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Research Paper

The relationship between cryptomarket drug purchase, social networks and adverse drug events: A cross-sectional study

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ABSTRACT

Introduction: Drug use and trading are typically social activities; however, supply through cryptomarkets can occur without any in-person social contact. People who use drugs alone may be at higher risk of experiencing harms, for example, due to lack of others who may call for emergency assistance. Alternatively, cryptomarkets may be a source of harm reduction information and drugs with better-known content and dose, potentially reducing the risk of adverse events. This study examines relationships between cryptomarket use, drug-using social networks and adverse drug events for MDMA, cocaine and LSD.

Method: A subsample of 23,053 respondents from over 70 countries was collected in the 2018 Global Drug Survey. People who reported using MDMA, cocaine or LSD were asked about using cryptomarkets to purchase these drugs; any adverse drug events requiring medical treatment (combining seeking treatment and should have sought treatment but did not); and social networks who they had used the specific drug with. All measures referred to the last 12 months, hereon referred to as 'recent'. Binary logistic regressions examined relationships between cryptomarket use, drug-using social networks, and adverse drug events, controlling for age, gender, and frequency of drug use.

Results: Adverse events from any drug type were low (5.2%) and for each drug; MDMA (3.5%); cocaine (3.3%); and LSD (3.5%). After controlling for covariates, recent cryptomarket use was associated with increased likelihood of having no drug-using network for each drug type. People who recently used cryptomarkets were more likely to report adverse cocaine (AOR = 1.70 (1.22-2.37)) and LSD (AOR = 1.58 (1.12-2.09)) events. For those reporting a network size >1, network characteristics did not differ with recent cryptomarket use; however, those reporting recent cryptomarket use were more likely to report adverse LSD events (AOR = 1.86 (0.99-3.51)).

Conclusion: People who reported purchasing drugs from cryptomarkets more commonly reported having no drug-using network, and cryptomarket purchase was associated with reported adverse events. Our results support the notion that cryptomarket use increases drug-related harm, but further disentanglement of multiple complex mechanisms is needed in future research.

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Introduction

Cryptomarkets are online marketplaces hosting multiple vendors that provide anonymity via their location on the hidden web and use of cryptocurrencies for payment, and aggregate and display customer feedback ratings and comments (Barratt & Aldridge, 2016). Illegal drugs are the most common products sold and purchased on cryptomarkets (Christin, 2013; Christin & Thomas, 2019). The relationship between cryptomarket drug purchase and risk of drug-related harm is complex. Cryptomarkets have mechanisms that may increase or reduce drug-related harm. Aldridge, Stevens and Barratt (2018) outline ways harm can increase, including an increase in the amount and range of substances available, as well as possible decreases in harm, with access to harm reduction information and discussion forums. Martin (2014) has argued that cryptomarkets may have protective features (e.g. feedback systems and discussion forums) that reduce the likelihood of adverse drug events. The feedback system characteristic of cryptomarkets allows people to better assess the potential quality of the drugs they intend to purchase. The reviews are reported by other customers via star rating systems and/or open feedback similar to legal online marketplaces with five stars being the best. It is this feedback mechanism that serves to inform people who use cryptomarkets to judge products sold by a vendor (Christin, 2013; Van Hout & Bingham, 2013). Barratt and Aldridge argued that cryptomarkets may reduce harm through this feedback system (a proxy for quality control), as vendors would be incentivised to sell drugs with fewer and/or less harmful adulterants.

The discussion forums that are built into cryptomarket platforms similarly have the potential to reduce drug harm. Bancroft and Reid (2016) analysed discussions on cryptomarkets around safer drug use and drug quality. Interestingly, unlike face-to-face drug transactions, people who use cryptomarkets were forthright in questioning the strength and adulteration of drugs sold by a vendor and pressed vendors to justify their claims. Open discussions as such, may incentivise cryptomarket vendors to offer accurate information about the content and purity of the substances they sell.

