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Is This Safe? Examining Safety Assessments of Illicit Drug Purchasing on Social Media Using Conjoint Analysis

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Peer reviewed

# 1 **Is This Safe? Examining Safety Assessments of Illicit Drug Purchasing on**

## 2 **Social Media using Conjoint Analysis**

3 Illicit substance sales facilitated by social media platforms are a growing public health  
4 issue given recent increases in overdose deaths, including an alarming rise in cases of  
5 fentanyl poisoning. However, little is known about how online users evaluate what features  
6 of social media posts convey safety, which can influence their intent to source illicit  
7 substances. This study adapts conjoint analysis which assessed how attributes of social  
8 media posts (i.e., features) influence safety evaluations of mock posts selling illicit  
9 substances. 440 participants were recruited online for self-reporting use or purchase of  
10 controlled substances or prescription medicines recreationally. The following attributes  
11 were tested: drug packaging, drug offerings, profile photo of seller, payment info provided,  
12 and use of emojis. Results from the conjoint exercise found that packaging was ranked the  
13 most important attribute (Average Importance =43.68, Offering=14.94, Profile=13.86,  
14 Payment=14.11, Emoji=13.41), with posts that displayed drugs in pill bottles assessed as  
15 the most safe. Attribute levels for advertising multiple drugs, having a blank profile photo,  
16 including payment information, and including emojis also ranked higher in perceived  
17 safety. Rankings were consistent across tested demographic factors (i.e., gender, age, and  
18 income). Survey results show that online pharmacies were most likely to be perceived as  
19 safe for purchasing drugs and medications. Additionally, those who were younger in age,  
20 had higher income, and identified as female were more likely to purchase from a greater  
21 number of platforms. These findings can assist in developing more precise content  
22 moderation for platforms seeking to address this ongoing threat to public safety.

23 Keywords: Online drug purchasing; Controlled substances; Drug dealing; Social media;  
24 Online content moderation; Conjoint analysis

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1 **Introduction**

2 The US has been experiencing a rapidly escalating public health crisis over the past decade  
3 concerning drug-related overdoses and deaths. Between 2010 and 2017, the opioid-involved  
4 overdose death rate rose from 21,088 to 47,600, and by 2019 increased again to 49,860 (National  
5 Institute on Drug Abuse, 2023). Between 2013 to 2019, the death rate for synthetic opioids, such  
6 as fentanyl, increased by a staggering 1,040% (3,105 to 36,359 deaths), reflecting a new chapter  
7 in the crisis characterized by the dangers associated with counterfeit products and other illicit  
8 drugs laced with fentanyl (Mattson et al., 2021). While not as prevalent as natural and synthetic  
9 opioids, deaths due to the involvement of other drugs such as psychostimulants (e.g.,  
10 methamphetamine) and the non-medical use of prescription psychoactive drugs has been rising  
11 as well (Bonnie et al., 2017; Mackey et al., 2013). The COVID-19 pandemic also had a major  
12 impact on public drug use: since the beginning of the pandemic the US experienced a dramatic  
13 increase of over 20,000 additional drug-related deaths from the previous year, resulting in the  
14 largest single-year percentage increase on record since 1999 (Baumgartner & Radley, 2021).

15 While multiple factors have contributed to the opioid crisis (see Humphreys et al., 2022  
16 for review of causes), the increased use of social networking sites (SNS) further exacerbates this  
17 issue by providing convenient and accessible spaces for conducting drug sale transactions. In  
18 fact, drug transactions on SNS have been documented extensively by research and investigative  
19 reporting detecting illegal opioid sales and prescription drug dealing across several platforms  
20 such as Twitter, Facebook, Discord, Instagram, and TikTok (Fuller et al., 2023). See the  
21 following papers for a review of transactions across platforms and drugs types, and factors  
22 influencing online purchasing (Constine, 2018; Demant et al., 2020; Dwoskin, 2018; Hu et al.,  
23 2021; Lapowsky, 2018; Lytvynenko, 2018; Mackey et al., 2017; Mackey & Kalyanam, 2017;

1 Mackey et al., 2018; Oksanen et al., 2020a; 2020b; Peterson et al., 2021; Rutherford et al., 2022;  
2 Tikku, 2018; van der Sanden et al., 2022; Whelan et al., 2023; Yang & Luo, 2017). Additional  
3 evidence for online drug purchasing is shown in a recent study of US survey respondents  
4 conducted during COVID-19 which found that 18% have bought medications online, including  
5 from several social media and communication platforms such as Tumblr, Wickr, and Pinterest  
6 and specifically for prescription-controlled sedatives (e.g., Xanax, Valium), stimulants (e.g.,  
7 Adderall, Ritalin), and other narcotic medicines (e.g., Vicodin, Percocet, Oxycontin) (Moureaud  
8 et al., 2021). This despite the fact that, in the United States, it is explicitly illegal to purchase  
9 controlled substances through online platforms, including online pharmacies and social media  
10 (Liang & Mackey, 2009; Mackey et al., 2013). Further, online drug purchasing behavior may  
11 become more normalized due to the emergence of digital health platforms that provide drug  
12 coupons for discounts on medications such as GoodRx, and the increased involvement of  
13 established corporations such as CVS, Walgreens, and Amazon in telepharmacy. Importantly,  
14 these legal transactions can still introduce potential harm as recent studies raise concerns about  
15 telemedicine being associated with overprescribing from physicians (Hoffman, 2020; Ray et al.,  
16 2019).

17 Consistent health burden related to drug overdose despite increased restrictions on public  
18 gatherings during the peak of COVID-19 social-distancing measures suggests that networking  
19 sites continue to be popular environments for drug sale transactions, which have concomitantly  
20 experienced increased use during the pandemic (De' et al., 2020; Huang et al., 2021; Mouratidis  
21 & Papagiannakis, 2021; Nguyen et al., 2020). Older work examining drug dealer transactions  
22 previously argued that awareness and initiation of drug use is facilitated by long-term  
23 interpersonal relationships in order to reduce uncertainties associated with the illegality and lack

1 of reliable information of the product offered (Atkyns & Hanneman, 1974; Moeller, 2018).  
2 However, this model based solely on in-person interactions is lacking as the use of the internet  
3 and social media sites deemphasize the need for pre-existing long-term relationships for  
4 facilitating drug transactions. A more appropriate framework developed during the internet era  
5 that can account for online communication dynamics between drug sellers and potential buyers is  
6 called the information forager model (Pirolli, 2001; Pirolli & Card, 1999). According to the  
7 information forager framework, which is based on ecological models of food scavenging  
8 behaviors, online users are considered “foragers” who balance the value gained from finding new  
9 information with the time cost needed to obtain it. In order to make this assessment, users rely on  
10 “information scents” which are proximal cues on webpages (e.g., the title of a link, images) that  
11 indicate the value and relevance of new information based on the user’s goals (Pirolli & Card,  
12 1999). Within the context of illicit online drug purchasing, potential buyers may search for scents  
13 from social media posts that signal the legitimacy of the supplies and the credibility of the seller  
14 in order to assure themselves that the transaction is safe or is not fraudulent (e.g., non-delivery  
15 scam, identity theft, etc.). Hence, understanding what features of social media posts that signal  
16 safety to users despite lacking a prior relationship to the dealer is crucial for designing  
17 interventions that address illegal drug sales within virtual environments.

