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The influence of social media affordances on drug dealer posting behavior across multiple social networking sites (SNS)

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ABSTRACT

Social media has been documented as widely used for initiating online sales of illicit drugs such as opioids. However, not much is known about how affordances of social networking sites (SNS) influence how dealers advertise their supplies. To explore this topic, social media posts across 5 online platforms (Google Groups, Instagram, Twitter, Reddit, and Tumblr) were collected during 2020–2021. Biterm topic modeling (BTM) was used to identify signal posts specifically associated with the illegal online sale of opioids from drug selling social media accounts. Posts were analyzed by conducting a word count for drug names or slang terms associated with 5 categories: Opioids, Non-Opioid Prescription Controlled Drugs (e.g., Xanax, Valium), Other Illicit Drugs (e.g., Meth, Cocaine), Synthetic Opioids (Fentanyl), and Synthetic Marijuana. Number of mentions per post were calculated for each drug category and compared across platforms. Identifiers (e.g., publicly available email address) associated with posts were used to track dealers across different user accounts. Platforms with affordances for longer messages (e.g., Tumblr) had higher concentrations of drug mentions per post and higher variety of drug type mentions compared to SNS platforms Instagram and Twitter. Google Groups had the most drug mentions per post across all 5 categories. Additionally, each identifier was associated with multiple user accounts on a given platform. These results indicate that affordances of anonymity and message length may influence how drug dealers advertise their services on different platforms. Public health implications and strategies to counteract drug dealers and illicit drug diversion via SNS are also discussed.

1. Introduction

1.1. The ongoing opioid crisis

Since the beginning of the COVID-19 pandemic, the number of drug-related deaths in the US experienced a dramatic increase of over 20,000 additional deaths from the previous year, resulting in the largest single-year percentage increase on record since 1999 (Baumgartner & Radley, 2021). Of these drug-related deaths, over 60% involved synthetic opioids, exhibiting a sharp increase compared to only 18% of deaths from 2015. Similarly, other drugs such as methamphetamine and cocaine have also experienced increases in attributable deaths since the start of the pandemic (Baumgartner & Radley, 2021). However, even before COVID-19, the US has been experiencing a rapid escalating public health crisis over the past decade concerning drug-related overdoses and deaths, highlighted by opioids and opioid-derived products. Between 2010 and 2017, the opioid-involved overdose death rate rose from 21,088 to 47,600, and by 2019 increased again to 49,860 (National Institute on Drug Abuse, 2021). Between 2013 and 2019, the death rate for synthetic opioids such as fentanyl increased by a staggering 1,040% (3,105 to 36,359 deaths), reflecting a new chapter in the crisis characterized by the dangers associated with counterfeit products and other illicit drugs laced with fentanyl (Mattson, 2021). For the opioid crisis alone, the US Centers for Disease Control and Prevention (CDC) estimates that annual economic losses equate to US $78.5 billion due to costs related to health care, addiction treatment, the criminal justice system, and lost

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productivity (Bonnie et al., 2017; Florence et al., 2016). While not as prevalent as natural and synthetic opioids, deaths due to the involvement of other drugs such as psychostimulants (e.g., methamphetamine) had also been rising (Bonnie et al., 2017) as well as non-medical use of other prescription drugs (Mackey et al., 2013).

Despite social distancing guidelines and increased restrictions on public spaces during COVID-19, consistent health burden related to drug overdose and death suggests that drug sale transactions continue to take place within convenient and accessible spaces, such as via online Social Networking Sites (SNS) that have concomitantly experienced increased use during the pandemic (De' et al., 2020; Huang et al., 2021; Mouratidis & Papagiannakis, 2021; Nguyen et al., 2020). In fact, a recent study of US survey respondents conducted during COVID-19 found that 18% buy medications online, including from several social media and communication platforms such as Tumblr, Wickr, and Pinterest and specifically for sedatives, stimulants, and other narcotic medicines (Moureaud et al., 2021). It is worth noting that drug sales have been prevalent on social media platforms for years preceding the pandemic, as demonstrated in research and investigative reporting detecting illegal opioid sales and drug dealing across several social media platforms such as Twitter, Facebook, and Instagram (Constine, 2018; Dwoskin, 2018; Lapowsky, 2018; Lytvynenko, 2018; Mackey et al., 2017; Mackey & Kalyanam, 2017; Tiku & WIRED, 2018 Apr 6; Yang & Luo, 2017). Other work throughout the past decade has leveraged supervised machine learning classifiers and unsupervised topic modeling to detect internet pharmacies selling opioids (including fentanyl) (Katsuki et al., 2015; Mackey et al., 2017, 2018; Mackey & Kalyanam, 2017), examined social circles of users (Hanson et al., 2013), and used deep learning models to detect drug abuse (Hu et al., 2019).

Even though illegal prescription drug sales can be found by users through search engine results and internet pharmacy websites (U. S. Government Accountability Office, n.d.; Orizio et al., 2011), popular social media platforms have emerged as a widespread direct-to-consumer marketing tool for illegal sellers. A qualitative study of drug sellers and buyers across five Nordic countries found that popular platforms such as Facebook and Instagram showed high degrees of drug-dealing activity (Demant & Bakken, 2019). This finding is consistent with results from nationwide surveys conducted in the US and Spain of participants 15–25 years old, which found that 77% of those who reported purchasing drugs online used social media services for the transaction (Oksanen et al., 2021). Other work that implemented a survey collected from the subreddit "r/Drugs" (n = 358) and interviews of drug users indicates that smartphone-enabled messaging applications such as Snapchat and Whatsapp could grow as viable options for accessing drugs due to functionalities such as encrypted messaging services for facilitating transactions and providing social networking space to advertise drug supplies (Moyle et al., 2019). Additionally, prices for illicit drugs on social media have been shown to be similar with prices found on cryptomarkets, which is another common destination for online drug transactions (Moeller et al., 2021). Hence, the internet ecosystem, now populated by illegal internet pharmacies, social media posts from illegal sellers, and dark web vendors who have been implicated in illegal online opioid sales (Broséus et al., 2016; Dasgupta et al., 2013; Lytvynenko, 2018; Mackey et al., 2017, 2018; Pergolizzi et al., 2017), has rapidly proliferated and diversified, likely due to the anonymity of online transactions and increased consumer activity and demand.