Drug use is typically social, however the nature of cryptomarkets may promote solitary drug use, as cryptomarkets enable the possibility of accessing drugs without social contacts. While no representative studies have been undertaken, qualitative interviews have identified people who use cryptomarkets that report commonly using drugs alone (Barratt, Lenton, Maddox, & Allen, 2016). People who use drugs alone may be at heightened risk of acute drug-related harm as a result of consuming products with unknown content and purity. However, the main factors that increase drug-related harm are excessive use and co-use of multiple psychoactive substances. One of the most common pieces of advice given to people who use drugs as a harm reduction message is to not use drugs alone (Dietze, Jolley, Fry, Bammer, & Moore, 2006; Moore, 2004). The primary reason for this caution is that emergency services can be sought in case of an adverse drug event (Dietze et al., 2006; Moore, 2004). With no one nearby to make an emergency call, the person in need of emergency services may not be able to make that call due to an impaired ability (e.g., due to intoxication) potentially exacerbating harms. Having someone present allows that person to directly provide assistance or call for emergency services in the case of an adverse drug event. If cryptomarket users are more likely to use drugs alone they may be less able to follow this advice. Inherent in the transactional platform, drug procurement on cryptomarkets does not require social interactions, and consequently, it is possible that some people who use cryptomarkets may be more prone to using drugs alone.

Social networks

Research investigating the influence of social networks on drug use is mixed. On one hand there is a relationship between the number of connections an individual has and illegal drug use, such that more connections (i.e., higher number of people in their social network) has been associated with a higher likelihood of drug use (Alexander, Piazza, Mekos, & Valente, 2001; Haynie, 2001). Conversely, studies indicate that isolated individuals are more likely to engage in substance use (Ennett & Bauman, 1994; Pearson & Michell, 2000). Further, a U shape distribution has been proposed for the number of connections an individual has and their drug use (Mercken, Snijders, Steglich, & de Vries, 2009). That is, drug use was common in adolescents who had a high number of friendships relative to their peers, but also in adolescents who were isolated. Furthermore, simply measuring the number of connections an individual has may not adequately characterise the possible network effects. Social Network Analysis (SNA) is an increasingly utilised method adopted by researchers to analyse social structures. An example of how SNA provided insight into the nuances of peer influence was demonstrated by Haynie (2001) in an investigation of the role of peers in delinquent behaviour. Haynie indicated that the number of friends an individual had engaged in antisocial behaviour was not as important as their role and location in the individual's network. Therefore, it was the individual's network characteristics that were predictive of delinquency rather than the number of relationships with those engaging in antisocial behaviour.

The concept of structural holes (Burt, 1992) is important in social network analysis. It describes the lack of connection among individuals (individuals are 'nodes' in SNA parlance') in a network. Structural holes are in essence the empty spaces within a network with missing links between nodes. Structural holes have been posited by Burt to facilitate social capital (resources accessed through social connections) when an individual bridges the gap between two otherwise disconnected individuals. According to Burt, by acting as a broker over structural holes and forming new connections with nodes, access to knowledge can be gained. Further, Coleman (1988) and Granovetter (1983) suggested that network closure (dense networks without structural holes) would in fact foster better access to information. The networks of people who use cryptomarkets may have more structural holes if people use drugs alone. In addition, if people do not actively seek information about the drugs online, structural holes could result in a lack of access to relevant information on safer drug use.

Social networks and harm

Whether drug use results in harm is dependent on a myriad of factors from patterns of use, personal vulnerability and environment (including social context and function) of use. The relationship between social networks and drug-related harm is not well documented. Studies on solitary drug use are predominantly focused on alcohol and cannabis. Solitary alcohol use tends to be associated with problematic use (Keough, O'Connor, Sherry, & Stewart, 2015) and negative outcomes such as depression (Christiansen, Vik, & Jarchow, 2002; Cooper, Russell, Skinner, & Windle, 1992). Similarly, solitary cannabis use tends to be associated with problematic cannabis use such as emotion-focused coping (Creswell, Chung, Clark, & Martin, 2015; Spinella, Stewart, & Barrett, 2019; Tucker, Ellickson, Collins, & Klein, 2006). An argument advanced by Cooper et al. (1992) was that solitary drug use could lead to excessive and harmful consumption due to the lack of comparison with other people who use drugs.

Using drugs with others may be safer, subject to peer influence. Several studies showed that an individual's drug use is often linked to their immediate social environment: parents who use drugs (Brook, Richter, Whiteman, & Cohen, 1999; Etz, Robertson, & Ashery, 1998), siblings who use drugs (Brook, Balka, & Whiteman, 1999; Stormshak, Comeau, & Shepard, 2004), as well as peers who use drugs (Brook, Brook, Arencibia-Mireles, Richter, & Whiteman, 2001; Macleod et al., 2004). Additionally, Bahr, Hoffmann, and Yang (2005) showed that peer drug use was the strongest predictor of adolescent drug use (but not necessarily the pattern of use) beyond psychosocial factors such as attachment and parental monitoring. These studies indicate that norms formed by close social ties play a significant role in drug use. The literature suggests the presence and characteristics of physical social networks are influential factors in drug-related harms.