18 In order to investigate how online environments can promote illicit drug sales between  
19 individuals with weak or non-existent social ties, this study uses survey measures adapted from  
20 recent work (Moureaud et al., 2021) to assess safety perceptions and drug purchasing behavior  
21 across multiple platforms. To assure that the sample is relevant to online drug purchasing  
22 behaviors, participants were recruited if they self-reported ever using or purchasing controlled  
23 substances or prescription medicines recreationally. This study also uses conjoint analysis to

1 examine what specific scents (e.g., signals) of drug-selling social media posts are perceived as  
2 safe to online users. More specifically, 48 hypothetical social media posts advertising the sale of  
3 controlled substances and prescription medicines were created to test the following attributes:  
4 packaging of drugs, drug offerings, profile of seller, payment info provided, and use of emojis.  
5 These attributes have been associated with engagement and credibility evaluation in previous  
6 social media research, and therefore were selected in the present study as they could also signal  
7 safety for potential drug transactions.

8

### 9 *Overview of conjoint analysis*

10 This study uses a technique called conjoint analysis to assess which features of social media  
11 posts that advertise drugs convey safety when making a purchase. Conjoint analysis was  
12 developed in the field of mathematical psychology and was initially employed by market  
13 researchers to quantify preferences for different products or services among consumers (see the  
14 following for a more comprehensive review: Green et al., 2004; Green & Srinivasan, 1990).  
15 Conjoint analysis uses experimental design to mimic complex decision-making processes that  
16 require people to “consider jointly” multiple attributes and lets respondents choose, rate, or rank  
17 hypothetical product alternatives that differ by attributes and levels. For stated preference  
18 studies, conjoint is considered a decompositional method. Decompositional methods allow  
19 respondents to evaluate each product or situation, and through experimental design, estimate the  
20 utilities, decomposed, from the answers of the respondents. In conjoint analysis, a product is  
21 thought of as being made up of various attributes (e.g., Color) and each attribute has several  
22 possible levels (e.g., Blue, Red). By varying the levels of the attributes presented in the conjoint  
23 exercise, respondent preferences are revealed as part-worth utility scores.

1           The use and popularity of conjoint analysis in health-related research has grown in recent  
2 years (Al-Omari et al., 2022). Pharmacology researchers and medical scientists have used  
3 conjoint analysis for evaluating patient preferences for PreP HIV prevention medication  
4 (Shrestha et al., 2018), vaccine treatments (Sun et al., 2020), disease modifying therapies  
5 (Wilson et al., 2014), physician prescribing intentions (Chinburapa & Larson, 1988), and the  
6 impact of health policies when enrolling in medical coverage (Knudsen & Havens, 2021).  
7 Another advantage of conjoint analysis is that it has been shown to reduce social desirability bias  
8 in survey responses and identify covert attitudes that are not aligned with overt values (Caruso et  
9 al., 2009; Horiuchi et al., 2022; Korn et al., 2020). Avoiding social desirability bias is especially  
10 important for research questions that require respondents to disclose sensitive information such  
11 as drug purchasing preferences, and therefore was chosen for the current study to mitigate this  
12 concern.

13           While previous research has used conjoint analysis to examine drug preferences for  
14 treatments in legal settings, there is currently no work assessing illicit contexts such as when  
15 drugs are advertised on social media sites. As shown in **Table 1**, the attributes tested in the  
16 current study are *packaging*, *offerings*, *profile*, *payment*, and *emoji*, and are based on actual drug-  
17 selling posts on Instagram identified in previous research (Haupt et al., 2022; Li et al., 2019;  
18 Mackey et al., 2020; Shah et al., 2022, Yang & Luo, 2017). Instagram was tested in the current  
19 study due to its specialization in visual marketing (such as targeted ads), popularity among  
20 younger users, and previous work evidencing illicit substance sales on the platform (Haupt et al.,  
21 2022; Shah et al., 2022). The three levels for *packaging* (official packaging, pill in hand, no  
22 image) were selected to assess how visual display of drug supply or product influences trust in  
23 the seller. The levels for *offering*, which test whether only one drug is advertised (Adderall) as

1 opposed to multiple drugs, were selected to assesses if having a higher quantity of offerings  
2 signaled a more established dealer hence being associated with higher credibility and safety.  
3 Adderall was selected for the ‘only one’ drug level due to it having less stigma associated with  
4 use, its high use among youth and adolescents, and it generally not being equated to an illicit  
5 drug despite being commonly abused and subject to counterfeiting. For multiple offerings, other  
6 drugs such as weed, cocaine, LSD, and psilocybin (i.e., shrooms) were included in addition to  
7 Adderall. Similar to *offering*, inclusion of *payment* information was tested to see if providing  
8 information for facilitating a potential transaction also signals a more established dealer.

9         The remaining attributes assess the extent to which meta-features of posts not directly  
10 related to drug supplies are also considered when evaluating the safety of initiating illicit online  
11 drug deals. Previous research shows that profile photos and image content can influence  
12 engagement (e.g., “liking”), perception of the post’s author (Kramer et al., 2017; Li & Xie,  
13 2019), and cultural stereotypes of drug use (Bakken & Harder, 2022). We tested animated faces  
14 as we believed that other factors associated with real life images, such as gender, race, and age,  
15 would be confounding factors for safety perceptions and would require further ethical  
16 considerations. The inclusion of emojis in posts can increase understandability and believability  
17 of posts (Daniel & Camp, 2020) and are widely used by social media influencers as persuasion  
18 strategies (Ge & Gretzel, 2017). This study tested whether these features that encourage  
19 engagement also signal safety when interacting with a drug dealer online.

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1 **Table 1.** Tested attributes and levels of social media posts advertising illicit substance sales.

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<i>Attribute</i>	<i>Levels</i>	3
Packaging	Drug is displayed as pills with hand	4
	Drug is displayed in official packaging	5
	No picture of supplies (Blank White/Gray)	6
Offerings	Advertises only one type of drug (Adderall)	7
	Advertises multiple types of drugs	8
Profile	Human face (animated)	9
	Blank profile	10
Payment	No payment info	11
	Mentions payment methods (Venmo, paypal,	12
	BtC)	13
Emojis	Includes emojis	14
	Does not include emojis	15
		16

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20 **Methods**

21 The survey used in the current study is divided into 2 parts. In part 1 respondents answered  
 22 questions assessing safety perceptions and drug purchasing across multiple online platforms and  
 23 demographic factors (e.g., age, gender, income). In part 2 respondents completed the conjoint  
 24 exercise. See the following Open Science Framework (OSF) link for study materials and  
 25 anonymized dataset<sup>1</sup>.