Similar to how the introduction of mobile phones (pre-smartphones) had promoted the transition from open street-based markets, where drug transactions took place in specified public places, to 'closed' markets where drug trading occurred in private locations with decreased risk of police encounters (May & Hough, 2004), the proliferation of social networking technologies has impacted communication dynamics between buyers and sellers as well. While work on drug dealer communication had previously argued that awareness and initiation of drug use is facilitated by long-term interpersonal relationships in order to reduce uncertainties associated with the illegality and lack of reliable information of the product offered (Atkyns & Hanneman, 1974; Moeller, 2018), the use of the internet and social media sites deemphasize the need for pre-existing long-term relationships for facilitating drug transactions. However, recent work indicates that online drug markets still resemble open and closed market places depending on the platform. For instance, Facebook and Instagram serve more as public digital markets that allow sellers to expand their customer list while message-based SNS such as Snapchat and Wickr serve as private digital markets which are perceived as more secure (Bakken & Demant, 2019). Hence, in order to better understand how specific features of SNS can promote illicit drug sales between individuals with weak or non-existent social ties on public digital marketplaces, this study examines social media posts advertising illegal drugs and their associated user accounts using an affordance perspective, as popularly used in the field of human computer interaction (HCI) (Norman, 1988). More specifically, this study analyzes posts from drug dealers across 5 online platforms (Google Groups, Instagram, Twitter, Reddit, and Tumblr) to assess how SNS affordances, message length and anonymity, influence post content and dealer behavior. See Table 1 below for further description of each platform and related user activity.

1.2. Affordances of social networking sites

Recent literature defines an affordance as a multifaceted relational structure between a technology and a user that enables or constrains

Table 1
Description of social networking sites (SNS).

Platform	User Activity (Global AVG)[a]	User Age	Platform Description
Google Groups	Not publicly available[b]	Not publicly available	Discussion forum and email lists hosted by Google covering a range of topics. Users can join groups for free based on interests. While some groups require permission to join, many allow users to join directly.
Instagram	~2 billion monthly users	37% age 13–24 years old	A free photo and video sharing app. People can upload photos or videos and share them with their followers or with a select group of friends. They can also view, comment and like posts shared by their friends.
Twitter	~450 million monthly users	33% age 13–24 years old	A microblogging platform that enables users to send short 280-character messages called tweets. Registered users can read and post tweets as well as follow other users via update feeds.
Reddit	~430 million monthly users	25% age 20–29 years old	A social news website and forum where content is socially curated and promoted by site members through voting. Reddit member registration is free, and it is required to use the website's basic features.
Tumblr	~327 million unique visitors per month	40% age 18–25 years old	Microblogging platform that allows registered users to post multimedia content to their own customizable blogs. Members can follow one another, "like" content with the click of a button and comment on posts.

[a] Information for user activity, age, and platform description columns can be found at the following sources: Google Groups, n.d.; Iqbal, 2022a, 2022b; Curry, 2022; Finances Online, 2020.

[b] For Google Groups, any person with a Google account can post on the platform.

potential behavioral outcomes within a particular context (Evans et al., 2017; Faraj & Azad, 2012; Hutchby, 2001). First coined by psychologist James Gibson (1979) to refer to all potential action possibilities available to an animal within an environment, it was later extended into HCI research by cognitive scientist Donald Norman (1988) who defined affordances as 'the perceived and actual properties of the thing, primarily those fundamental properties that determine just how the thing could possibly be used' (1988: 9). While there have been calls in recent years to either clarify the definition of affordances within the literature (Bucher & Helmond, 2017; Evans et al., 2017) or to conceptually expand on it (Costa, 2018; Nagy & Neff, 2015), current definitions of affordances emphasize a relational framework of technology use that accounts for the dynamic interplay between the characteristics of users, features of the technology itself, and the situated nature of its use (Evans et al., 2017). Adopting an affordance lens allows researchers to recognize the mutual influence between users and environments (Gibson, 1979) and emphasizes the process or reasons for the relationship between a technology and outcome (Evans et al., 2017).

Even though affordances were initially used for conceptualizing interactions with features in physical environments, research in recent years have applied an affordance lens to shed light on the relationship between users and the features of communication platforms such as Social Networking Sites (SNS). SNS (i.e., social media platforms) are defined as web-based services that allow individuals to construct a profile, select other users with whom they share a connection, and view their connections and others within the system (Boyd & Ellison, 2007). Previous research shows that an affordance perspective of SNS can be used to assess how social media platforms influence the socialization of new employees (Leidner et al., 2020), inform online health intervention programs (Moreno & D'Angelo, 2019; Merolli et al., 2013), and counter COVID-19 misinformation spread (Islam et al., 2020). Other work has detailed how affordances related to social connectivity, content discovery, and content sharing are manifested across Facebook, Twitter, and YouTube (O'Riordan et al., 2012). A psychometrically validated scale to assess perceptions of affordances across communication channels including Facebook and non-SNS channels such as email, texting, and instant messaging has been developed in recent years as well (Fox & McEwan, 2017). Applying an affordance perspective can also reveal negative consequences of social media platforms, as reported in focus groups showing that affordances such as visibility and connectivity on Facebook can trigger emotions such as jealousy and anxiety due to constant social comparison (Fox & Moreland, 2015). Recent work in computational social science using data-driven agent simulations that models differences in available actions associated with the platforms Twitter, Reddit, and Github further demonstrates the importance of accounting for SNS affordances when investigating online user behavior (Murić et al., 2022).

In work investigating online anti-social behavior, Chan, Cheung, & Wong (2019) integrates an affordance perspective with an adaption of crime opportunity theory (Felson & Clarke, 1998) to assess how SNS affordances create environmental conditions more favorable to cyberbullying. According to crime opportunity theory, the two primary components that contribute to a crime being committed is the presence of a likely perpetrator and environmental conditions that offer criminogenic opportunities (Felson & Clarke, 1998). In their analysis, Chan et al. (2019) show that perceived affordances of an SNS environment that facilitate the identification of suitable bullying targets and permit perpetrators to disguise their culpability (e.g., being able to edit a post or comment) were positively associated with SNS cyberbullying. The results from this research indicate that perceived design-features associated with SNS can promote (or inhibit) anti-social behaviors within a platform.

Building on this prior research, this study will use the framework of crime opportunity theory to examine how the affordances of SNS relate to drug dealer behavior. This study will adopt the definition of affordances described in Evans et al. (2017) that recognizes an affordance as a mediator between the object (i.e., SNS) and the outcome (i.e., drug transaction) to examine how affordances of message length (based on word limit feature of SNS) and anonymity (not having to verify personal identity to make a profile) influence drug dealer posting behavior across multiple SNS platforms. Since longer message length for a SNS would allow for more text within a post, we hypothesize that:

H1. SNS with longer message lengths will have higher number of total drug mentions per post than SNS with shorter message lengths

H2. SNS with longer message lengths will have higher variety of drug mentions (i.e., % of posts with at least one mention of each drug category) than SNS with shorter message lengths.