Social networks play a significant role in the operation and structure of cryptomarket drug markets, influencing the production of user-generated content, and the diffusion of information. Duxbury and Haynie (2021) found that the position of an individual within a network impacts the likelihood of generating content on cryptomarkets. 'Furthermore, Duxbury and Haynie (2017a) reveal that information about drug cryptomarkets is disseminated through both online and offline networks, with the structure of these networks affecting the speed and extent of information diffusion. In another study, Duxbury and Haynie argue that drug cryptomarkets are not as decentralised as they may seem (Duxbury & Haynie, 2017b). Instead, a few highly connected individuals significantly influence their operation, suggesting a degree of centralisation (Duxbury & Haynie, 2017b). Duxbury (2018) further notes the role of social ties in their operation. These studies collectively underscore the importance of social network analysis in understanding the functioning and structure of darknet drug markets.

Cryptomarkets may facilitate solitary drug use that could lead to a greater risk of adverse drug events for people who use cryptomarkets. It is theorised that purchasing drugs in person may lead to more social drug use due to the interpersonal nature of the transaction (Werse et al., 2019). Interactions with people who use and/or sell drugs might encourage individuals to use drugs in social settings, as they could be introduced to new drug-using peers or be influenced by the social norms of their existing network. In contrast, online drug purchases may lack this norm-forming role, potentially contributing to increased solitary drug use and associated risks.

An important distinction to note in this study is the difference between the individual's physical world social network of peers who use drugs and the digitally facilitated social network represented by the cryptomarket. While this study focuses on the former, the literature shows that the latter also plays a significant role in drug use behaviours and outcomes (Bancroft & Reid, 2016). Cryptomarkets, as a digitally facilitated network, provide a platform for consumers to share information, experiences, and advice, potentially offering a form of safety and harm reduction. It is important to acknowledge the dual nature of these networks and their potential implications for understanding drug use and harm.

Aims

The current study aimed to investigate whether people who access cryptomarkets engage more in drug use without a drug-using network than others. It also investigated whether this linked to more adverse events and how these relate to social networks, among a global sample of people who reported using at least one of three drugs in the last 12 months: MDMA, cocaine, and LSD. Analyses were conducted on overall drug use (composite of MDMA, cocaine and LSD) and each of these drugs separately. This is one of the largest, transnational efforts to collect social network data among drug-using populations.

It was hypothesised that:

H1 – When comparing people reporting no recent drug-using network to those reporting any recent drug-using network:

- H1a) There will be significantly more people who report recent purchase of drugs from cryptomarkets reporting no drug-using network than people who do not report recent purchase of drugs from cryptomarkets, after controlling for age, gender, and frequency of drug use in the last 12 months.
- H1b) Having no drug-using network and reporting recent purchase of drugs from cryptomarkets will independently be associated with recent adverse drug events, after controlling for age, gender and frequency of drug use in the last 12 months.

H2 – When comparing the network characteristics of those reporting any drug-using social network (that is, those with no network were excluded from these analyses due to having no social network characteristics):

- H2a) There will be significantly more people who report recent purchase of drugs from cryptomarkets with structural holes in their network than people who do not report recent purchase of drugs from cryptomarkets.
- H2b) Social network characteristics (including structural holes) and the recent purchase of drugs from cryptomarkets will be associated with recent adverse drug events, after controlling for age, gender and frequency of drug use in the last 12 months.