26

27 **Data collection**

28 A total of 440 respondents were recruited from Amazon Mechanical Turk (MTurk) after filtering  
 29 for data quality (i.e., outlier speed and failed attention checks) between October 13<sup>th</sup>-14<sup>th</sup>, 2022.  
 30 As described by Amazon, MTurk is “a marketplace for completion of virtual tasks that requires

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<sup>1</sup> <https://bit.ly/3RxSBHS>

1 human intelligence” and is traditionally used for recruiting humans to improve training datasets  
2 for artificial intelligence software (Bohannon, 2016). MTurk has become widely used as a  
3 sampling source in social science research (Bohannon, 2011; 2016) and recently used for  
4 surveying online drug purchasing preferences (Moureaud et al., 2021). Respondents were  
5 selected based on whether they reported having ever purchased or used a prescription drug  
6 recreationally (defined to participants as pharmaceutical drugs that legally requires a medical  
7 prescription by a licensed healthcare professional to be dispensed), or having ever purchased or  
8 used a controlled substance (defined as drugs or other substance tightly controlled by controlled  
9 substance act regulations due to their potential for abuse or addiction to the substance, including:  
10 opioids, stimulants, depressants, hallucinogens, and anabolic steroids).

11 Ethics approval for this study was granted by the University of California, San Diego (IRB  
12 protocol number: 804899). MTurk workers had access to the survey on the worker website,  
13 completed it anonymously, and were compensated based on standard survey-taking rates on the  
14 platform.

15

### 16 *Online drug purchasing perceptions and behaviors*

17 The following survey questions were adapted from related work (Moureaud et al., 2021) to  
18 measure safety perceptions and drug purchasing across online platforms. For safety perceptions,  
19 participants were asked to rate from 1 to 6 (1 = Very unsafe and 6 = Very safe) how safe it is to  
20 buy drugs/medications for 24 platforms (e.g., online pharmacy, Amazon, eBay) based on their  
21 own self-reported assessment. The responses “Safe” and “Very safe” were aggregated to  
22 compare safety perceptions across platforms and demographic subgroups. For online drug  
23 purchasing, participants were asked to select platforms that they have ever used to purchase a

1 drug or medication of any kind. 48 platforms were asked in total, ranging from online  
2 pharmacies, e-commerce site, messaging platforms, to social media sites. Age, gender, and  
3 income were chosen as demographics for analysis as they are relevant to drug-use and online  
4 behaviors (Boardman et al., 2001; Fittler et al., 2018; Spigner et al., 1993; van der Sanden et al.,  
5 2021).

6

### 7 *Conjoint exercise*

8 48 hypothetical drug advertising posts were created based on every possible combination of the  
9 tested attributes (*Packaging* (3 levels) x *Offering* (2 levels) x *Profile* (2 levels) x *Payment* (2  
10 levels) x *Emojis* (2 levels) = 48). Each respondent evaluated 21 posts selectively chosen to assure  
11 sufficient exposure for each attribute. The variant of conjoint analysis used in the current study is  
12 called Conjoint Value Analysis (CVA), which uses ratings-based evaluations of tested concepts.  
13 Within the conjoint exercise, respondents were shown 1 post at a time and asked to rate how safe  
14 it would be to purchase from the user of the post. The scale used to measure safety ranged from 1  
15 = Definitely would not be safe to 5 = Definitely would be safe. Posts were produced using an  
16 online mock social media post generator. In order to assure variety of the posts, 3 different  
17 versions for each attribute level were created (e.g., 3 different images were used to represent the  
18 level “pill in hand” for packaging). See **Figure 1** and **Figure 2** for examples of mock posts and  
19 conjoint exercise task.

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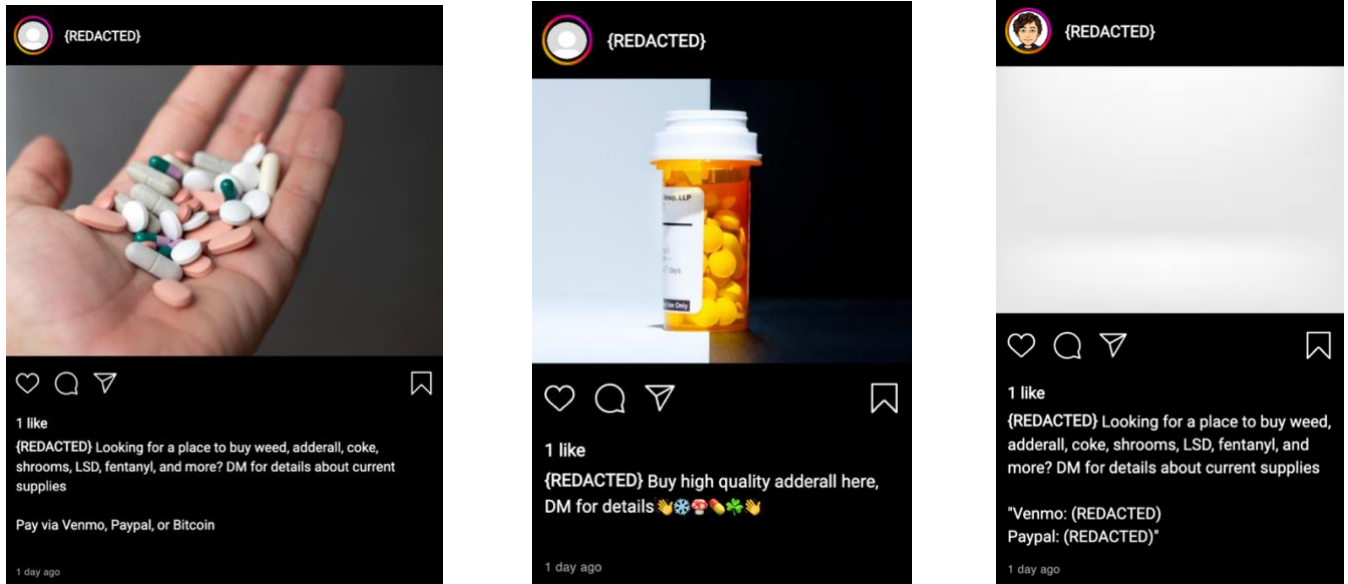
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1 **Figure 1.** Example social media posts for conjoint exercise.

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4 **Attribute combinations displayed in figure:** (Left) Packaging = Pill in hand, Offerings = Multiple, Profile = None, Payment Info = Included, Emojis = None; (Center) Packaging = Official, Offerings = Adderall only, Profile = None, Payment Info = None, Emojis = Included; (Right) Packaging = Blank, Offerings = Multiple, Profile = Animated human face, Payment Info = Included, Emojis = None

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9 **Figure 2.** Example of task from conjoint exercise.