Due to the fact that all SNS examined in the current study do not require extensive verification of identity to create a user account, anonymity will be examined by assessing the number of accounts associated with identifier information as further described in the methods section. Since data collection for the current study only occurred during the pandemic, we are unable to assess how drug transaction behavior may have changed before the start of COVID-19. However, a benefit of using an affordance lens is that it can still generate insights into how functionalities that exist across SNS influence drug posting content regardless of the study's timeframe.

2. Methods

2.1. Data collection

Data was collected from Instagram, Reddit, Twitter, YouTube and Tumblr between September 2020 to May 2021 and included a total of 608,617 posts filtered for select keywords associated non-synthetic drugs and synthetic drugs aligned with the study aims (see further explanation and Tables 1A and 1B). Posts were then filtered using topic modeling (further description in the next section) to detect drug selling activity resulting in 2,654 posts across all platforms that were selected for further analysis (76.8%, n = 2,037 from Google Groups; 15.6%, n = 413 from Instagram; 4.0%, n = 106 from Twitter; 0.3%, n = 8 from Reddit; 3.4%, n = 90 from Tumblr). These platforms were chosen on the basis of known drug discussions and illicit drug selling activity as reported in prior studies (Barenholtz et al., 2021; Lu et al., 2019; Mackey et al., 2017; Mackey & Kalyanam, 2017; Yang & Luo, 2017; Zhao et al., 2020), publicly available news reporting (Lapowsky, 2018; Lytvynenko, 2018), as well as the general availability of data and methods of data mining used in this study. Due to limited API access across social media platforms, we developed our own data mining approaches for each platform using a set of drug-related keywords validated based on prior work (Katsuki et al., 2015; Mackey et al., 2017, 2018; Mackey & Kalyanam, 2017) and informed by publicly available unclassified information on drug names and slang terms from the US Drug Enforcement Agency (Drug Enforcement Administration, 2018) that were also converted to hashtags (#) for select platform searchers (e.g., Instagram). Data collected using these data mining approaches produced social media post data that were returned in multiple drug-related keyword searches in JSON format, which also included data containing the post text and metadata (e.g., post id, timestamp, username, interaction data including likes, favorites, retweets, and some publicly available profile information). All data collected was publicly available and did not include any private posts or direct messages between users. Data collection, parsing, and topic modeling was conducted using available packages in the Python programming language, with additional statistical analysis conducted using the R programming language.

2.2. Data processing and topic modeling

For each platform, we cleaned the text by eliminating the following attributes:

- Imbedded Hyperlinks: The hyperlink in the text does not provide relevant information needed for further classification of the post as a drug advertiser or seller. In most of these cases, hyperlinks posted by users relate to sharing news and do not link to self-reporting information.
- Stop words: Stop words (such as the, a, an, in) are commonly used in messages but do not provide much context to the theme or category of the message itself. They are not key words in the text but occupy a high volume of words within social media datasets and can make the process of topic modeling subject to greater noise (i.e., posts not relevant to drug selling activity). The NLTK python package was used to filter out stop words in messages collected.
- Special characters and punctuation marks: Special characters like emoji and punctuation marks may relate to user sentiment or convey a message. We did not prioritize these characters in this study as their interpretation can be subjective and most contextual information is in the form of text.

Following data cleaning and preparation, we then used an unsupervised topic modeling approach known as the biterm topic modeling (BTM) to help us find underlining patterns and themes derived from the texts of the full corpus of social media posts from each platform (Yan et al., 2013). BTM has been used in several studies examining substance use behavior (Shah et al., 2022), characterizing online drug diversion (Mackey et al., 2017), and for other public health topics such as tobacco control (Mackey et al., 2018), COVID-19 misinformation (Haupt et al., 2021a, 2021b), and characterizing forms of health corruption (Li et al., 2020; Mackey et al., 2020). BTM is a Natural Language Processing (NLP) based topic model that categorizes text into k different clusters based on the content of the underlining corpus of texts. Each cluster generated will contain a list of keywords that should be correlated to the topic of the cluster. In order to determine the number (k) of topics, we used the u-mass coherence score (Rosner et al., 2014). A coherence score is a value used to measure the performance of a topic model based on the k value, and can help distinguish between topics that are semantically interpretable and topics that are artifacts of statistical inference. A k value with a higher coherence score means the clusters it categorizes are more identical to each other. Clusters with k values that had the highest coherence score and contained keywords related to drug selling activity-related keywords (e.g., shipping, deliver, buy, sale) were manually coded for "signal" texts that contain the selling or trading content as shown in the example post below in Fig. 1 (the contact information has been removed for the purposes of de-identification) and as further detailed in Section 2.3 below:

2.3. Text analysis of social media posts

Five drug categories were used to examine the prominence of drug mentions across social media posts. Table 2A shows the keywords associated with the categories for non-synthetic drugs, including Opioids, Non-Opioid Prescription Controlled Substances, and Other Illicit Drugs. Table 2B shows keywords associated with synthetic drugs, organized into two categories: Synthetic Opioids (fentanyl) and Synthetic Marijuana (e.g., K2/Spice). Following the output of BTM clusters of keyword filtered posts, authors manually inspected clusters and then selected and extracted posts from clusters that were highly correlated with word groupings of drug selling- and activity related keywords. Posts were then manually annotated by authors JL and MN to confirm if they included drug selling activity, which consisted of: (a) including the name of a study drug of interest in the post or including an image or other media of drug-related products or substances; and (b) including some form of contact information or a link to a website or other means of facilitating a selling or trading transaction with another user. Following signal post classification, the total number of mentions for each drug category were based on the count of keywords associated with the respective category. Other metrics such as the average number of mentions per post (i.e., total count of keywords divided by total number of posts) and percentage of posts with at least one mention of a drug category were also calculated for each platform. Differences between platforms were tested for statistical significance using one-way ANOVA and Tukey's Honest Significant Differences mean comparisons.

- Order adderall30mg ir worldwide without prescription contact us now on: website: XXXXX.com

  snapchat: XXXXX wickrme:XXXXX

Fig. 1. Example of post containing drug-related keywords.

Table 2A
Keywords for drug categories.

Category	Keywords
Opioid	heroin |oxycodone|oxycontin|percocet|vicodin|pethidine|lavorphanol|meperidine|propoxyphene|dextropropoxyphene|methadose|dolophine|diskets|abstral|actiq|fentora|onsolis|sublimaze|ultram|ryzolt|conzip|demerol|levo-dromoran|darvocet|di-gesic|darvon|tramadol | methadone
Non-Opioid Prescription Controlled Substances	valium|xanax|adderall|ritalin
Other Illicit Drugs	cocaine|coke|meth|methamphetamine

Table 2B
Keywords for synthetic drug categories.