Method

Design & participants

Data collection for the 2018 Global Drug Survey (GDS) occurred between November 8 and December 30, 2017. The Global Drug Survey (GDS) is a large annual cross-sectional online survey of individuals aged 16 years or older who report use or former use of legal and/or illegal drugs, designed to evaluate existing and emerging patterns of substance use. The GDS 2018 was available in 20 languages and individuals in more than 40 countries were invited to participate through extensive collaboration with media partners such as The Guardian, Fairfax media, Mixmag, and global social media networks such as Facebook and Twitter. The GDS uses a non-probabilistic technique, purposive sampling, to recruit its participants (Barratt et al., 2017). The sample for this paper was restricted to people who reported the use of MDMA, cocaine and/or LSD in the last 12 months. These three drug types are the most reported drug types in GDS apart from cannabis, alcohol and tobacco. Cannabis was excluded because of its more varied legal status globally relative to other substances, which may impact use and related harms. To prevent respondent fatigue, participants were asked to complete the social network module only once by selecting one of the three drugs they had most often used in the last 12 months. This study was approved by the University of New South Wales Human Research Ethics Committee (approval number HC17769).

Measures

Cryptomarket use

Participants were asked if they had "Personally purchased drugs through a darknet market for your own consumption?". Response choices included "No", "Yes, in the last 12 months", or "Yes, but not in the last 12 months". Participants were classified as people who use cryptomarkets if they had used the cryptomarket to buy drugs for themselves in the last 12 months.

Adverse drug events

Participants who had used MDMA, cocaine, or LSD in the last 12 months were asked "In the last 12 months have you sought emergency medical treatment following the use of [drug]?". Response format was dichotomous "Yes" or "No". Participants were then asked, "In the last 12 months have you thought you should seek emergency medical treatment following the use of [drug] but did not seek such treatment?". Response format was dichotomous "Yes" or "No". These two items were combined to create an indicator of 'adverse drug events' because in each item there was an adverse drug event, and there was low incidence in each variable (see Appendix A). Participants who responded to at least one item were classified as reporting an adverse drug event whereas participants responding no to both were classified as not reporting an adverse drug event.

Drug-using network size

Participants who reported using MDMA, cocaine, or LSD in the last

12 months were asked, "In the last 12 months how many people do you know by name that you have used [drug] with?". Response format was open and ranged from 0 to 150 with no 'don't know' option possible. Respondents scoring zero were classified as not having a drug-using social network whereas respondents scoring at least one were classified as having a drug-using network.

Network characteristics

For each drug type, participants were asked "In the last 12 months how many people do you know by name that you have used [drug] with?": number of people was used as the degree variable (Marsden, 2002). Participants willing to complete the social network module of the GDS were asked "Which drug have you taken most often in the last 12 months?" with responses including "MDMA", "cocaine", or "LSD". Participants were then asked, "Thinking about the people you have taken [drug] with most often in the last 12 months, choose up to five of these people and make up a nickname for each one". Based on their answers, follow up questions included "Has person 1 taken [drug] with person 2?" "Has person 2 taken [drug] with person 3?" and were presented up to a maximum of five people. A minimum of one "yes" response was required to calculate network characteristics. Responses of "Don't know/unsure" did not inform network characteristics.

Social network variables included degree, Burt's constraint, network efficiency and effective network size. Degree is a measure of the number of connections (alters) than an individual (ego) has (Freeman, 1979). The remaining variables are structural hole measures. Burt's constraint is a measure of how connected alters are to each other (Burt, 1992). An ego is constrained when alters are highly connected and do not rely on the ego to connect to each other. Effective network size is measured by subtracting the average degree of alters from the degree of the ego (Hanneman & Riddle, 2005). The larger the differential, the more structural holes. Efficiency is the effective network size normed by the degree of the ego (Borgatti & Halgin, 2011). Efficiency is a measure of non-redundant connections in the network. A network can be effective (more structural holes) without being efficient (more non-redundant connections). Equally, a network can be non-effective (less structural holes) and be highly efficient (less non-redundant connections). Social network variables degree, Burt's constraint, network efficiency and effective network size were calculated in R using the package *igraph*.

Control variables

Control variables included participants' age (in years), gender (female, male, non-binary and different identity), frequency and type(s) of drug used. Non-binary and different identity were excluded due to low sample size. For this specific section of the survey, participants were asked about their use of MDMA, cocaine, and LSD in the last 12 months. The item pertaining to frequency of drug use was measured by asking participants "During the last 12 months on how many days have you used [drug]?" to record how many days they used the drug in the last 12 months (range 1 to 365).

