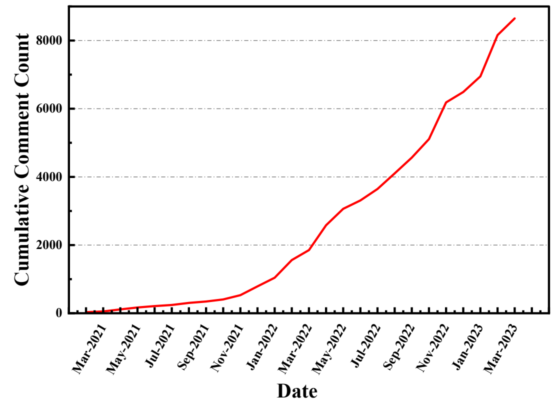

Figure 4: Cumulative count of unique drug-referral comments gathered by our scrapers on TikTok.

reports on illicit drug promotion [2, 4, 7, 8, 10], and we collected their abbreviations from relevant websites [17, 58, 75].

Using the collected social media names and abbreviations as keywords, along with regular expressions to identify website URLs, we successfully extracted the corresponding platform information. For seller accounts, we utilized regular expressions to extract the associated usernames. Our heuristic method identified 99.8% of storefront platforms and seller accounts in our *ground truth* dataset. Applying our methods to the entire dataset, we extracted 166,784 potential drug-referral comments, which linked to 3,464 potential seller accounts across self-built websites and eight social media platforms.

Drug seller account validation. After collecting storefronts, descriptions, and posts from potential seller accounts, we proceeded to validate whether these accounts were selling illicit drugs. Our dataset revealed that advertiser and seller accounts employed specific drug names, slang terms, or images strategically to attract potential buyers. For instance, as shown in Figure 1, the advertiser accounts mentioned "MDMA" in their drug-referral comments and the seller account "[redacted]i7" showcased illegal drug images on its storefront. Based on these observations, we classified an account as an *illicit drug seller account* if either the associated potential drug-referral comment mentioned illicit drug names or if the account's storefront displayed illicit drug names or images.

Out of the 3,464 accounts we examined, we identified 3,253 illicit drug seller accounts. Among these seller accounts, 2,373 promoted illicit drug names in their referral comments, while 880 displayed illicit drug names on their storefronts. From the 3,253 illicit drug seller accounts, we further refined our dataset and isolated 154,753 drug-referral comments.

3.5 Ethical Considerations

This study adheres to the ethical guidelines set by our institute's Institutional Review Board (IRB). We took proactive measures to address two primary ethical concerns that arose during our research: (1) the collection and analysis of data from YouTube, TikTok, and Instagram, and (2) potential experiments to validate the authenticity of drug dealers.

Our study collected publicly available data from YouTube, TikTok, and Instagram. For YouTube and Instagram, we utilized official data scraping APIs [12, 55] provided by platforms. However, TikTok's data scraping API became available only after we had completed our data collection phase [61]. To collect TikTok comments, we developed our data scraper. To restrict the burden we added to TikTok during our data collection, we set parameters such as sleeping time to limit the speed of crawling. Regarding the analysis and storage of the collected data, our experimental procedures were reviewed and approved by our institute's IRB. Our research process was designed to minimize any potential ethical concerns. Specifically, the raw data was securely stored on physical servers at our institution with limited access granted solely to authorized administrators. Once the project concludes, the data will be permanently deleted to ensure proper handling and protection.

To verify the authenticity of drug dealers and potentially identify the individuals operating these advertiser accounts and seller accounts, our initial plan was to communicate with them via private messaging. However, this approach was rejected by our institution's IRB due to the potential interpretation of such inquiries as aiding others in committing illegal actions, which would violate Instagram's Terms of Service (ToS). Thus, our ability to directly engage with drug dealers or make purchases for the purpose of verifying their authenticity was constrained.

Responsible disclosure. We proactively shared our findings with platforms including TikTok, YouTube, Instagram, Telegram, and others. However, as of the time of our submission, we have not yet received feedback from these platforms regarding our findings and recommendations.

4 Measuring Referral Traffic Ecosystem

In this section, we report our measurement study on the 154,753 drug-referral comments and 3,253 illicit drug seller accounts collected by our pipeline (Section 3). We start by measuring the scope and scale of the emerging referral traffic ecosystem in Section 4.1. Subsequently, we analyze the promotion strategies employed by advertiser and seller accounts in Section 4.2. Furthermore, we analyze the interconnections between advertiser and seller accounts across different platforms and extract their campaigns in Section 4.3.

4.1 Overview

Scope and magnitude. Our study revealed a significant presence of illicit drug-related activities in the form of 154,753 drug-referral comments. These comments were attributed to 6,122 advertiser accounts and linked to 3,253 seller accounts. Notably, contact information for 105 of these seller accounts was displayed in comments on both TikTok and YouTube, as depicted in Figure 5. However, we acknowledge that due to potential reporting delay and comment deletion, it's challenging to ascertain a definitive trend in cross-platform illicit drug promotion over time. Additionally, among the 16,402 videos featuring targeted drug-related hashtags, it was found that 19.00% carried comments referring to corresponding drugs. These videos collectively garnered over 7 billion views, indicating their wide reach and substantial audience engagement.