Category	Keywords
Synthetic Opioid	Fentanyl
Synthetic Marijuana	k2|spice|synthetic cannabinoids|synthetic marijuana|fake weed|yucatan fire|bombay blue|zohai|kkronic|black mamba|blaze|genie|skunk

2.4. Creating identifiers across user accounts

In order to track dealers across user accounts for each platform, we created an identifier variable using publicly available metadata associated with each account. Metadata included purported phone number, email address, and usernames for messaging platforms Wickr and Snapchat that were included in the text of a post or in the metadata of a user's profile. If a phone number was associated with an account, it was used as the identifier. If there was no phone number available, an email address was then used instead, followed by Wickr and Snapchat usernames. In cases where there was more than one phone number, the most commonly used number across accounts was used.

2.5. Assessing affordances across SNS

Since all SNS examined in this study do not require a verification of identity beyond providing an email or phone number (though certain platforms may "verify" accounts though this is not necessary), all 5 platforms are considered to provide equal levels of anonymity since users can choose how much personally identifying information they want to disclose. Effects from this affordance were assessed by examining the number of user accounts across all platforms associated with each identifier. Message length was determined based on the word count limit of each platform. Since an affordance is defined as a mediator between a feature and an outcome of interest according to the framework described in Evans et al. (2017), within the context of this study the word count limit is the feature and the number of drug-related keywords in a post is considered the outcome of interest. Message length of a post is an affordance since it is directly influenced by the word count limit and subsequently influences the type of content included in a message. SNS with no formal word limit (Google Groups, Tumblr) and those with exceptionally high limits such as Reddit (40,000 character limit per post) were classified as “Long” for message affordance (see Table 3). Twitter, which has more stringent limits (character limit 280), was classified as “Short”. While Instagram allows 2,200 characters per post, the captions get truncated at 125 characters when displayed on the newsfeed. For this reason, Instagram was classified as “Short” since first exposure to the message is more relevant for the ways drugs are advertised on a newsfeed for initiating a sale.

3. Results

3.1. Comparing drug mentions across platforms

After employing BTM and conducting content analysis to confirm drug selling activity of posts, Google Groups had the highest number of drug selling posts ($n = 2037$) and unique user accounts ($n = 64$), followed by Instagram (posts = 413, users = 59), Twitter (posts = 106, users = 46), Tumblr (posts = 90, users = 24), and Reddit (posts = 8, users = 6) as seen in Table 3. Tables 4A and 4B shows the total number of mentions for each drug category including mentions per post and the percentage of posts that have at least one mention of the drug (column “% Mention”). Compared to other platforms, Google Groups has the highest number of mentions and mentions per post across all drug categories (45,844 total drug mentions, 22.51 mentions per post). This result was most pronounced with Opioids, where Google Groups had 9.76 mentions per post compared to the next highest ranking platform Tumblr (2.38 mentions), and Non-Opioid Prescription Controlled Substances where Google Group had 7.61 mentions per post compared to 1.88 mentions from Reddit. Across non-synthetic drug categories, differences in mentions per post between Google Groups and all other platforms were highly significant ($p < .001$), and over 90% of Google Group posts included at least one mention of non-synthetic drugs. Instagram had the second highest number of total drug mentions across all categories, however it tended to rank consistently in the middle for mentions per post and posts with at least one mention compared to other platforms. This indicates that drug mention categories are less concentrated within a single post and less prevalent across multiple posts compared to SNS with higher message lengths such as Google Groups. Twitter had the third highest number of posts in total but, similar to Instagram, ranks low in number of mentions and lowest in mentions per post across multiple drug categories. While Reddit had the lowest number of posts overall ($n = 8$, comments were not included in analysis), the percentage of posts with at least one drug mention were high especially for Opioids (88%), Illicit drugs (100%), Non-Opioid Prescription Controlled Substances (100%), and Synthetic Opioids (88%). However, due to the low sample of Reddit posts these findings are more descriptive rather than generalizable for the platform. Among Opioids and Illicit categories, Tumblr ranks second in mentions per post (2.38, 2.08) and has a high percentage of posts with at least one mention of Non-Opioid Prescriptions Controlled Substances (91%).

In order to facilitate comparing drug type percentages across platforms, Fig. 2A and B visualize the percentage of posts with at least one mention of each drug type by platform. These figures show that Instagram has a higher percentage of non-synthetic drug mentions compared to synthetic drugs. Twitter shows a spike in percentage of posts with Non-Opioid Prescription Controlled Substances but then ranks lowest for all other drug categories across SNS. Mentions of Synthetic Marijuana were lowest across all platforms: only 5% of Google Group posts and 2% of Instagram posts included at least one mention in the dataset examined.

Table 3
Overview of platforms.

Platforms	Message Length Affordance	Total Posts	# User Accounts	Total Drug Mentions (All)	Drug Mentions per Post
Google	Long	2037	64	45,844	22.51[a]
Instagram	Short	413	59	1,893	4.58
Twitter	Short	106	46	361	3.41
Reddit	Long	8	6	37	4.62
Tumblr	Long	90	24	564	6.27

[a] All differences between Google Groups and the other platforms are statistically significant ($p < .001$). There were no other statistically significant differences detected between other platforms. Statistical significance was calculated using ANOVA and Tukey’s Honest Significant Differences mean comparisons.

3.2. Comparing identifiers across platforms

As shown in Table 5A, most platforms had identifiers associated with each drug selling user account, with the exception of Twitter, which has 26 accounts that did not include an identifier. On average, there were approximately 2 user accounts associated with each identifier across platforms. Additionally, Instagram and Google Groups have dealers with the highest number of accounts associated with a single identifier (Instagram = 12, Google = 10). Upon further examination of identifiers with number of posts in the top 10 percentile as seen in Table 5B, the average number of user accounts associated with an identifier increases to 5.75 and 3.33 for Google Groups and Instagram respectively. Linear regression was used to test for a statistically significant correlation between number of posts on a platform associated with an identifier and the number of user accounts associated with that identifier on that platform, as shown in Table 5. The results show a positive correlation between post number and number of accounts for Google Groups ($\beta = 38.27$, $p < .001$) however this effect is only marginally significant for Instagram ($\beta = 3.18$, $p < .10$). Table 4C compares identifier types and shows that phone number was the most commonly available identifier across platforms except for Instagram and Twitter. For these platforms, accounts were more often associated with a Wickr identifier.

In order to show the relationship between identifiers and user accounts, a network graph visualization of the platforms with the highest number of posts (Google Groups and Instagram) was created as Figs. 3 and 4. Each identifier is represented by a black square and each user account is represented as a circle with the color reflecting the respective platform. A black square with more than one circle tie indicates that multiple user accounts were created under a single identifier. Larger circles and squares indicate a higher number of posts associated with the account and identifier respectively. Network visualizations for both platforms visually reflect the regression results from Table 5 where identifiers with a higher number of accounts also tend to have larger circles, signifying higher number of posts. However, this pattern is less prominent on Instagram compared to Google Groups where there are more cases of user accounts with lower post output despite being tied to identifiers that have multiple accounts.