Analyses

Analyses were conducted for each drug separately and in combination. For hypothesis 1a, four binary logistic regressions were performed to assess the relationship between the presence of a drug using network and cryptomarket use, after controlling for age, gender, and frequency of drug use in the last 12 months. Four binary logistic regressions were conducted to assess the relationship between cryptomarket use, no-drug using network, frequency of drug use, age and gender with adverse drug events, for MDMA, cocaine, LSD combined and separately. For hypothesis 2a, binary logistic regressions were used to determine whether the four social network variables were associated with cryptomarket use for each drug combined and for each drug separately. Further, four binary logistic regressions were conducted among a subset of the sample who reported drug-using networks of two or more people (minimum number to calculate network characteristics) to investigate whether demographics (age and gender), frequency of drug use, social network variables (degree, Burt's constraint, network efficiency and effective network size) and cryptomarket use were associated with adverse drug events for MDMA, cocaine and LSD combined and for each drug separately. All variables were included in the models; however, frequency of drug use was not included in the combined model because it cannot be reasonably combined from the individual drug variables. Missing data are reported in S4 (Appendix C). No imputations were conducted given the risk of introducing bias and reducing variability (Little & Rubin, 2019). Given the occurrence of adverse drug events were rare, countries were analysed together to retain a larger sample size. Software packages R Statistical Software, Stata and IBM Statistics Package for Social Sciences were used. R was used to calculate social network characteristics. Stata was used for logistic regressions examining the associations with adverse drug events using a penalised maximum likelihood estimation (Firthlogit) to reduce bias in examining rare events (Firth, 1993; Leitgöb, 2013). All other analyses were conducted using SPSS version 25. All analyses were read using an alpha level of .05.

Results

Sample characteristics

Adverse events from any drug type were low (5.2%) and for each drug; MDMA (3.5%); cocaine (3.3%); and LSD (3.5%). There were 2,871 people who reported purchasing from cryptomarkets in the last 12 months (recent cryptomarket use) from a sample of 23,380. Of those with recent cryptomarket use, 1,717 (90.2%) reported MDMA use in the last 12 months, 1,016 (80.3%) reported cocaine use in the last 12 months and 1,515 (84.7%) reported LSD use in the last 12 months. Those with recent cryptomarket use also reported 64 adverse MDMA events (3.7%), 48 adverse cocaine events (4.7%), 76 adverse LSD events (5.0%) with a combined 171 adverse drug events overall (7.6% of 2,255, which represents the combined total reporting use of any of the three drugs (MDMA, cocaine, or LSD) and purchase from cryptomarkets). The age of people who reported buying MDMA, cocaine, or LSD on cryptomarkets ($M = 24.24$, $SD = 7.47$; $n = 2{,}871$) was lower than the remaining sample ($M = 28.51$, $SD = 11.54$; $t(3{,}424.38) = 29.30$, $p < .001$; $n = 20{,}182$). People who recently used cryptomarkets were more likely to be male (88.6%, $n = 2{,}544$) compared to the remaining sample (60.4%; $\chi^2(3) = 1{,}024.55$, $p < .001$; $n = 20{,}509$). People who recently used cryptomarkets did not significantly differ to the remaining sample in terms of the number of times they reported using MDMA in the last 12 months ($M = 2.19$, $SD = 3.22$ v $M = 2.18$, $SD = 2.51$), the number of times they reported using cocaine in the last 12 months ($M = 3.93$, $SD = 4.95$ v $M = 3.59$, $SD = 4.41$) or in the number of times they reported using LSD in the last 12 months ($M = 2.30$, $SD = 3.03$ v $M = 2.04$, $SD = 2.68$). The most commonly reported countries were Germany (2,648), United States (695), United Kingdom (662), Denmark (641), Netherlands (490), Poland (432), and Australia (382). Of those reporting MDMA use in the last 12 months, 1,717 (10.1%) used cryptomarkets in the last 12 months; of those reporting cocaine use in the last 12 months, 1,016 (7.7%) used cryptomarkets in the last 12 months; and of those reporting LSD use in the last 12 months, 1,515 (17.2%) used cryptomarkets in the last 12 months. For those in the social network module, descriptive statistics are presented in Table S1 (Appendix A) for overall and by whether people reported social network characteristics for MDMA, cocaine, or LSD. For those in the social network module, descriptive statistics are also presented in Table S2 (Appendix B) for a distribution of responses ("yes", "no", "Don't know/unsure" to "Has person 1 taken [drug] with person 2?" up to "Has person 4 taken [drug] with person 5?"). Additionally, for those in the social network module, the distribution of the number of nominated peers in their drug-using network is also presented in Table S3 (Appendix B).