Platforms and distribution. We conducted an analysis of the platforms impacted by the drug-referral comments and seller accounts, as detailed in Table 4. Specifically, out of the 154,753 drug-referral comments identified, 93.80% were found on YouTube, with the remaining 6.20% originating from TikTok. We also scrutinized the community guidelines and policies of both YouTube and TikTok, as summarized in Table 3. Both platforms explicitly prohibit illegal drug-related activities, including the facilitation of trade via links. Notably, despite such prohibitions, YouTube's search functionality allows users to look up drug names. This feature could inadvertently facilitate the proliferation of illicit drug transactions, thereby challenging the platform's enforcement of its community guidelines. Additionally, the YouTube Data API [12], which enables developers to automate comment posting and edit their comments, can be exploited to promote the illicit drug trade. For instance, our investigation identified 23 advertiser accounts potentially leveraging the API, evidenced by their posting of multiple distinct comments exceeding six words at identical timestamps.

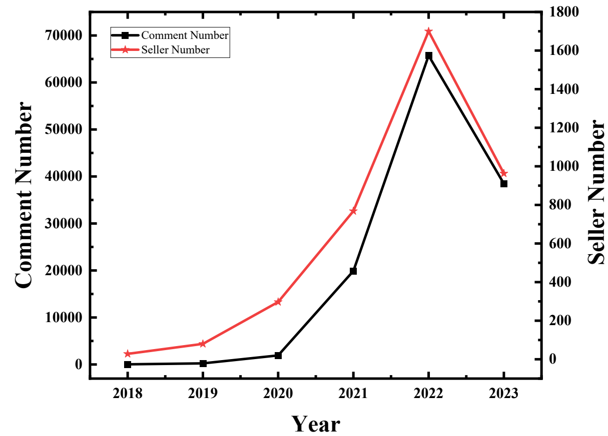

Figure 5: The number of drug-referral comments and seller accounts over the years. The statistics for the year 2023 are within 6 months (January - June).

Table 3: Social media platforms policies.

Social Media Policies	YouTube	TikTok
Sale of illegal or regulated goods	Prohibit	Prohibit
Link to sites selling illicit drugs	Prohibit	Prohibit
Search for drug name on social media	Support	Prohibit
Usage of API to post comments	Support	Not Supported

Furthermore, we observed that the seller accounts associated with these drug-referral comments are dispersed across eight primary storefront platforms: Instagram, WhatsApp, Telegram, Wickr Me, Snapchat, Kiki, Facebook, and Signal. Among these platforms, Instagram stands out as the predominant storefront platform, accounting for 79.96% of the identified seller accounts.

Advertiser accounts characterization. To gain deeper insights into the behaviors of advertiser accounts on video platforms, we conducted a further analysis of their profiles and related metadata,

Table 4: Scope and magnitude of the collected data.

Social Media	Instagram Sellers	WhatsApp Sellers	Telegram Sellers	Snapchat Sellers	Wickr Me Sellers	Website Sellers	Facebook Sellers	Kik Sellers	Signal Sellers
YouTube	1,498	181	133	76	50	117	5	9	7
YouTube comment	136,772	1,650	17,258	1,652	827	2,932	17	34	76
TikTok	1,103	3	39	27	3	0	2	0	0
TikTok comment	9,378	23	515	103	16	0	2	0	0

Table 5: More contact options on seller accounts' homepages.

Platform Name	Num.	Platform Name	Num.
Telegram	81 (52.26%)	Facebook	7 (4.52%)
Self-built website	33 (21.29%)	Snapchat	3 (1.94%)
WhatsApp	28 (18.06%)	Wickr Me	3 (1.94%)

such as creation time. Our dataset consisted of 6,122 advertiser accounts, 95.41% of which were still accessible for analysis.

During our investigation, we uncovered a concerning phenomenon: 281 advertiser accounts had been terminated by the platform due to violations of community guidelines. However, the drug-referral comments they had previously posted remained, serving as an ongoing channel for the promotion of illicit substances. This persistence of drug-related content despite account termination highlights the existing flaws in content review on these platforms. Interestingly, our analysis revealed instances where certain advertiser accounts engaged in promoting drugs also advertised other services, including investments, account recovery, and password cracking. It suggests these advertisers are diversifying their services across multiple domains, to extend their visibility and income.

These findings underscore the need for platforms to address the shortcomings in their content review processes and implement more effective measures to combat the promotion of illicit activities.

Finding #1: *A concerning phenomenon has been observed where 281 advertiser accounts are terminated by the video platform, but their prior drug-referral comments persist, enabling the ongoing promotion of illicit drugs.*

Seller accounts characterization. To understand the behaviors of seller accounts, we conducted a detailed analysis of their homepage content. From the 154,753 drug-referral comments we collected, we identified 3,253 distinct seller accounts, of which 1,196 (36.77%) remained active. Among these active accounts, 321 were message-based social media accounts (e.g., WhatsApp, Signal, and Wickr Me) that did not provide any data on their homepages or posts. Additionally, 186 of them were private accounts (e.g., Instagram private accounts), and we were not able to access their data. Subsequently, we focused on the remaining active illicit drug seller accounts and obtained data on 689 such accounts. These seller accounts had an average of 3,988 followers and displayed an average of 99 posts on their homepages. Furthermore, they had an average of 319 accounts that they followed. Notably, 155 drug seller accounts also listed alternative contact options, including Telegram, WhatsApp, Facebook, etc., on their homepages (see Table 5).

Account lifetime. To understand the activity within the referral traffic ecosystem, we performed a longitudinal analysis focusing on the advertiser and seller accounts. Specifically, we examined the activity levels of the advertiser accounts. Notably, our analysis of the creation time of these accounts revealed that active advertiser accounts tend to have a long lifespan. To estimate the lifetime of an advertiser account, we calculated the duration between its creation and the most recent instance of posting a drug-referral comment. In cases where the creation time was unavailable, we determined the duration between the first and most recent instances of posting referral traffic comments. Among the 6,122 unique advertiser accounts we analyzed, we found that 12.91% had a lifespan exceeding three years. On average, active advertiser accounts had a lifetime of 1.81 years, with the longest recorded lifespan exceeding 16 years. Regarding accounts with lifespans exceeding three years, 10.87% of them initially posted normal comments but later transitioned to advertising comments, suggesting potential hijacking of user accounts. Given that lifespan alone may not be sufficient for understanding account activity, we further investigated the duration of active engagement between the initial and final instances of advertising postings. Our findings revealed that 32.68% of the accounts had an active interval exceeding 30 days, with the longest one spanning 966 days.