4. Discussion

4.1. Assessing effects of affordances on opioid dealer posting behavior

The results from this study show that platforms with a longer message length affordance such as discussion boards and blog type SNS (Google Groups, Reddit, and Tumblr) have higher concentrations of overall drug mentions per post, which was most pronounced for Google Groups which reported highly significant differences ($p < .001$) compared to all other platforms. While the higher number of mentions per post for Reddit and Tumblr were not significantly different from SNS that have shorter message length, these results in addition to the findings seen in Google Groups still provide preliminary evidence supporting hypothesis H1. Fig. 2A and B shows that when assessing the prevalence of posts with at least one drug mention, SNS with short message length are influenced more by drug type (e.g., Twitter has much more posts with at least one Non-Opioid Prescription drug mention compared to other drug categories). Overall, SNS with long message length consistently had higher percentage of posts with at least one drug

Table 4A
Non-synthetic drug type mentions (per post and % of posts with at least one mention) by platform.

	Opioid			Non-Opioid Prescription			Other Illicit		
Platforms	Total Mentions	Mentions per Post	% Mention	Total Mentions	Mentions per Post	% Mention	Total Mentions	Mentions per Post	% Mention
Google	14,524	9.76 $_{I,Tw,R,Tu}$	1.00 $_{I,Tw,Tu}$	15,499	7.61 $_{I,Tw,R,Tu}$	.97 $_{I,Tw}$	8,956	4.40 $_{I,Tw,R,Tu}$	.98 $_{I,Tw,Tu}$
Instagram	490	1.65 $_{G}$	.86 $_{G,Tw}$	755	1.83 $_{G}$	.77 $_{G,Tu}$	358	0.87 $_{G,Tu}$	.82 $_{G,Tw}$
Twitter	86	1.37 $_{G}$	.53 $_{G,I,R,Tu}$	121	1.14 $_{G}$	.71 $_{G,R,Tu}$	82	0.77 $_{G,Tu}$	.45 $_{G,I,R,Tu}$
Reddit	7	0.88 $_{G}$	.88 $_{Tw}$	15	1.88 $_{G}$	1.00 $_{Tw}$	8	1.00 $_{G}$	1.00 $_{Tw}$
Tumblr	171	2.38 $_{G}$	.88 $_{G,Tw}$	128	1.42 $_{G}$	.91 $_{I,Tw}$	187	2.08 $_{G,I,Tw}$	.89 $_{G,Tw}$

Note: Subscripts indicate a statistically significant difference ($p < .05$) between platforms. Subscripts in bold-italic indicate significance level of $p < .001$. Platforms correspond to the following subscripts: $_{G}$ = Google, $_{I}$ = Instagram, $_{Tw}$ = Twitter, $_{R}$ = Reddit, $_{Tu}$ = Tumblr. Statistical significance was calculated using ANOVA and Tukey's Honest Significant Differences mean comparisons.

Table 4B
Synthetic drug mentions (per post and % of posts with at least one mention) by platform.

	Synthetic Opioid			Synthetic Marijuana		
Platforms	Total Mentions	Mentions per Post	% Mention	Total Mentions	Mentions per Post	% Mention
Google	6,754	0.69 $_{I,Tw,Tu}$	.59 $_{I,Tw,Tu}$	111	0.05	.05
Instagram	270	0.19 $_{G,R,Tu}$	.19 $_{G,R,Tu}$	20	0.05	.02
Twitter	72	0.12 $_{G,R,Tu}$	.12 $_{G,R,Tu}$	0	0.00	.00
Reddit	7	0.88 $_{I,Tw}$	.88 $_{I,Tw,Tu}$	0	0.00	.00
Tumblr	78	0.39 $_{G,I,Tw}$	.39 $_{G,I,Tw,R}$	0	0.00	.00

Note: Subscripts indicate a statistically significant difference ($p < .05$) between platforms. Subscripts in bold-italic indicate significance level of $p < .001$. Platforms correspond to the following subscripts: $_{G}$ = Google, $_{I}$ = Instagram, $_{Tw}$ = Twitter, $_{R}$ = Reddit, $_{Tu}$ = Tumblr. Statistical significance was calculated using ANOVA and Tukey's Honest Significant Differences mean comparisons. There were no statistical differences detected between platforms for the synthetic marijuana category.

Table 4C
Comparison of identifier types across platforms.

	Phone		Email		Wickr		Snapchat	
Platforms	Avg	Max	Avg	Max	Avg	Max	Avg	Max
Google	1.00	1	1.05	6	0.54	2	0.00	0
Instagram	0.76	1	0.28	1	0.92	2	0.12	1
Twitter	0.56	1	0.24	2	0.60	1	0.32	1
Reddit	1.00	1	0.00	0	0.50	1	0.00	0
Tumblr	0.78	1	0.50	1	0.61	1	0.28	1

mention compared to short message length SNS, with many of these differences being statistically significant ($p < .05$). These results indicate support for hypothesis 2.

Among the platforms examined in this study, Google Groups had the most drug mentions per post across all 5 drug categories and these results were most pronounced with Opioids and Non-Opioid Prescription Controlled Substances. The higher number of mentions per post for Google Groups compared to the other platforms were also statistically significant ($p < .001$) and indicate that posts from SNS that afford higher message length are more likely to consist of a full catalogue of supplies across a variety of drug type categories. Due to the higher concentration of mentions and drug-type variety associated with SNS that have a high message length affordance, public health and law enforcement officials may consider focusing on these platforms when investigating drug dealer activity since these accounts are more likely to be linked to suppliers with a wide array of illicit drug offerings.

The lower concentration of drug mentions and drug-type variety for Instagram and Twitter posts could also be attributed to the restraints provided from the word limit features on the platforms. However, it is possible that other affordances produced by platform features such as formatting layouts, user policies and demographics, the effect of content moderation, and social conventions specific to each site are also influencing why certain types of drugs are featured more often on a given SNS more than others. Previous work investigating social motivations for using SNS have argued for a needs-affordances-features (NAF) perspective that posits that an individual's psychological needs (such as need for autonomy or self-identity) motivate their use of social media platforms to the extent to which these platforms provide affordances that satisfy these needs (Karahanna, Xu, Xu, & Zhang, 2018). In other words, the NAF perspective claims that users will be drawn towards certain sites based on their own specific psychological needs and the affordances produced from the features of the platform, which implies that psychological dispositions and other demographic characteristics of users would differ across SNS. Previous research examining associations between narcissism and SNS behaviors provides evidence for the NAF perspective showing that among college students, posting on Twitter was positively correlated with narcissism while adults high in narcissism were more likely to use Facebook (Panek et al., 2013). Other work examining older Facebook users shows that affordances related to gratifications such as community-building and agency-enhancement are associated with different behaviors on the platform (Jung & Sundar, 2018). These findings indicate that individuals factors such as age and personality traits influence motivations for using SNS.