Table 1
Descriptive statistics and binary logistic regressions examining associations between MDMA, cocaine, and LSD using network with cryptomarket drug purchase after controlling for covariates (age, gender and frequency of drug use) in the last 12 months*.

Recent MDMA use (n=17,097)	No drug-using network % (n=59)	Drug-using network % (n=14,583)	AOR (95% CI)	p
Recent cryptomarket drug purchase	31.0%	9.7%	3.40 (1.91-6.06)	< .001
Female	12.8%	31.7%	2.01 (0.98-4.15)	.058
Frequency MDMA use (median, IQR)	1 (1-2)	1 (1-2)	0.93 (0.88-0.98)	.008
Age (median, IQR)	23 (20-28)	23 (19-29)	0.99 (0.95-1.03)	.712
Recent cocaine use (n=13,245)	**No drug-using network % (n=79)**	**Drug-using network % (n=11,159)**	**AOR (95% CI)**	**p**
Recent cryptomarket drug purchase	22.8%	7.5%	3.66 (2.15-6.22)	< .001
Female	18.1%	30.2%	1.34 (0.77-2.32)	.304
Frequency of use (median, IQR)	2 (1-4)	1.5 (1-4)	0.86 (0.80-0.92)	< .001
Age (median, IQR)	24 (21-30)	24 (20-32)	0.96 (0.92-1.00)	.039
Recent LSD use (n=8,841)	**No drug-using network % (n=160)**	**Drug-using network % (n=6,672)**	**AOR (95% CI)**	**p**
Recent cryptomarket drug purchase	32.2%	16.9%	2.39 (1.68-3.41)	< .001
Female	10.4%	23.1%	2.05 (1.26-3.33)	.004
Frequency of use (median, IQR)	1 (1-2)	1 (1-2)	0.95 (0.93-0.98)	.002
Age (median, IQR)	22 (19-27)	23 (19-29)	1.03 (1.01-1.05)	.011

H1 – Drug-using network vs no drug-using network

H1a) Relationship between drug-using network and cryptomarket use

Four binary logistic regressions were conducted to examine the relationships between cryptomarket use, frequency of drug use, age, and gender with the presence of a drug-using network for MDMA, cocaine, LSD, combined and separately. The results are shown in Table 1 below. For MDMA use, recent cryptomarket drug purchase was associated with 3.40 (95% CI: 1.91-6.06) times higher odds of being in a drug-using network. Each unit increase in frequency of MDMA use was associated with 0.93 (95% CI: 0.88-0.98) times lower odds of being in a drug-using network. For cocaine use, recent cryptomarket drug purchase was associated with 3.66 (95% CI: 2.15-6.22) times higher odds of being in a drug-using network. Each unit increase in frequency of cocaine use was associated with 0.86 (95% CI: 0.80-0.92) times lower odds of being in a drug-using network, and each year increase in age was associated with 0.96 (95% CI: 0.92-1.00) times lower odds of being in a drug-using network. For LSD use, recent cryptomarket drug purchase was associated with 2.39 (95% CI: 1.68-3.41) times higher odds of being in a drug-using network. Being female was associated with 2.05 (95% CI: 1.26-3.33) times higher odds of being in a drug-using network. Each unit increase in frequency of LSD use was associated with 0.95 (95% CI: 0.93-0.98) times lower odds of being in a drug-using network, and each year increase in age was associated with 1.03 (95% CI: 1.01-1.05) times higher odds of being in a drug-using network.

H1b) No drug-using network and cryptomarket use associated with adverse drug events after controlling for covariates (age, gender and frequency of drug use (n=23,053))