Additionally, our investigation revealed that illicit drug seller accounts also exhibited relatively long lifespans. Out of the 3,253 collected seller accounts, 1,196 remained active during our study. We estimated their lifespan by computing the duration between their creation and the current time. For seller accounts without available creation information, we determined their lifespan by noting the duration between their username's initial appearance in drug-referral comments and the time they became inaccessible. On average, illicit drug seller accounts had a lifespan of approximately 2.84 years, with 36.79% of them remaining active for over three years. The oldest seller account in our data was created in June 2012. These findings emphasize the enduring presence of illicit advertiser and seller accounts within the referral traffic ecosystem.

Finding #2: *The average lifetime of advertiser and seller accounts, exceeding 1.8 years, suggests potential challenges in how social media platforms address illicit referral traffic.*

Drug-referral comment lifetime. To assess the effectiveness of platform content review and determine the duration of drug-referral comments, we conducted a prolonged observation of a random subset of drug-referral comments. Specifically, our methodology involved selecting 55 drug-related videos randomly from the dataset described in Section 3.1. We then collected drug-referral comments posted on the same day as these videos. Subsequently, we embarked on a continuous daily observation spanning nearly two months, starting from December 13, 2023, and concluding on January 28, 2024. The primary objective was to monitor the activity of these drug-referral comments throughout the observation period. Initially, we gathered a total of 1,132 drug-referral comments posted on December 13, 2023, corresponding to the selected videos. During our continuous daily observation, we discovered that 886 of these drug-referral comments remained active. This implies that approximately 78.27% of drug-referral comments successfully evaded the current platform content review mechanisms and persisted for over 47 days. These findings expose the limitations of the current platform's content review process, emphasizing the need to strengthen strategies for effectively addressing this issue.

Drug category. Using the drug-referral comments we gathered, we conducted an analysis to determine the categories of drugs being sold within the illicit drug-referral traffic ecosystem. Prior studies [33, 34, 71] have indicated that online promotion of illicit drugs often involves combining drug name keywords [3] with promotional terms [71], such as "sell D_1, D_2, D_3 ...," "offer D_1, D_2, D_3 ...," "D_1, D_2, D_3 ... for sale," etc, where "D" represents a drug name. By utilizing these combinations, we were able to identify drug-referral comments that included offers for illicit drugs. Upon analyzing the collected data, we found that a total of 2,373 unique seller accounts mentioned illicit drugs in their drug-referral comments. Among these seller accounts, the three most commonly offered drugs were psilocybin mushrooms (85.40% of the seller accounts), LSD (70.13% of the seller accounts), and heroin (38.47% of the seller accounts).

Payment and delivery options. Within the drug-referral comments, we identified 721 seller accounts that disclosed the delivery options for their drugs. These sellers claimed to use mainstream shipping services such as EMS, UPS, DHL, TMT, among others. Significantly, 76.14% of these seller accounts offered discreet shipping methods to attract potential buyers, while 44.80% provided worldwide shipping options. Furthermore, we examined the supported payment instruments among the seller accounts. Of the 721 accounts, 24 accepted online payment platforms such as CashApp, Paypal, Zelle, and Venmo, while 5 seller accounts were willing to conduct transactions using cryptocurrencies, notably Bitcoin. we investigated the pricing information for the drugs based on the contents of the seller accounts' storefront websites. Out of the 117 seller accounts with their own websites, 42.73% remained active. To perform our analysis, we sampled and crawled these active websites. Table 6 displays the average prices of the sampled drugs. Liquid LSD had the highest average price at $400 per vial, followed by MDMA at $100 per gram, and DMT at $83.2 per gram.

Comparison with darknet. In contrast to previous studies primarily focusing on dark web forums like SilkRoad [16], our research has identified noteworthy shifts in drug categories, unit prices, and payment methods within the realm of social media platforms. Drug seller accounts on social media platforms demonstrated a preference for psilocybin mushrooms, LSD, and heroin, whereas SilkRoad showcased higher popularity for cannabis in various forms, including weed, marijuana, resin, and concentrates [16]. Moreover, our findings indicate that the unit prices of drugs on social media platforms tend to be relatively higher compared to those reported in previous research [16]. For instance, the study [16] showed that cocaine had the highest average price at $163.88 per gram, followed by MDMA ($82.57 per gram), marijuana ($17.51 per gram), LSD ($13.76 per blotter), and Xanax ($2.50 per milligram).

Figure 6: An example comment of a drug advertiser account using emoji to indicate its identity and attract buyers.

Table 6: Prices of sampled drug sold by seller accounts.

Drug	Avg. Price	Drug	Avg. Price
Liquid LSD	$400/vial	2CB	$15/pill
MDMA	$100/gram	Capsule	$4.73/pill
DMT	$83.2/gram	MicorDoses	$6/pill
Chocolate bars	$42.87/bar	Molly	$4.1/pill
Psilocybin mushroom	$40/gram	Xanax	$3.8/pill

Additionally, while illicit drug seller accounts on SilkRoad predominantly relied on cryptocurrencies, particularly Bitcoin, as their primary payment method [16], our findings revealed that seller accounts on social media platforms accepted a variety of payment methods, including CashApp, Paypal, Zelle, Venmo, and cryptocurrencies. Although these shifts in payment methods have reduced transaction secrecy, they have increased accessibility and user-friendliness for a broader audience.