10

How safe do you think it would be to purchase from this user?



- Definitely  
Would  
**Not** Be  
Safe
- Probably  
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**Not** Be  
Safe
- Unsure
- Probably  
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Each tested level is used as an independent variable for multiple regression modeling while the dependent variable is the safety rating. The program Lighthouse Studios developed by Sawtooth Software produced part-worth utility scores (i.e., beta coefficients) using hierarchical bayes estimations that account for choices from individual respondents and the sample average. Utilities per attribute are averaged and scaled to be normalized "zero-centered diffs," which cause the utilities to sum to 0 within each attribute. When interpreting results from conjoint analysis, the levels with the highest average utility scores indicate higher preference. Further, only utility scores of levels within the same attribute can be compared, but not across attributes. For example, the levels "Drug is displayed as pills with hand" and "Drug is displayed in official packaging" within the *packaging* attribute can be directly compared with each other but not with "Advertises only one type of drug (Adderall)" from the *offerings* attribute. While levels cannot be directly compared across attributes, it is possible to assess which attributes overall are weighted most heavily in respondent decision-making processes (e.g., comparing the influence of the *packaging* attribute vs *offering*) by using importance scores, which are computed for each attribute by taking the difference of the range in utility values and then dividing it by the sum of the differences in ranges across all attributes.

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**Results**

22 Average age of MTurk respondents was 35.44 (SD = 10.58) and 60% identified as male. The  
23 racial and ethnic background of the sample consists of 85.9% White, 4.1% Black, 3.2% Asian,  
24 and 19.5% of respondents identified as Hispanic or Latino. 44.5% of respondents reported  
25 earning a household income of \$60,000 USD or more. For previous drug purchasing behaviors of

1 respondents, 48.4% reported having both purchased and used prescription medicines  
2 recreationally, 15.9% have used recreationally but never purchased, 27.7% have purchased but  
3 never used recreationally, and 8.0% have never purchased or used prescriptions recreationally.  
4 For previous experience with controlled substances, 44.3% have purchased and used, 25.9%  
5 have used but never purchased, 23.6% have purchased but never used, and 6.1% have never used  
6 or purchased.

7 For analysis, age and income were converted into binary variables to distinguish between  
8 older and younger respondents, and respondents with low vs high income. The cutoff for older  
9 respondents was 35 or older based on the mean age of the sample (35.44). Respondents were  
10 classified as high income if they earned at least \$60,000 or higher based on the median of the  
11 sample. This threshold is also consistent with the median household income among the general  
12 US population.

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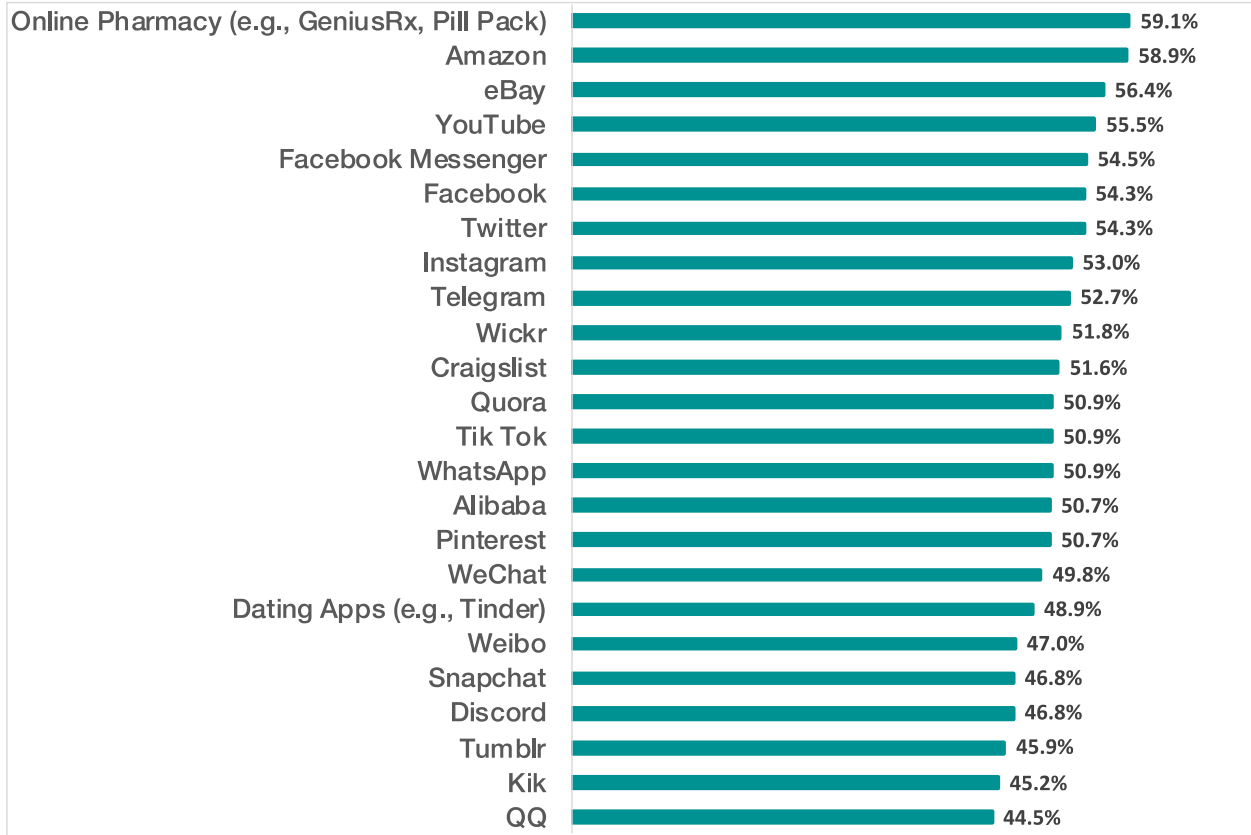
#### 14 *Online platforms - perceptions & behaviors*

15 When evaluating safety perceptions of platforms, online pharmacies (59%) and Amazon (59%)  
16 were most likely to be perceived as safe for purchasing drugs while Kik (45%) and QQ (45%)  
17 (e.g., Kik and QQ and are private messaging applications that could be used to transact in drug  
18 sales) were the least likely as shown in **Figure 3**. **Figure 4** shows that Amazon Pharmacy was  
19 used most often (58%) for ever purchasing a drug or medicine of any kind (including non-  
20 controlled drugs) followed by Instagram (42%) and Facebook (40%). The least used platforms  
21 were Element (9%), Line (9%), Twitch (7%), and Simple Meds (6%).