Therefore, using an NAF perspective, it is possible that drug dealers may target a specific SNS if certain drugs are more likely to sell among

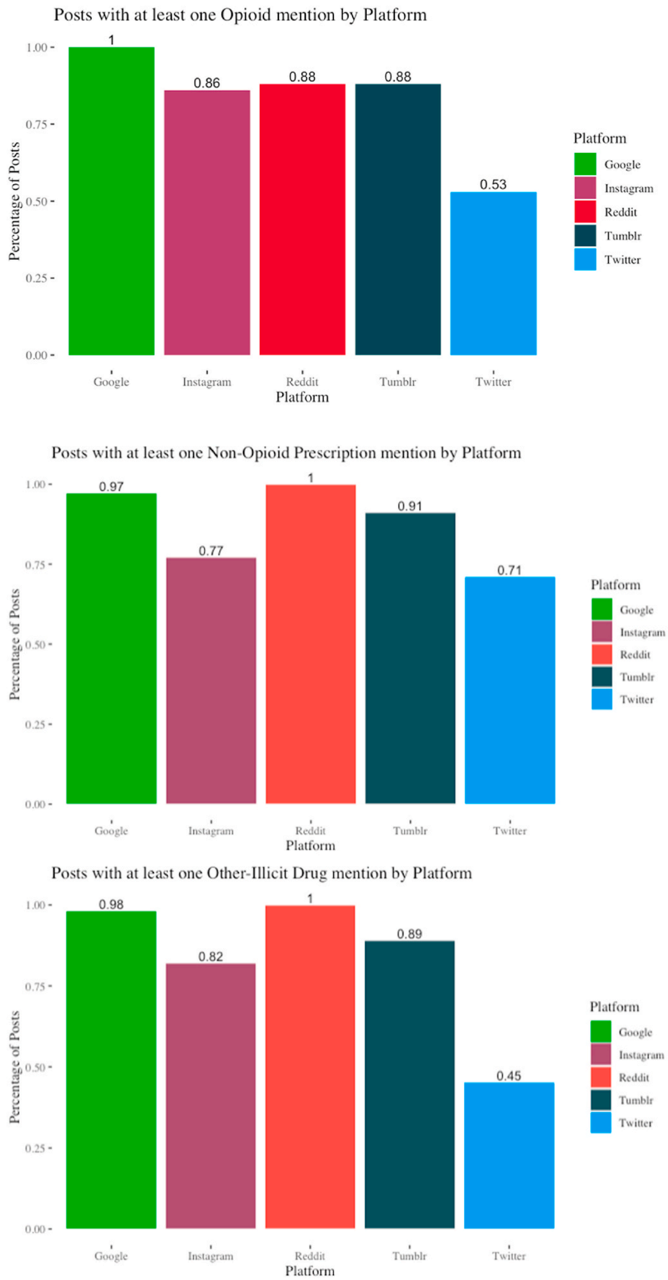

Fig. 2A. Posts with at least one mention of Opioid, Non-Opioid Prescriptions, or Other Illicit Drug by Platform.

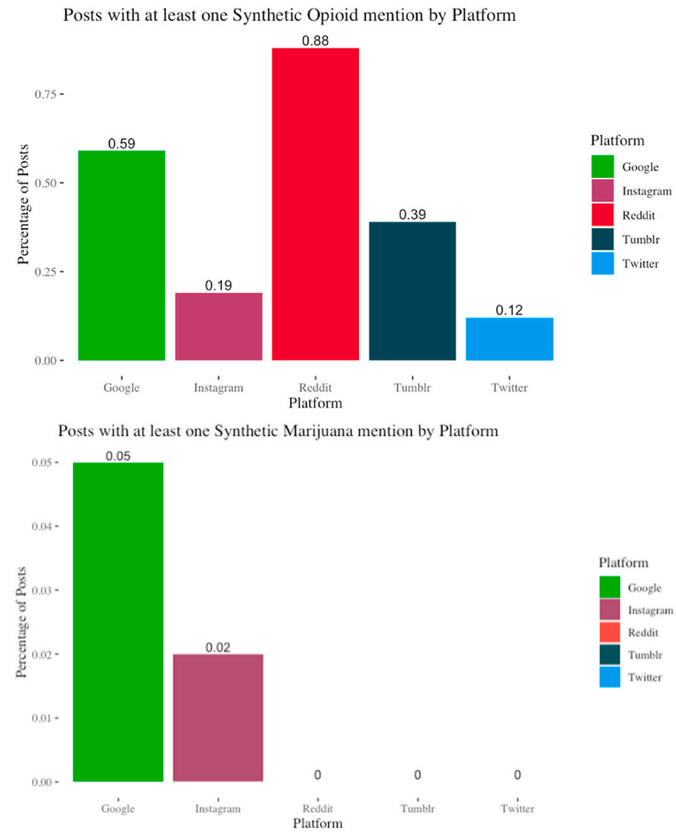

Fig. 2B. Posts with at least one mention of Synthetic Opioid or Synthetic Marijuana by Platform.

the types of users drawn to that platform. For example, Non-Opioid Prescription Controlled Substances might be more appealing to those who are psychologically drawn to have a Twitter account or a user base demographic more likely to abuse prescription drugs compared to illicit drugs, which could make the SNS a target for those types of drug transactions. Illicit and synthetic drugs may find more resonance on Reddit as recent work shows that users discuss drug use behavior and experimentation with new and emerging drug products on the platform (Balsamo et al., 2021; Barenholtz et al., 2021; Bunting et al., 2021). Further evidence of demographic targeting is shown in findings from a digital ethnography of Swedish Facebook groups that sold illegal substances, which found that groups were more likely to convene around demographic factors (Demant et al., 2020).