4.2 Promotion Strategies

To implement referral traffic, advertiser accounts on social media platforms employ specific strategies to promote illegal drug sales. These strategies involve selecting targeted videos and posting well-designed comments that include referral links. The aim is to attract potential customers while evading detection by social media platforms. In this section, we investigate the strategies employed by advertiser and seller accounts to promote illegal drug sales. Firstly, we examine the strategies employed by advertiser accounts to enhance the visibility of their advertisements and attract potential customers. Subsequently, we also delve into the tactics utilized by seller accounts to entice potential customers, enhance their credibility, and establish recognition within the illicit drug market.

• ***Creating hot threads to drive illicit referral traffic.*** To ensure the drug-referral comments appear natural and persuasive, advertiser accounts employ a strategy known as "initiator-advertiser conversation." In this approach, an advertiser account masquerades as a customer interested in illicit drugs and initiates a conversation, expecting a response from another advertiser account with a referral traffic comment. This creates a seemingly organic interaction. For example, an advertiser account creates a fake customer persona named Alice and posts a comment (initiator comment) expressing interest in purchasing drugs. Another advertiser account named Bob then replies to Alice's comment, providing referral links related to illicit drug businesses.

To analyze these initiator-advertiser conversations, we collected all comments from advertiser accounts and established connections between two comments within the same thread, with one serving as the initiator comment. Through this process, we gathered 6,018 initiator-advertiser conversations from our collected comments. The most active pair in the initiator-advertiser conversations involves YouTube accounts "Je[redacted]y" and "Sa[redacted]h," interacting 49 times across 48 different videos. Moreover, we discovered a total of 2,598 pairs of accounts that engage in identical discussions across multiple videos. Also, we found that certain accounts exhibit an anomalous behavior of alternating between different roles at different times. For example, these accounts act as both sellers and buyers within the discussions. Additionally, we observed a consistent pattern in some advertisements, which matches the templates present in Table 9. Based on these observations, we speculate that these accounts may be operated by automated bots.

Using the NetworkX [5] library, we identified all components of the graph based on these conversations. Specifically, each account involved in an initiator-advertiser conversation was treated as a node, and an edge was created to connect *Alice* and *Bob*. By utilizing the NetworkX library and Tarjan's algorithm, we constructed the undirected graph and identified 159 clusters. The largest cluster comprises 503 advertiser accounts, generating 210 threads of initiator-advertiser conversations, which contain contact information for 204 drug dealers. The most commonly used comment by the initiator *Alice* to initiate the conversation was "*Psilocybin saved my life. I was addicted to heroin for 15 years and after Psilocybin treatment I will be 3 years clean in September. I have zero cravings. This is something that truly needs to be more broadly used in addiction treatment.*" (Additional examples can be found in Appendix A.4)

Finding #3: *To enhance the visibility of illicit drug-referral comments, a promotional strategy entails leveraging multiple advertiser accounts to generate hot threads.*

• ***Precise promotion to potential customers.*** In Appendix A.3, we observed that advertiser accounts commonly selected videos with drug-related hashtags when posting drug-referral comments, aiming for targeted promotion. Additionally, we noted that advertiser accounts specifically responded to comments where the audience expressed an interest in drugs. Figure 6 provides an example of such comments. To determine the number of advertiser accounts that utilized this strategy to attract potential customers, we collected all drug-referral comments and their corresponding parent comments. We then identified parent comments that indicated audience interest in drugs based on expressions like "I want," "I like," "where I can buy," "where?," among others. Our analysis showed that 22.62% of drug-referral comments were in response to parent comments where audiences displayed an interest in drugs. Among these comments, the most frequently used reply by advertiser accounts was "*Psilocybin, LSD, shrooms and ketamine are absolutely life changing substances that have so much potential to help people with mental health issues.*", which appeared 93 times in the replies from advertiser accounts.

Finding #4: *To facilitate precise promotion targeting potential customers, advertiser accounts employ a strategic approach of selecting videos that feature drug-related hashtags for posting advertisements. Additionally, they strategically choose comments where audiences display an interest in drugs to engage in replies.*

• ***Enhance credibility and recognition of drug trades.*** To enhance their credibility, increase product visibility, and strengthen brand recognition, some seller accounts adopt certain strategies on their platforms. These strategies include prominently featuring drug products on their storefronts, within descriptions, and in posts. For instance, our analysis in Section 3.1 revealed that every drug seller account on Instagram showcases drug images in their posts.

Interestingly, we observed that 154 seller accounts publicly disclosed shipping information or shared feedback from customers to prove the authenticity and credibility of their drug sales. During our analysis, we unintentionally obtained the shipping tracking numbers of 27 drug traffickers. Following a thorough review, we confirmed the validity of these tracking numbers and verified the successful delivery of the packages. Furthermore, we found that 20 drug seller accounts revealed 60 bitcoin addresses in customer feedback. For example, the seller account named "the[redacted]vendor" displayed customer feedback, which disclosed 8 shipping tracking numbers and 4 bitcoin addresses to enhance its credibility and recognition (an example can be found in Appendix A.5).

In our examination of seller account usernames, we identified specific affixes that imply an association with illicit drug sales. For instance, a subset of these accounts incorporate the affix "myco," which suggests involvement in the distribution of psilocybin mushrooms. We systematically collated and analyzed these distinct affixes derived from seller usernames, and the findings are delineated in Table 7. It shows that the affix "myco" emerges as the most predominant among seller accounts, followed by "trip" and "spore."