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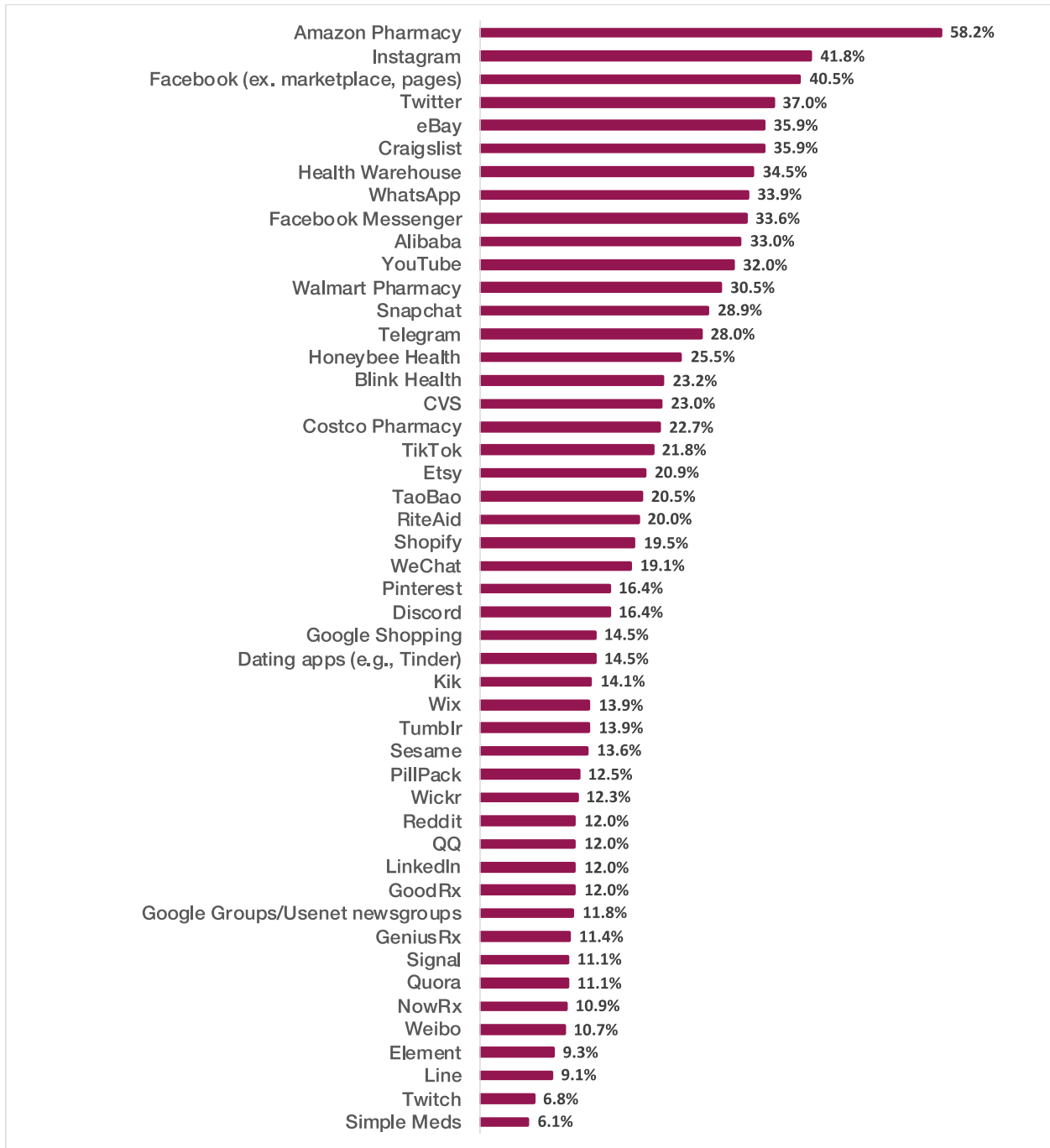
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1 **Figure 3.** Safety Perceptions of Purchasing Drugs and/or Medications from Online Platforms (%  
 2 Rated Safe or Very Safe)  
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1 **Figure 4.** Platforms Used to Purchase Drug or Medicine  
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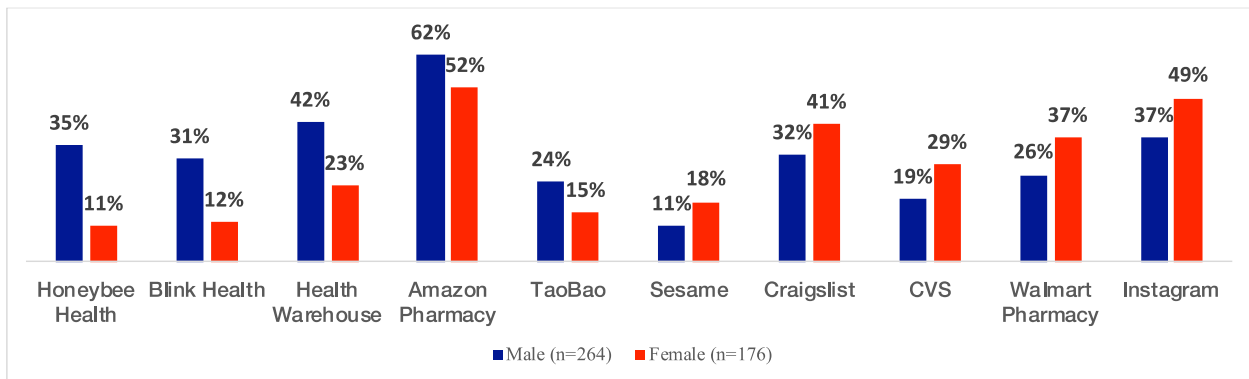
6 There were also demographic differences in platforms used to purchase a drug. As seen  
 7 in **Figure 5**, men were more likely than women to have made a purchase on TaoBao, Amazon