Four binary logistic regressions were conducted to examine the relationships between cryptomarket use, the presence of a drug-using network, frequency of drug use, age and gender with adverse drug events, for MDMA, cocaine, LSD, combined and separately. The results are shown in Table 2 below. For combined adverse drug events, being female was associated with 1.50 (95% CI: 1.32-1.96) times higher odds of experiencing an adverse event, and each year increase in age was associated with 0.95 (95% CI: 0.94-0.96) times lower odds of experiencing an adverse event. For adverse MDMA events, being female was associated with 1.76 (95% CI: 1.48-2.09) times higher odds of experiencing an adverse event, each unit increase in frequency of MDMA use was associated with 1.02 (95% CI: 1.01-1.02) times higher odds of experiencing an adverse event, and each year increase in age was associated with 0.91 (95% CI: 0.89-0.92) times lower odds of experiencing an adverse event. For adverse cocaine events, recent cryptomarket drug purchase was associated with 1.70 (95% CI: 1.22-2.37) times higher odds of experiencing an adverse event, being female was associated with 1.54 (95% CI: 1.24-1.92) times higher odds of experiencing an adverse event, each unit increase in frequency of use was associated with 1.01 (95% CI: 1.01-1.01) times higher odds of experiencing an adverse event, and each year increase in age was associated with 0.98 (95% CI: 0.97-1.00) times lower odds of experiencing an adverse event. For adverse LSD events, recent cryptomarket drug purchase was associated with 1.58 (95% CI: 1.12-2.09) times higher odds of experiencing an adverse event, each unit increase in frequency of use was associated with 1.01 (95% CI: 1.00-1.01) times higher odds of experiencing an adverse event, and each year increase in age was associated with 0.91 (95% CI: 0.88-0.93) times lower odds of experiencing an adverse event.

H2 – Drug-using network characteristics among a subset of the sample who reported drug-using networks of two or more people (n=7,117)

H2a) Drug-using network characteristics and cryptomarket use

Four binary logistic regressions were conducted to examine the relationships between degree, constraint, effective size and network efficiency with cryptomarket use for MDMA, cocaine, and LSD, combined and separately. There were no significant differences in network characteristics between people who used cryptomarkets for drug purchase in the last 12 months and people who had not used cryptomarkets. The results are shown in Table 3 below.

H2b) Drug-using network characteristics and adverse drug events

Four binary logistic regressions were conducted to examine the relationships between cryptomarket use, degree, constraint, effective size, network efficiency, frequency of drug use, age and gender with adverse drug events, for MDMA, cocaine, and LSD, combined and separately. The results are shown in Table 4 below. There were no significant differences in network characteristics for reporting adverse drug events in the last 12 months. For combined adverse drug events, each year increase in age was associated with 0.95 (95% CI: 0.93-0.96) times lower odds of experiencing an adverse event and being female was associated with 1.44 (95% CI: 1.19-1.74) times higher odds of experiencing an adverse event. For adverse MDMA events, each year increase in age was associated with 0.90 (95% CI: 0.87-0.93) times lower odds of experiencing an adverse event, being female was associated with 1.87 (95% CI: 1.36-2.59) times higher odds of experiencing an adverse event, and each unit increase in frequency of drug use was associated with 1.02 (95% CI: 1.01-1.03) times higher odds of experiencing an adverse event. For adverse cocaine events, each year increase in age was associated with 0.97 (95% CI: 0.94-0.99) times lower odds of experiencing an adverse event, being female was associated with 1.61 (95% CI: 1.11-2.36) times higher odds of experiencing an adverse event, and each unit increase in

Table 2
Descriptive statistics and binary logistic regressions examining associations between adverse drug events from MDMA, cocaine, LSD and combined drugs with no drug-using network and cryptomarket drug purchase after controlling for covariates (age, gender and frequency of drug use) in the last 12 months*.