Finding #5: *Illicit drug seller accounts enhance their credibility and recognition by disclosing drug lists, shipping information, and customer reviews.*

• ***Increase in public reachability.*** Social media platforms often provide users with various comment sorting options to facilitate reading and engagement, such as sorting by popularity or by the most recent postings. For example, platforms like YouTube and TikTok offer sorting options, such as "Newest first" and "Top comments." While these sorting algorithms are convenient for users, they also leave exploitable features for malicious attackers. In response to this, advertiser accounts have developed two strategies to enhance the visibility of their drug-referral comments and increase their click-through rates.

To investigate these strategies, we collected comments from the first page of videos tagged with drug-related hashtags. Our analysis revealed that 11.20% of these comments contained drug-referral content. We also considered that some users prefer sorting comments by the "Newest first" option. Therefore, we focused on comments directly posted as replies to the video, rather than being part of comment threads. Our analysis found that 5.24% of comments were

Table 7: Special usernames of drug seller accounts.

Affixes	Illicit Seller Accounts from TikTok	Illicit Seller Accounts from YouTube
"myco"	295	411
"trip"	269	388
"spore"	54	126
"psych"	66	118
"shroom"	71	110
"dr"	45	96

Figure 7: An example comment of a drug advertiser account concealing seller information in its username.

directly replied to the video, indicating that advertiser accounts are not inclined to utilize the "Newest first" option.

To determine the preferred type of comments for advertiser accounts to reply to, we examined comment threads that included drug-referral comments. We calculated the average like count and average reply count of the parent comment for each video. For each parent comment, we compared its like count and reply count to the respective average values for all comments. Our analysis revealed that 86.46% of advertiser accounts chose to participate in conversations with comment threads that had a high number of replies, while 16.57% of advertiser accounts responded to comment threads with a high like count. These findings suggest that advertiser accounts prioritize replying to comment threads with a substantial number of replies.

Finding #6: *Advertiser accounts prioritize responding to comment threads that have garnered a significant number of replies; however, they are less inclined to directly reply to the video itself.*

4.3 Campaigns of Illicit Drug Promotion

To study and uncover illicit drug campaigns, it is essential to explore the connections between advertiser and seller accounts. Below we present our methodology, which focuses on investigating these connections, and provide in-depth insights into our findings.

Methodology. We consider each advertiser account and seller account as a node. If an advertiser account (node A) has posted advertisements for a seller account (node B), we establish an edge between node A and node B. In this way, we constructed a graph and identified 1,948 clusters, with 11 of them consisting of over 50 nodes. The largest cluster comprises 87 advertiser accounts and 16 seller accounts, primarily focusing on the sale of substances such as psilocybin mushrooms, DMT, LSD, chocolate bars, and Xanax.

Discoveries. We conducted a detailed analysis of the clusters of advertiser and seller accounts, examining their metadata, including usernames, platforms, comments, and profiles. The key findings from our analysis are summarized below:

• ***Consistent advertisement templates.*** We observed that 95% of the clusters exhibited consistent advertisement templates used by advertiser accounts to attract potential buyers. These templates often included phrases such as "*look up that handle, he ships swiftly, and he got shrooms, dmt, lsd, mmda, psilocybin, chocolate bars, be got a lot*," "*contact this legit plug, he got all kinds of psychedelic stuff, he ships discreetly!!*," and "*check out on Instagram.*"

• ***Advertiser account naming patterns.*** We identified specific naming patterns used by advertiser accounts within the clusters. Our analysis revealed the following patterns: **(1)** To attract user searches, some advertiser accounts incorporated seller account usernames and relevant platform names into their usernames, such as "My■ ■ ■rea on Instagram got good microdosing product" and "MY■ ■ ■ZZ ON INSTAGRAM"; **(2)** We suspect some advertiser accounts to be bots, evident from their randomly assigned usernames typical of certain social media platforms, like "user9051■■■216816," "user6852■ ■ ■321394," and "user912■ ■ ■91909."

• ***Signs regarding the entities behind these accounts.*** We identified 62 groups of seller accounts with similar usernames (e.g, "_jam■ ■ ■ay," "_jam■ ■ ■ay1," and "_jam■ ■ ■ayy"), along with 433 groups of advertiser accounts with similar usernames while promoting ads for the same seller account. However, confirming the entities behind these accounts is challenging and may raise ethical concerns, such as potential Personally Identifiable Information (PII) leakage. More details about limitations are shown in Section 6.

• ***Multi-platforms promotion.*** In our analysis, we discovered that 105 seller accounts engaged in multi-platform promotion, advertising their drugs on multiple social media platforms such as TikTok and YouTube through referral traffic. This strategic approach aims to expand their potential buyer base. Additionally, these seller accounts utilized a total of 11,622 drug-referral comments to facilitate illegal drug sales.

Finding #7: *Illicit drug seller accounts employ multiple advertiser accounts across diverse platforms as a strategy to promote their products.*

Case study. Among the clusters we analyzed, one of the largest clusters we discovered included 87 advertiser accounts and 16 seller accounts. These accounts were involved in the illicit promotion of various substances, including psilocybin mushrooms, DMT, and LSD. Notably, we discovered that the seller account "my■ ■ ■il" leveraged 44 advertiser accounts posting drug-referral comments on its behalf. Upon examining the names of these advertiser accounts, we discovered nine advertiser accounts that employed promotional emoji descriptors in their usernames. These emojis were utilized to symbolize specific substances, such as "mushroom" to denote psilocybin mushrooms and "chocolate" to signify chocolate bars.

Subsequently, these advertiser accounts strategically utilized suggestive comments to encourage potential buyers to check out their usernames. Examples of such comments include: *"check out the name above"* and *"look up that handle, he ships swiftly, surest plug."* These tactics aim to conceal their business activities and evade content review on video platforms.