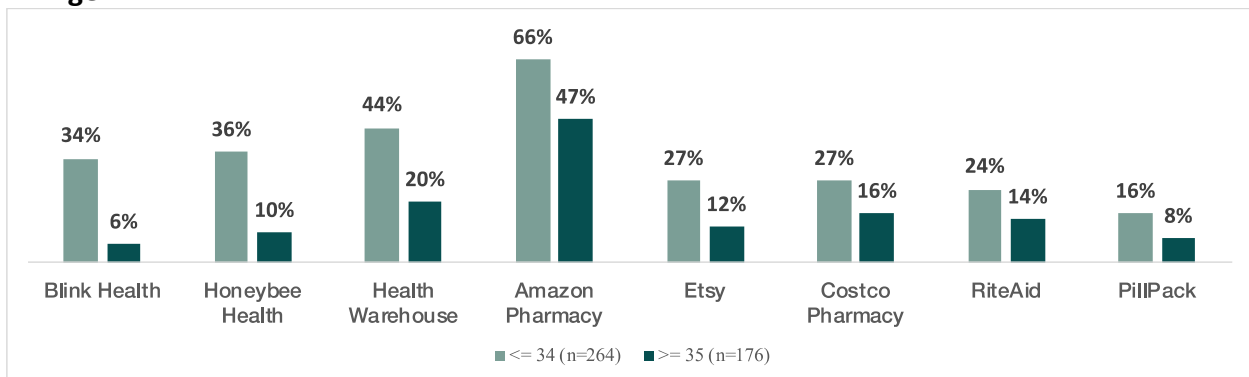
1 Pharmacy, Health Warehouse, Honeybee Health, and Blink Health while women were more  
 2 likely to use Craigslist, Walmart Pharmacy, CVS, Sesame, and Instagram ( $p < .05$ ). Among age  
 3 groups, respondents 34 or younger were more likely to have made a drug purchase on Etsy,  
 4 Amazon Pharmacy, Costco Pharmacy, Health Warehouse, RiteAid, Pillpack, Honeybee Health  
 5 ( $p < .05$ ) compared to respondents 35 or older. There were no platforms that were more likely to  
 6 be used by older respondents that showed a statistically significant difference. For income, those  
 7 who earned \$60,000 or higher were more likely to ever purchase a drug on Alibaba, Walmart  
 8 Pharmacy, Costco Pharmacy, CVS, Facebook, and Twitter compared to those who earned less  
 9 than \$60,000 ( $p < .05$ ). There were no platforms that lower income respondents used more often  
 10 than those with higher incomes.

11 **Figure 5.** Significant Differences ( $p < .05$ ) in Drug Purchasing Platforms by Gender, Age, and  
 12 Income

13  
 14 **A - Gender**



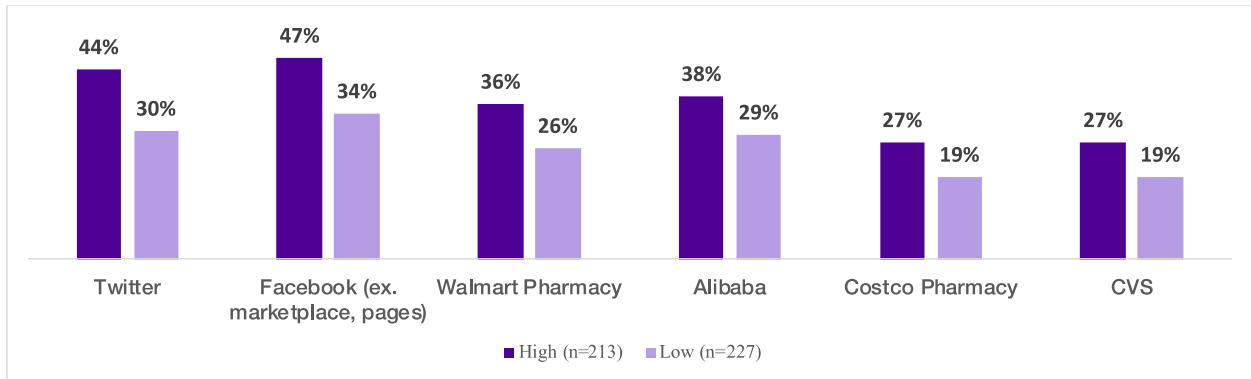
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 17 **B - Age**



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### C - Income



### Conjoint analysis

As shown in **Table 2**, packaging was ranked the most influential tested attribute by a large margin (Avg importance = 43.68, SD = 20.48). Of the different packaging options tested, posts that include drugs displayed in official pill bottles were assessed as the most safe (Avg utility (AU) = 53.93, SD = 94.29). For the other tested attributes, posts were assessed as safer if they advertised multiple drugs compared to only one type of drug (AU = 1.53, SD = 46.80), had a blank profile compared to having an animated face as a profile (AU = 6.25, SD = 43.06), included payment info compared to not having payment info (AU = 4.73, SD = 44.86), and included emojis compared to not having emojis (AU = 3.35, SD = 44.57). Additional comparisons were made assessing if average utility scores for attributes and levels differed based on demographics for gender, age, and income. However, average utility scores remained consistent across all tested sub-groups, indicating that safety evaluations of post features were weighted the same regardless of these relevant demographic differences.

**Table 2.** Average importance scores and utility scores (zero-centered diffs) for tested attributes and levels.

1

<i>Attribute</i>	<i>Average Importances (Std Dev)</i>	<i>Levels</i>	<i>Average Utilities (Std Dev)</i>
Packaging	43.68 (20.48)	Drug is displayed as pills with hand	-13.32 (85.91)
		<b>Drug is displayed in official packaging</b>	<b>53.93</b> <b>(94.29)</b>
		No picture of supplies (Blank White/Gray)	-40.61 (105.28)
Offerings	14.94 (11.28)	Advertises only one type of drug (Adderall)	-1.53 (46.80)
		<b>Advertises multiple types of drugs</b>	<b>1.53</b> <b>(46.80)</b>
Profile	13.86 (10.50)	Human face (animated)	-6.25 (43.06)
		<b>Blank profile</b>	<b>6.25</b> <b>(43.06)</b>
Payment	14.11 (11.23)	No payment info	-4.73 (44.86)
		<b>Mentions payment methods (Venmo, paypal, BtC)</b>	<b>4.73</b> <b>(44.86)</b>
Emojis	13.41 (11.81)	<b>Includes emojis</b>	<b>3.35</b> <b>(44.57)</b>
		Does not include emojis	-3.35 (44.57)

2 *Note: Bold* indicates the level with the higher utility score within the attribute

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7 *Platform perceptions and conjoint*

8 Count variables were calculated to measure: the number of online platforms that participants

9 rated as “Safe” or “Very safe,” the number of online platforms that participants have ever

10 purchased drugs or medication from, and the number of hypothetical posts from the conjoint task

11 that were rated with at least 4 “Probably would be safe.” As seen in **Table 3**, 12.3 platforms on

12 average (sd=8.1) out of 24 were perceived as safe, 10.1 platforms on average (sd=10.2) were

1 used to make a drug purchase, and 12.4 posts on average (sd=5.8) out of 21 from the conjoint  
 2 task were rated as safe by participants. Female participants on average perceived a greater  
 3 number of platforms as safe (14.1) compared to males (11.1), and this difference was significant  
 4 ( $p<.001$ ). Further, female participants tended to purchase from a greater number of platforms  
 5 (10.7) compared to males (9.7,  $p<.05$ ). Younger participants on average perceived a greater  
 6 number of hypothetical social media posts as safe for purchasing drugs (13.6) compared to older  
 7 participants (10.6,  $p<.001$ ). Younger participants also tended to purchase drugs on a higher  
 8 number of online platforms (11.1) compared to those 35 and older (8.6,  $p<.01$ ). In comparison to  
 9 participants with low income, high income participants were more likely to rate a greater number  
 10 of social media posts as safe (13.3 vs 11.8,  $p<.01$ ), perceive more platforms as safe (13.4 vs 11.5,  
 11  $p<.05$ ), and tend to purchase drugs on a higher number of platforms (11.0 vs 9.3,  $p<.05$ ).