The NAF perspective can also be used to guide interventions preventing online drug transactions more generally. Recent work has shown that lower self-control, higher psychological distress, and excessive gambling behavior and internet use were all associated with online drug purchasing while having strong social bonds offline served as a protective factor (Oksanen et al., 2021). Even though the current literature shows mixed evidence for associations between social media use and mental health outcomes (Seabrook et al., 2016), with some researchers showing positive correlations between use and symptoms such as depression, anxiety, and loneliness (Hunt et al., 2018; Lin et al., 2016; O'Day & Heimberg, 2021; Perlis et al., 2021; Vidal et al., 2020), while others have found little to no significant effects between social media use and mental wellbeing (Coyne et al., 2020; Orben & Przybylski, 2019; Stieger & Wunderl, 2022), there is mounting evidence over the past decade indicating increased social media use among those diagnosed with mental disorders, especially within younger cohorts (Naslund et al., 2020). Due to the high comorbidity between mental health disorders and drug use (Bukstein et al., 1989; Regier et al., 1990; Weaver et al., 2003), SNS that adopt features which mitigate stress and discourage impulsive actions may result in a decrease of online drug seeking or transactions on the platform, though would need further study. As concluded from multiple review articles in the literature (O'Day & Heimberg, 2021; Seabrook et al., 2016; Vidal et al., 2020), there is also a need for further work investigating the motivations, social factors, and underlying mechanisms that mediate the association between social media use and mental health. Follow up work using an affordance lens comparing how SNS features are used between those with mental health disorders and users not exhibiting mental health symptoms may identify relevant factors that could shed light on why reported effects between social media use and mental health are inconsistent across studies. In summary, drug dealers may more purposefully use SNS for targeted drug sales based on the user demographics associated with a specific platform such as age, gender, race, psychological disposition, as well as permissiveness of drug-related content for user-generated discussions. Future research should examine how demographics and dispositional traits of

Table 5
Linear regression models for Google and Instagram – number of posts by number of user accounts.

Predictors	Outcome					
	Number of Posts (Google)			Number of Posts (Instagram)		
	Estimates	CI	p	Estimates	CI	p
(Intercept)	−20.44	−57.14 – 16.25	0.266	8.43	−4.21 – 21.07	0.182
Google: Number of User Accounts	38.27	25.09–51.44	<0.001			
Instagram: Number of User Accounts				3.18	−0.60 – 6.96	0.095
Observations	37			26		
R^2	0.498			0.112		

Table 5A
Accounts associated with identifiers across platforms.

Platforms	Accounts w/ Identifier	Accounts w/NO identifier	Avg User Accounts	Max User Accounts
Google	37	0	2.00	10
Instagram	25	2	2.36	12
Twitter	25	26	1.08	2
Reddit	2	0	3.00	5
Tumblr	18	3	1.22	4

Table 5B
Accounts in Top 10 percentile based on number of posts.

Platforms	Account w/ Identifier	Post Total	Avg User Accounts	Max User Accounts	Avg Email	Max Email
Google	4	1275	5.75	10	3.25	6
Instagram	3	205	3.33	5	0.33	1

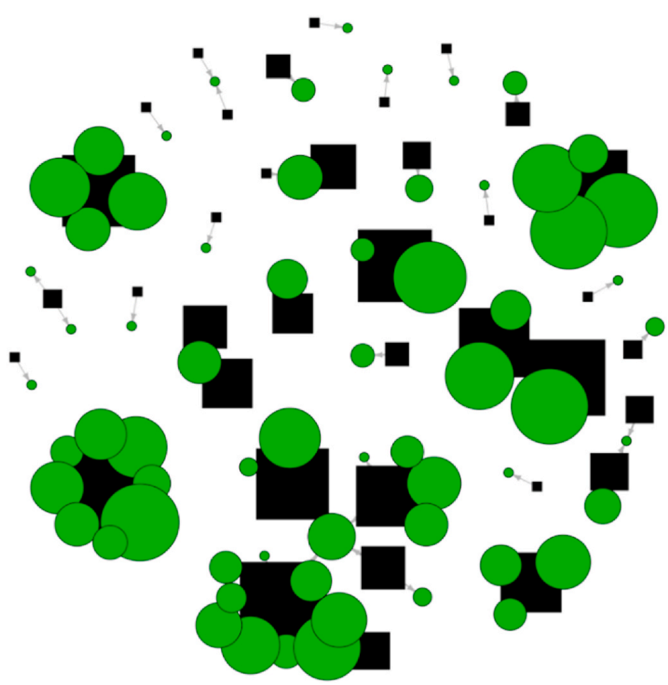

Fig. 3. Google Group Network:
Black Square = Identifier, Green Circle = Google Group Account. A black square with more than one circle tie indicates that multiple user accounts were created under a single identifier. Larger circles and squares indicate a higher number of posts associated with the account and identifier respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

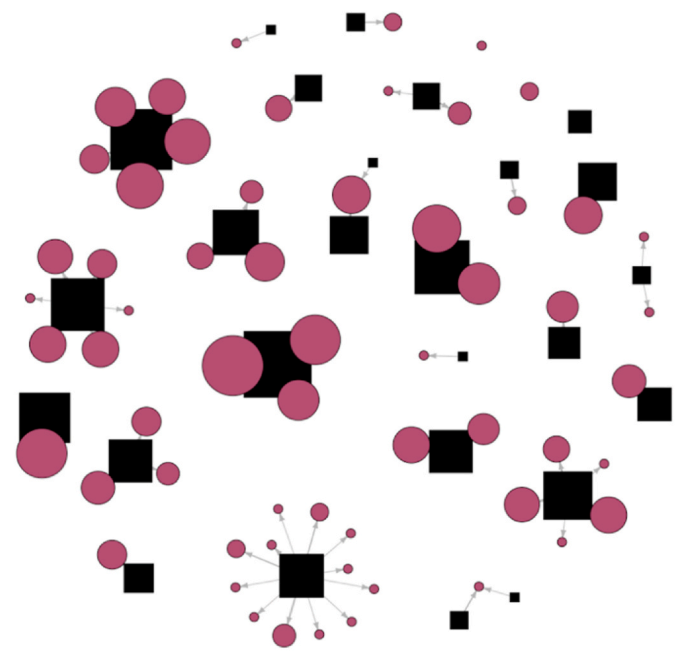

Fig. 4. Instagram Network:
Black Square = Identifier, Purple Circle = Instagram Account. A black square with more than one circle tie indicates that multiple user accounts were created under a single identifier. Larger circles and squares indicate a higher number of posts associated with the account and identifier respectively. . (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

SNS users are specifically targeted for sales transactions based on the type of drug.