5 Security Risks of Affected Parties

In this section, we present our research on the security risks associated with social media platforms within the referral traffic ecosystem, particularly focusing on video and storefront platforms.

5.1 Security Risk in Video Platforms

Security vetting on video platforms. Security vetting serves as a governance mechanism employed by social media platforms to regulate user participation and prevent abuse. These platforms utilize a combination of content moderation policies, privacy policies, copyright policies, and more to implement security vetting. Notably, platforms like TikTok and YouTube have established community guidelines that clearly outline prohibited content, such as pornography, incitement to violence, harassment, and hate speech [27, 67]. To enforce these policies, YouTube relies on human reviewers and automated flagging systems to identify and remove inappropriate content, including comments, videos, and channels [78].

Despite the implementation of content restriction policies, various studies have highlighted the prevalence of inappropriate behaviors on video platforms. For instance, Sultan et al. found a significant number of inappropriate comments on children's YouTube videos, with comments related to toxicity accounting for 15.54%, followed by insults at 7.96%, and obscenities at 6.84% [18]. In another study by McMann et al [53], it was found that 69.44% of the examined TikTok videos promoted the sale of K2/Spice. Furthermore, multiple studies have identified inappropriate content on TikTok, including unflagged calls for violence [38], the harmful tide pod challenge [74], and antisemitism [73]. These findings underscore the need for more effective measures to ensure the safety and appropriateness of social media platforms for all users.

Evasion techniques against detection on video platforms. Popular social media platforms such as TikTok [67] and YouTube [27] have strict policies against the sale and promotion of drugs or controlled substances, as indicated in Table 3. To enforce these policies, these platforms have implemented content review mechanisms to identify and address any violating content. However, advertiser accounts have devised various strategies to evade detection measures.

For instance, some advertiser accounts conceal seller information in their usernames or descriptions and post suggestive comments to entice potential customers to check out their usernames. As shown in Figure 7, an advertiser account employed the "Index Pointing Up" emoji in his comment, indicating that potential buyers should check out its username. The username, in this case, was "Buy from za[redacted]03 on IG", implying that the seller account "za[redacted]03" sells illicit drugs on Instagram. Our analysis of the 6,122 advertiser account usernames revealed that 31.07% displayed seller contacts.

Additionally, advertiser accounts employ various other methods to avoid detection, such as posting videos or images that carry referral traffic and using homoglyphs to disguise drug-related text.

Table 8: Top slang and emoji in comments posted by illicit drug-promotion advertiser accounts.

Slang	# Comments	Emoji	# Comments
Shrooms	56,331	Mushroom	39,867
Bars	23,048	Chocolate bar	22,112
Cola	21,745	Pill	20,696
Chocolate	21,552	Plug	10,670
Stuff	21,237	Weed	803

In an analysis of 15,753 drug-referral comments, we found that 1.77% of these comments were images with seller account usernames, while 19.14% of them utilized homoglyphs to make their comments more difficult to detect using text detection mechanisms on video platforms. Advertiser accounts frequently use slang terms like "shrooms," "plug," and "bars," as references to controlled substances, aiming for evading oversight on video platforms. Among the comments posted by advertiser accounts, 68.70% and 21.75% contained slang terms and drug-related emoji slang expressions, respectively. Furthermore, 746 advertiser accounts incorporated slang terms into their usernames. The most commonly used slang terms and emojis are listed in Table 8.

Finding #8: *To circumvent content reviews on video platforms, drug advertiser accounts employ various tactics, including concealing seller information in their usernames and utilizing slang terms or emojis to allude to controlled substances.*

5.2 Security Risks in Storefront Platform

Validation on storefront social media. The security vetting process on storefront social media platforms raises concerns, especially regarding illicit drug dealers [71]. Despite the existence of content restriction policies [26, 54, 62], several storefront platforms do not require submitted content to undergo verification. For instance, when registering a store on Facebook, business owners are directed to a newly published business page where they can upload photos, provide website links, and describe their business without any verification process. While Facebook offers optional verification for business pages, it is not mandatory [15]. Similarly, Foursquare instantly publishes submitted content as soon as the business name, category, and address are provided [46]. Furthermore, even when platforms require information verification, business owners can still set up unverified listings, which users can access via local search services. For example, Wang et al. [71] uncovered illicit drug promotion and listings on local search services, including local knowledge panels, map search, and voice search.

The vulnerable content review process on storefront platforms has prompted extensive research in identifying illicit online drug sales through social media. For instance, Mackey et al. [47] developed a machine learning model to detect illicit online pharmacy tweets that illegally sell controlled substances. Li et al. [41] utilized a deep learning approach to identify Instagram posts associated with illicit online drug trading.

Evasion against content review of storefront platforms. As the sale of illicit drugs on social media platforms is prohibited [27, 54, 65, 67], several social media platforms have revised their policies and introduced measures to detect and eliminate illegal drug sales [49]. For example, Instagram has modified its algorithms and search system to proactively address individuals who use hashtags to market drugs like Oxycontin and Percocet[25]. Similarly, Snapchat has enhanced its proactive detection capabilities to remove drug dealers from its platform before they can cause harm [49]. However, illicit drug dealers continue to employ various strategies to evade detection on storefront platforms.

A common tactic used by seller accounts is to display illicit substances on their public storefronts. They then prompt potential buyers to engage in private messaging or even use other message-based applications to communicate. Through an analysis of 689 public living seller accounts, we found that 22.50% of them created multiple accounts (one for drug displaying and another for communication) for illicit drug businesses, as shown in Table 5. For example, the seller account "[redacted]i7" showed drug-related slang and drug product images on its Instagram storefront, then encouraged potential buyers to join its Telegram channel for communicating as shown in Figure 1. This approach not only avoids leaving a complete evidence trail of the drug trading on a single platform but also protects the privacy of both the seller account and the buyer account. Additionally, our analysis revealed that none of the active public seller accounts provided drug-related information in their public responses. Even when customers showed interest in their products, seller accounts consistently directed them to private messaging.