12

13 **Table 3.** Mean Comparisons of Platform and Post Perceptions by Gender, Age, and Income.  
 14

Count variables (Range)	Overall (Std Dev)	Gender		Age		Income	
		Male (n=264)	Female (n=176)	$\leq 34$ (n=264)	$\geq 35$ (n=176)	High (n=213)	Low (n=227)
Conjoint Safe Count (0-21)	12.4 (5.8)	12.6	12.1	<b>13.6***</b>	10.6	<b>13.3**</b>	11.8
Platform Safe Count (0-24)	12.3 (8.1)	11.1	<b>14.1***</b>	12.7	11.8	<b>13.4*</b>	11.5
Platform Purchase Count (0-48)	10.1 (10.2)	9.7	<b>10.7*</b>	<b>11.1**</b>	8.6	<b>11.0*</b>	9.3

15 Note: Statistically significant differences from Mann-Whitney Test are **bolded** and marked as \* =  $p<.05$ , \*\* =  
 16  $p<.01$ , \*\*\* =  $p<.001$

17

18

1           Lastly, correlations were run to examine associations between perceptions and  
2 purchasing across online platforms with safety evaluations of drug-selling social media posts  
3 from the conjoint exercise. Spearman's rho was used since the tested variables are not normally  
4 distributed as shown in a Shapiro-Wilk test ( $W_{\text{Conjoint}} = .954, p < .001$ ;  $W_{\text{PlatformS}} = .923, p < .001$ ;  
5  $W_{\text{PlatformP}} = .819, p < .001$ ). Analysis shows that the number of platforms perceived as safe is  
6 moderately correlated with number of platforms purchased from (.41) and the number of social  
7 media posts perceived as safe (.31), and these effects are highly significant ( $p < .001$ ). The number  
8 of platforms ever purchased from and number of hypothetical posts perceived as safe also show a  
9 small but significant correlation (.11,  $p < .05$ ). These results increase confidence in the safety  
10 ratings from the conjoint exercise since they are correlated with platform safety perceptions, and  
11 indicate that safety perceptions and purchasing behavior are associated but still have distinct  
12 variance.

13

## 14 **Discussion**

15 This study examines drug purchasing behaviors across several online platforms and  
16 experimentally tested attributes of drug-advertising social media posts to assess which features  
17 convey perceptions of safety. Consistent with previous work (Moureaud et al., 2021), online  
18 pharmacies and Amazon were assessed as most safe for purchasing drugs. This indicates that the  
19 general category of online pharmacies, which includes legitimate licensed pharmacies and illegal  
20 "rogue" cyberpharmacies, were generally deemed the most safe by participants, followed by the  
21 world's largest e-commerce marketplace (i.e., Amazon) that is also becoming more invested in  
22 telepharmacy (Mackey & Nayyar, 2016). This despite estimates that 96% of online pharmacies  
23 fail to adhere to legal and safety requirements (Mackey, 2018). Among the most popular

1 platforms used to purchase drugs from were SNS such as Instagram, Facebook, Twitter, and  
2 messaging platforms such as WhatsApp. The common use of platforms that are most directly  
3 tied to personal relationships that extend offline and the less frequent use of sites where real life  
4 identity can be anonymous (e.g., Reddit, Tumblr) suggests that social relationships may still be a  
5 contributing factor for facilitating drug sales transactions within online environments. It is  
6 possible that public platforms and personal messaging apps may be used to facilitate transactions  
7 between people who may already know each other or who have mutual network connections. In  
8 contrast, the information forager framework may be more applicable to virtual spaces where  
9 users do not know each other in any other context, which increases the importance of post cues  
10 that signal credibility. These platforms may be used when certain drugs are out of reach within a  
11 user's personal network and could increase risk associated with the transaction.

12         Several demographic differences were detected as well when comparing safety  
13 perceptions and purchasing behavior. For gender, female participants on average perceived a  
14 greater number of platforms as safe for drug purchasing and were more likely to have purchased  
15 from a platform compared to males. When examining specific platforms used for drug  
16 purchasing, men were more likely to use online pharmacies such as Honeybee Health or Health  
17 Warehouse. Women also showed a preference for online pharmacies (e.g., Walmart Pharmacy,  
18 CVS), and were more likely to purchase from social networking sites (SNS) such as Instagram  
19 and Craigslist. However, there were no significant differences in safety perceptions when  
20 evaluating drug-selling social media posts, suggesting that differences in safety perceptions  
21 between genders is influenced more by environmental factors of online spaces such as features  
22 associated with a given platform. These findings are inconsistent with older work showing that  
23 females tend to perceive greater risk associated with drug use (Spigner et al., 1993). However,

1 the higher safety perceptions among females observed in the current study may be partly driven  
2 by the sample, which was screened for previous drug use, and also associated with effects  
3 showing that females tend to be more active on social networking sites (Kimbrough et al., 2013;  
4 Twenge & Martin, 2020) that could subsequently increase comfort with initiating online  
5 transactions.

6         When assessing age, younger participants were more likely to perceive a higher number  
7 of social media posts as safe and had purchased from a greater number of platforms compared to  
8 participants 35 and older, which is consistent with previous work (Fittler et al., 2018; van der  
9 Sanden et al., 2021). Younger participants were also more likely to use online pharmacies for  
10 drug purchasing than older participants. These differences in safety perceptions may be due to  
11 the greater comfort or familiarity that younger people have with technology and the internet,  
12 which can lead to a higher likelihood of making online purchases regardless of it being drug-  
13 related. Income also showed a notable influence on engagement with online drug purchasing.  
14 Those with high income perceived more posts and platforms as safe and have purchased drugs  
15 on a greater number of platforms compared to those with lower income. This effect may be  
16 attributed to the fact that those with higher income are more likely to have disposable earnings  
17 that can be used for purchasing specific classes of drugs or engage in online purchasing behavior.  
18 High income participants also showed a greater tendency than those with low income to purchase  
19 drugs from both online pharmacies such as Walmart Pharmacy and SNS such as Twitter and  
20 Facebook. These findings are inconsistent with previous work showing that those with low  
21 income are more likely to purchase prescription medicine outside of the US (Hong et al., 2020).  
22 However, this discrepancy may be due to a greater inclination among those with higher income  
23 to use online platforms and legitimate companies for domestic drug purchasing.