The results also show that each identifier was associated with an average of 2 user accounts across SNS, with Google Groups having a max of 10 accounts and Instagram having a max of 12. Regression results show a positive correlation between number of accounts and number of posts, however this effect is only statistically significant for identifiers selling drugs on Google Groups. These findings indicate that drug dealers likely take advantage of the anonymity affordance provided by these SNS to create multiple accounts in order to advertise their services and illegal products, while also using these tactics in possible response to account suspension and to avoid detection by platforms and law enforcement. Social media bots, which are prominent in online misinformation spread (Himelein-Wachowiak et al., 2021; Shao et al., 2018; Wang et al., 2018), can also be used to create fake user accounts that produce multiple posts for initiating sales. Even though it is possible to purchase social media bots across multiple SNS (Kolomeets & Chechulin, 2021), Google Groups in particular could be susceptible to bot activity due to what appears to be low moderation on the platform. However, even if the majority of the drug post activity identified on a platform was bot generated, this most likely would not influence the risk of initiating a drug sale. Bots can serve as a tool for propagating drug advertising posts, which can then result in a sales interaction with a human dealer if the user interacts with the post. This would be analogous to sending out an automated message on multiple email listservs reaching hundreds or thousands of people and then responding to the few that reply. The prominence of advanced chatbots that use natural language processing and machine learning techniques to simulate human conversations (Chakrabarti & Luger, 2015), as used to assist online activities such as shopping, bank communication, meal delivery, and healthcare among other applications (Hasal et al., 2021), could also be used to facilitate fraudulent transactions with users (Poster, 2022). In fact, the differences between human and bot-generated activity is becoming increasingly blurry, as recent studies have used bots as fake accounts in online field experiments to assess and influence the opinions of users (Bail et al., 2018; Mosleh et al., 2022), and have also shown that bots can even be influential figures in online political discourse (Chang & Ferrara, 2022).

Counter measures for addressing the use of anonymous accounts could involve SNS platforms adopting more stringent reviews of common metadata used to create multiple user profiles on platforms, particularly when accompanied by a high volume of posts that include sensitive or concerning keywords, such as those associated or flagged with illegal drug trading or selling. Qualitative findings from another study shows that drug dealer accounts with higher number of likes and comments were perceived as more credible (Moyle et al., 2019), suggesting a potential way in which dealers can build trust with buyers despite using anonymous accounts. Activity from other users who engage with profiles of identified dealers should be examined further in future work. The lack of a significant effect between the number of accounts and number of posts for Instagram also suggests there are other differences in affordances between Instagram and Google Groups that may impact how drug dealers use the platforms that should be explored in future studies.

4.2. Other public health applications of SNS affordances

Despite being originally conceptualized for physical spaces, applying frameworks such as crime opportunity theory and affordances to online environments can shed light on how features of SNS are associated with outcomes concerning public health, as demonstrated in the current study. In the same way that features of an environment such as low levels of lighting and foot traffic can increase the likelihood of crimes such as robbery within a location, features available on a SNS can both enable (or restrict) the actions available to users, including actions that were not anticipated by the developers of the platform. While not strictly a criminal activity, spreading false information about health-related issues on SNS can negatively impact public response to crises. Misinformation spread related to the COVID-19 pandemic is prominent across multiple social media platforms culminating into what has been described as an "infodemic" (The Lancet Infectious Diseases, 2020; Zarocostas, 2020). On Twitter for example, covid-related misinformation was shown to be higher in volume and persisted for a longer duration of time compared to accurate scientific evidence (Haupt et al., 2021), with similar misinformation dynamics being observed on the platform before the pandemic (Shin et al., 2018; Vosoughi et al., 2018). Islam et al. (2020) have already started to address this issue showing that social media users who are drawn to affordances of self-promotion and entertainment in Bangladesh are more likely to share unverified information. However, further work is needed to examine how affordances facilitate misinformation spread, such as identifying affordances of a platform that explain why misinformation tends to persist for longer periods of time compared to accurate information and in higher volume. For example, the affordance of message length, as examined in the current study, could also be used to compare number of mentions and variety of keywords in textual content of posts containing misinformation across SNS. Follow-up research should also experimentally test features that increase the difficulty of sharing false news or encourage the spread of factual information. In general, the use of an affordance lens on SNS can guide the design of healthy and safe online environments by promoting the spread of truthful and respectful discourse while inhibiting anti-social communication.

5. Limitations

Sample size of posts for Reddit was particularly small ($n = 8$), which limits the confidence in the results reported about the platform. The small sample of identifiers used for the linear regression analysis between number of accounts and number of posts ($n = 37$ for Google, $n = 26$ for Instagram) also limit generalizability of our results, although the high level of significance observed for Google ($p < .001$) helps mitigate this concern. Differences in available metadata across SNS could introduce bias to the results from the identifier analysis. This is most prominent for Twitter where more than half of Twitter accounts had no identifier, which limited the extent to which we could examine how dealers create accounts on the platform. However, the lack of available identification metadata for Twitter compared to other SNS could be another indicator of SNS-specific affordances influencing how dealers use Twitter. It is also likely that our web scraping approach did not capture every possible drug-related post for each SNS, which can bias our findings by excluding posts that did not use the same keywords used when identifying posts for analysis. Due to the low moderation typically associated with Google Groups, it is also possible that posts on the platform could be bot generated. However, bot-generated content could be used for initial advertising of supplies, and could still lead to a drug transaction if users respond to the post. Even in cases where bot-generated content is not associated with an actual drug supplier, these posts can be used for other nefarious online behavior such as enabling online scams, extracting personal and financial information from users, or prompting users to click a link that installs malware (Abraham & Chengalur-Smith, 2010). Lastly, the current study examines affordances as distinct sets, but there are likely interaction effects between varying affordances on a given SNS that were not measured. Future work should also investigate how combinations of affordances impact behaviors on SNS.

6. Conclusion

US Federal law, under the Ryan Haight Online Pharmacy Consumer Protection Act of 2008 (named after teenager who died from purchasing drugs online) expressly prohibits the online sale of controlled substances, which by extension should include SNS platforms (Mackey et al., 2013). Further, SNS platforms generally include user terms and conditions and community guidelines that prohibit the sale of any controlled substances, meaning that these user are in violation of federal law and platform policies. Despite these prohibitions, users selling drugs via SNS may use a variety of tactics to create new contexts with platform features and engagement with users to continually participate in this form of online criminal activity that perpetuates the current public health crisis of drug overdose and death. As reported by ethnographic work in Turkey examining Facebook use (Costa, 2018), intended uses and affordances put forth by designers are not always recognized while the original platform can be appropriated to align with the social realities of the users. In the same way that cultural differences can greatly influence perceptions of what a technology could be made to do, different user intentions for an SNS (e.g., using a platform to sell drugs versus using a platform to connect with friends) can also produce unexpected applications of a platform, which includes facilitating illegal activity that can generate real-world public health harms. This study has generated evidence that affordances attributed to SNS may impact how drug dealers leverage the specific nature of a platform to tailor their posts to more effectively market their products. Future work should continue using an affordance lens when examining illicit behavior on SNS for guiding law enforcement strategy and identifying susceptible populations to online soliciting.

Ethics approval and consent to participate

All information collected from this study was from the public domain and the study did not involve any interaction with users. User indefinable information was removed from the study results.

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Author contributions

MH: Conceptualization, Methodology, Formal Analysis, Writing – Original Draft RC: Writing – Review & Editing, Supervision JL: Software, Data Curation MN: Data Curation TM: Writing – Review & Editing, Supervision.

Patient consent for publication

Not applicable.

Declaration of competing interest

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