To circumvent detection mechanisms on storefront platforms, illicit drug seller accounts frequently use slang terms such as "shrooms," "mush," and "bars," as well as drug-related emojis like "mushroom," "chocolate," and "pill" to reference their products. Among the 689 alive public illicit drug seller accounts, 544 (78.96%) utilized slang terms, and 551 (79.97%) incorporated illicit drug-related emojis in their storefront descriptions.

Finding #9: *To evade content review on storefront platforms, illicit drug seller accounts employ multiple strategies, such as communicating through private channels, refraining from discussing product details in public areas, and creating multiple accounts for their businesses.*

6 Discussion and Limitation

In this section, we propose some intervention strategies to mitigate this emerging threat. We also discuss the limitations of our iDRT detection methodology.

Intervention strategies. Our study revealed a limitation of prior intervention strategies [71] due to the unique patterns of cross-platform drug referral. These strategies focused solely on information gathered from a single platform. It is evident that collaborations between storefront platforms and video platforms are highly necessary to address this issue, such as sharing information related to drug activities. Establishing a comprehensive evidence trail for drug trading allows platforms to combat illicit drug activities more effectively, yielding mutual benefits. It is important to note that privacy concerns and legal risks associated with cross-platform information sharing should be addressed. State-of-the-art privacy-preserving techniques such as Data Masking [64], Tokenization [9], and Federated Learning [52]) can be adopted to protect privacy and mitigate these risks. We leave more concrete implementation of intervention strategies as future work.

Broader implications. In our study, our primary focus is on the analysis of illicit drug promotions across two prominent social media platforms, namely YouTube and TikTok. However, the implications and insights garnered from our investigation go way beyond these platforms. Particularly, our manual analysis additionally revealed the presence of illicit drug promotion on various other platforms such as Instagram, Facebook, and Twitter, which could also be captured by extension of our methodology. Moreover, our observations are also relevant to other forms of illicit promotional activities, including explicit content dissemination and gambling. For example, we found that cross-platform referral traffic for sexual services (notably from YouTube to live streaming websites) also followed the same patterns as those of cross-platform drug selling. This indicates that the same technique we used for detecting drug selling could also be applied to capture other malicious activities.

Limitations. Our iDRT detection methodology might be subject to bias, as it relies on comment content to collect comments associated with illicit drug promotion. Due to ethical concerns, we did not make any attempt to identify the individuals behind the detected accounts, since this requires explicit communications with these parties, which violates Instagram's Terms of Service. Nor can we confirm the involvement of a given account in drug selling, because this can only be done by making payments to the account and receiving drug packages. Therefore, our analysis primarily focused on finding the intention of seller accounts engaging in illicit drug business through their names, storefronts, descriptions, and other relevant factors. It is worth noting that we observed instances where illicit drug dealers offered shipping tracking numbers and customer feedback to establish their credibility. However, the reliability of such information needs a further investigation, considering the possibility of manipulation or inherent biases. More information on this can be found in Section 4.2. While our study specifically targeted TikTok and YouTube, our approach can be adapted for other platforms as well. However, it is important to acknowledge that the effectiveness of our methods may diminish if illicit drug dealers adapt or significantly change their promotional tactics. For instance, dealers might shift towards establishing connections with potential buyers through covert channels like the dark web. We recognize the pressing need for continued research to delve deeper into this challenge and to conceive novel strategies.

7 Related Work

Illicit online promotion. In recent years, illicit online promotion has emerged as a significant threat to the global internet landscape, aiming to disseminate misinformation and achieve commercial success. Extensive research has been conducted on the various tactics employed by adversaries to manipulate search engine results and inject promotional content into websites. These tactics include keyword stuffing [43], semantic-inconsistency techniques [44], link farm spam [76], search redirection [39], and cloaking malicious pages with benign webpages containing commonly searched keywords [31, 70]. Additionally, studies have explored illicit online promotion on popular platforms beyond traditional search engines, including local knowledge panels [71], maps [30, 71], and Wikipedia [45]. However, existing research has primarily focused on illicit online promotion targeting a single platform and has not extensively explored the use of cross-platform referral traffic to attract users across multiple platforms.

Illicit online drug trade. E-commerce has emerged as a crucial strategy for both Business-to-Business (B2B) and Business-to-Customer (B2C) marketing and sales, offering numerous advantages over traditional retail. Consequently, there has been a noticeable shift in the illicit drug trade, with an increasing number of dealers transitioning from traditional street exchanges to online transactions [32]. Previous studies have examined various facets of the illicit drug market ecosystem. For example, Sarkar [60] highlighted how criminals and counterfeiters exploit the lack of effective regulation on social media platforms to engage in the illicit sale of drugs. Additionally, McCoy et al. [51] conducted a study on illicit online pharmacies and their pharmaceutical affiliate programs. Other researchers have explored online anonymous marketplaces like Silk Road, revealing that controlled substances related to illicit drugs were among the top-selling products [22, 42, 63]. Furthermore, to gain insights into the illicit drug business within social media platforms, prior studies [20, 21, 24, 33, 48, 56, 68, 77] have identified and quantified illicit drug marketing activities on platforms such as Facebook, Snapchat, Twitter, Instagram, YouTube, Wickr Me, and Reddit. In contrast, our work focuses on exploring the cross-platform referral traffic, which serves as the upstream component of the illicit drug market ecosystem. Additionally, our research enhances understanding of the traffic flow within this ecosystem and the influence of referral traffic.