1           Of all 5 tested attributes in the conjoint exercise, packaging was ranked the most  
2 influential by a large margin with the most preferred level being drugs displayed in official pill  
3 bottles followed by pills being held in a hand. Not including a picture of the supplies was the  
4 least preferred level. The average importance for the remaining attributes do not differ by more  
5 than 1-2 points, indicating that those attributes are weighted similarly when evaluating post  
6 safety. The higher average utility scores for packaging compared to all other attributes and the  
7 higher preference for levels with visible drugs indicate that respondents place heavier importance  
8 on the visual display of drug supplies when evaluating the safety of making a potential purchase  
9 via a social media source. Additionally, the higher scores for packaging remains consistent in  
10 sub-group comparisons based on demographics (gender, age, income) indicating that the  
11 importance of the visual display of drug supplies is robust across relevant factors. The greater  
12 safety perceptions of displays with official packaging may be due to pill bottles conveying higher  
13 credibility by allowing the user to see the purported supplies before making a purchase and  
14 diminish concerns about counterfeits, or may assure users that the seller has possession of  
15 product and is less likely to be an online scammer. Since posts with visual displays of drugs are  
16 perceived as safer for making a purchase, moderation interventions should particularly target  
17 posts that include images using tools such as image recognition software and deep learning  
18 approaches to identify specific controlled drug supplies that are illegal to purchase online,  
19 whether as pills or in prescription packaging.

20           For the offerings attribute, the level with multiple advertised drugs scored higher than  
21 only advertising one drug. This suggests that users may perceive dealers who offer multiple  
22 types of drugs as more safe or credible due to having a larger inventory. Users may also be  
23 conflating this perception with legitimacy, believing that a seller with multiple drug offerings is



1 more likely to not be a scammer or a seller who does not actually possess drugs for sale (e.g.,  
2 non-delivery scheme). This finding may reflect lack of awareness among online users on the  
3 basis that legitimate manufacturers, suppliers, and dispensers do not advertise multiple drug  
4 products in social media posts for purchase and that prescription-controlled substances cannot be  
5 sold online. Future research should examine how altering combinations of drug types offered in  
6 posts can influence safety and legitimacy perceptions.

7 For the profile attribute, having a blank profile photo scored higher than a profile with an  
8 animated face. Due to the discretionary and covert nature of online drug transactions,  
9 respondents may feel more at ease with explicit displays of anonymity that can also lessen the  
10 risk of getting caught by authorities. When comparing levels for the payment attribute, including  
11 payment information was perceived as safer than not including. While providing payment  
12 methods increases the risk of getting caught by authorities, the inclusion of payment information  
13 could further signal that the dealer is an established seller, therefore increasing user trust. This is  
14 similarly an area in need of additional consumer education, as purchasing drugs online using  
15 payment processors such as Venmo and Paypal or cryptocurrencies (e.g., Bitcoin) indicates high  
16 risk of illegal sale.

17 Lastly, the level for including emojis had a higher utility score than the level for not  
18 including emojis. Recent work has shown that authors of messages (both bots and humans) that  
19 use emojis are rated higher in social attractiveness, competence, and credibility compared to  
20 authors of text-only messages (Beattie et al., 2020). The addition of emojis in a drug-advertising  
21 post might signal to users that the post's author is more relatable and less likely to be a bot,  
22 which can subsequently influence safety assessment. Online drug dealers share similar  
23 perceptions as emojis are frequently used to advertise drugs across platforms (McCulloch &

1 Furlong, 2019) and effective use of emojis can be viewed as a sign of professionalism (Demant  
2 et al., 2019).

3

#### 4 ***Limitations***

5 There are notable limitations concerning the current study. First, lack of education and awareness  
6 among consumers and the general public regarding what drugs are legal to purchase online, what  
7 online sources are legal versus those that are illicit, and what constitutes nonmedical or  
8 recreational use, has the potential to bias our sample. Further, as typical with conjoint analysis,  
9 using hypothetical social media posts makes the tested attributes dependent on the researcher's  
10 decisions. Therefore, it is possible that we did not test all relevant features of social media posts  
11 related to safety perceptions. Results from conjoint analysis are also dependent on the prompt  
12 used in the task, as different elicitation formats can influence estimations of utility scores. While  
13 the present study focused on safety evaluations, follow-up research should examine prompts that  
14 measure related perceptual dimensions to drug purchasing such as trust and credibility of the post  
15 author, product legitimacy, and likelihood to purchase, which would generate more nuanced  
16 insights into the types of information scents transmitted by a post. Additionally, this study only  
17 tested one type of drug (Adderall, which is a controlled substance) against multiple types of  
18 drugs in the offering attribute, however, it is likely that these results are influenced by the type of  
19 drug used for the single drug offering. Lastly, importance scores in conjoint analysis are  
20 influenced by the number of levels included within tested attributes. While in the current study  
21 packaging showed a higher margin of importance, the higher ranking may be partly due to  
22 having one more level than the other tested attributes.

23

1 *Future directions and concluding remarks*

2 The use of conjoint analysis to test user perceptions of social media posts can aid public health  
3 interventions such as identifying which posts to prioritize for platform targeting and removal.  
4 More specifically, these results can be used to develop metrics that score posts based on how  
5 many high ranked features it contains from the conjoint exercise (e.g., posts containing pills in  
6 bottles with emojis and payment information) which can guide content moderation, development  
7 of algorithmic classification systems for prohibited content, and assist the operation of platform  
8 safety teams by identifying posts that are more likely to elicit a sales transaction associated with  
9 online drug sourcing. These more targeted approaches could better enable digital harm reduction  
10 by prioritizing removal of posts and accounts that are likely harmful to users.

11 While the current study only tested attributes of hypothetical Instagram posts, future  
12 work using a conjoint design should consider how other platforms and platform-specific features  
13 can influence the information scents of posts. Previous work already shows that differences in  
14 virtual environments can influence how drugs are advertised online. For example, sites with  
15 higher word count limits (e.g., Tumblr) had higher concentrations of drug mentions per post and  
16 higher variety of drug type mentions compared to platforms limited to shorter message lengths  
17 such as Twitter (Haupt et al., 2022). It is also likely that advertising strategies from dealers will  
18 adapt to platforms featuring video content such as TikTok. In response, conjoint analysis can be  
19 adapted to test how cues that signal safety and credibility for video stimuli differ from written  
20 text posts.

21 The nature of drug purchasing within virtual environments is complex where both the  
22 attributes of a post itself and the platform that it resides on influences how users evaluate the  
23 safety of a potential transaction. Designing effective solutions for platforms is further

1 complicated when accounting for differences in legal status of drugs across countries and  
2 jurisdictions (Fuller et al., 2023). As demonstrated in the current study, approaches such as  
3 conjoint analysis can account for some of these complexities and shed light on the risk  
4 evaluations of potential drug purchasers. Most importantly, understanding which features of  
5 social media posts signal safety for an otherwise high-risk transaction can inform interventions  
6 that make online spaces less accessible for conducting illicit drug sales and aide in addressing the  
7 ongoing opioid crisis in the US that challenges both communities and digital spaces.

8

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12

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23

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