8 Conclusion

In this paper, we present the first comprehensive study of the cross-platform ecosystem associated with illicit drug promotion and sales, yielding novel insights into emerging cybercriminal activities. Through a detailed analysis of 154,753 drug-referral comments, 6,122 advertiser accounts, and 3,253 seller accounts, we uncover the underlying mechanisms driving cross-platform illicit drug referral traffic. Our study elucidates the extent, impact, and promotional strategies employed by these illicit enterprises. Furthermore, we examine the security measures within the current referral traffic ecosystem. Our findings highlight the inadequate regulation of upstream video platforms, which lack robust vetting procedures. This oversight permits the spread of contaminated information to significant downstream storefront platforms. These insights provide a deeper understanding of the wider consequences of illicit drug trading and emphasize the urgent need to address related security issues on social media platforms.

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Appendix A

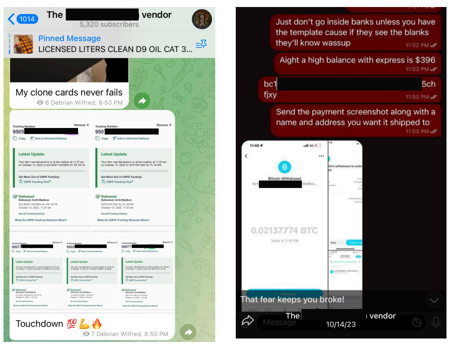
A1. Annotated Cases with Disagreement

In the dataset annotation, annotators encountered 968 comments with disagreement (see § 3.3). To resolve the disagreement, two annotators reached a consensus on 883 drug-referral comments and 85 benign comments through further discussion and analysis. More specifically, all of the drug-referral comments that initially elicited disagreement among annotators, such as *"s■ ■ ■p check*

Table 9: Examples of echo-advertiser conversation.

Initiator *Alice*	Advertiser *Bob*	Times	# Videos	Initiator's Comment	Advertiser's Comment
Je[redacted]y	Sa[redacted]h	49	48	Comment[1]	[_ja[redacted]tray] got psychs
Br[redacted]t J	F[redacted]d Tyler	24	24	Comment[3]	yeah mate... @ted[redacted]ston21
Bar[redacted]a krimbel	Hei[redacted]berg	22	22	Comment[3]	Comment[4]
Mi[redacted]l Watson	Ar[redacted]s	19	19	Comment[5]	Comment[6]
Mi[redacted]l Watson	Z[redacted] kos	17	17	Comment[2]	Yeah, I got mine from dr[redacted]s345

[1] Psychedelic's definitely have potential to deal with mental health symptoms like anxiety and depression, I would like to try them again but it's just so hard to source here
[2] I've heard a lot of tripping stories, and they are very exciting,I would love to try magic mushrooms but I can't easily get some, Is there any realiable source I can purchase from??
[3] Psychedelics are just an amazing discovery. It's quite fascinating how effective they are for depression and stress disorders. Saved my life
[4] Saw reviews about Mr Win[redacted]n , checked him out and be I must say he is very good at what he does and his products are pure.
[5] Psilocybin saved my life. I was addicted to heroin for 15 years and after Psilocybin treatment I will be 3 years clean in September. I have zero cravings. This is something that truly needs to be more broadly used in addiction treatment.
[6] ber[redacted]y11 is the best, he's been my go to for anything psychedelics.



Customer feedback included shipping tracking numbers

Customer feedback included drug dealer's bitcoin address

Figure 8: An example showing that seller accounts disclose shipping information and customer feedback to enhance their credibility and recognition.

them on instagram...," "hit up j[redacted]z he helped me," "came across comments about p[redacted]nn...," etc, do not explicitly mention illicit drugs. However, these comments are linked to homepages that promote illicit drugs, as confirmed through further examination.

A2. Validation of Data Completeness

Prior to utilizing the dataset, we conducted a validation process to ensure the completeness of the dataset. Our primary concern was the potential impact on data quality due to potential significant downtime of the crawlers on TikTok. To address this issue, we adopted the methodology employed in previous studies [23, 72]. Figure 4 displays the cumulative count of unique drug-referral comments gathered by our scrapers on TikTok. The graph exhibits a consistent upward trend, indicative of robust data integrity. This observation further supports the reliability and comprehensiveness of our collected data.

A3. Coverage of Our Dataset

Our pipeline, which relies on drug-related hashtags, may miss some drug-referral comments associated with other hashtags on video platforms. To assess the coverage of our pipeline, we conducted an additional experiment. For this experiment, we searched YouTube videos using the top 100 popular hashtags and five randomly selected drug-related hashtags. We manually examined comments on the first page of the retrieved videos to determine if they contained drug-referral content. Our findings indicated that 2.12% of videos with popular hashtags had referral traffic for illicit drug sales, whereas 92.38% of videos with drug-related hashtags featured at least one drug-referral comment. These results emphasize that drug advertiser accounts predominantly post drug-referral comments on videos labeled with drug-related hashtags, reinforcing the validity of our approach.

A.4 Examples of Initiator-advertiser Conversation

From Table 9, we observed that "initiator *Alice*" most frequently used comment was "*Psychedelic's definitely have potential to deal with mental health symptoms like anxiety and depression, I would like to try them again but it's just so hard to source here*" with 49 times, followed by "*Psychedelics are just an amazing discovery. It's quite fascinating how effective they are for depression and stress disorders. Saved my life*" with 24 times.

A.5 Customer Feedback for Enhancing the Credibility and Recognition

As shown in Figure 8, the seller account "the[redacted]vendor" displayed customer feedback, which disclosed 8 shipping tracking numbers and 4 bitcoin addresses, for enhancing its credibility and recognition.