Combined adverse drug events # (n=23,053)	Adverse event % (n=1,204)	No adverse event % (n=21,849)	AOR (95% CI)	p
Recent cryptomarket drug purchase	7.0%	9.3%	0.93 (0.76-1.14)	.465
No drug-using network	5.3%	4.5%	1.19 (0.78-1.83)	.416
Female	36.7%	29.0%	1.50 (1.32-1.96)	< .001
Age (median, IQR)	21 (19-26)	23 (20-29)	0.95 (0.94-0.96)	< .001
Adverse MDMA events (n=16,544)	**Adverse event % (n=579)**	**No adverse event % (n=15,965)**	**AOR (95% CI)**	**p**
Recent cryptomarket drug purchase	10.7%	10.1%	1.18 (0.90-1.57)	.236
No drug-using network	1.2%	1.0%	1.17 (0.55-2.51)	.686
Female	43.9%	31.0%	1.76 (1.48-2.09)	< .001
Frequency MDMA use (median, IQR)	10 (4-20)	5 (2-10)	1.02 (1.01-1.02)	< .001
Age (median, IQR)	20 (18-24)	23 (20-28)	.91 (0.89-0.92)	< .001
Adverse cocaine events (n=12,530)	**Adverse event % (n=384)**	**No adverse event % (n=12,146)**	**AOR (95% CI)**	**p**
Recent cryptomarket drug purchase	11.2%	7.6%	1.70 (1.22-2.37)	.002
No drug-using network	1.7%	0.9%	0.78 (0.37-1.64)	.518
Female	36.5%	29.9%	1.54 (1.24-1.92)	< .001
Frequency of use (median, IQR)	27.50 (10-63.75)	5 (2-12)	1.01 (1.01-1.01)	< .001
Age (median, IQR)	23 (20-30)	24 (21-30)	0.98 (0.97-1.00)	.018
Adverse LSD events (n=8,334)	**Adverse event % (n=284)**	**No adverse event % (n=8,050)**	**AOR (95% CI)**	**p**
Recent cryptomarket drug purchase	24.9%	16.9%	1.58 (1.12-2.09)	.001
No drug-using network	3.7%	3.8%	1.02 (0.63-1.64)	.997
Female	23.9%	22.4%	1.18 (0.88-1.58)	.246
Frequency of use (median, IQR)	4 (2-9.75)	3 (1-6)	1.01 (1.00-1.01)	.001
Age (median, IQR)	20 (18-23)	22 (19-27)	.91 (0.88-0.93)	< .001

Note: All variables were measured over the last 12 months, described here as 'recent'.
* Adverse drug events included reporting seeking emergency medical treatment following the use of a drug and/or needing to seek medical treatment but not actually doing so.
# Frequency of use was not included in the combined drugs regression as it was not able to be calculated accurately.

frequency of drug use was associated with 1.01 (95% CI: 1.01-1.02) times higher odds of experiencing an adverse event. For adverse LSD events, recent cryptomarket drug purchase was associated with 1.86 (95% CI: 0.99-3.51) times higher odds of experiencing an adverse event, and each year increase in age was associated with 0.88 (95% CI: 0.82-0.94) times lower odds of experiencing an adverse event.

Discussion

Recent cryptomarket use was reported by a minority of those recently using MDMA (10.1%), cocaine (7.7%) and LSD (17.2%). Overall, adverse drug events were rare for those with recent cryptomarket use (7.6%) as well as the remaining sample (5.0%). People reporting recent cryptomarket use were more likely to be male, and younger in age compared to the remaining sample. The current study aimed to investigate if people who recently used cryptomarkets were more likely to report an absence of a drug-using network, which was supported for each drug type (H1a). It was also expected that those without a drug-using network and using cryptomarkets would be more likely to report adverse drug events (after controlling for covariates; H1b). This was partially supported with recent cryptomarket use only associated with adverse cocaine and adverse LSD events, but not adverse MDMA events.

Cryptomarkets were associated with a higher likelihood of no drug-

Table 3
Descriptive statistics and binary logistic regressions examining associations between use ofMDMA, cocaine, LSD and combined drugs with cryptomarket drug purchase using network characteristics degree, effective size, efficiency and constraint in the last 12 months.

Combined drugs (n=7,866)	Recent cryptomarket drug purchase (n=491)	No recent cryptomarket drug purchase (n=7,255)	AOR (95% CI)	p
Degree	4.48 (1.00)	4.36 (1.10)	0.84 (0.65-1.10)	.189
Effective size	2.36 (1.21)	2.25 (1.21)	1.06 (0.84-1.35)	.622
Efficiency	0.54 (0.26)	0.54 (0.26)	1.04 (0.30-3.63)	.949
Constraint	0.60 (0.20)	0.62 (0.20)	1.01 (0.39-2.64)	.990
MDMA (n=4,159)	Recent cryptomarket drug purchase (n=356)	No recent cryptomarket drug purchase (n=3,803)	AOR (95% CI)	p
Degree	4.58 (0.86)	4.42 (1.10)	.99 (0.67-1.46)	.930
Effective size	2.30 (1.14)	2.21 (1.19)	.86 (0.60-1.22)	.372
Efficiency	0.51 (0.24)	0.52 (0.26)	1.58 (0.24-10.58)	.622
Constraint	0.60 (0.20)	0.62 (0.19)	1.21 (0.27-5.59)	.809
Cocaine (n=2,148)	Recent cryptomarket drug purchase (n=128)	No recent cryptomarket drug purchase (n=2,020)	AOR (95% CI)	p
Degree	4.66 (0.81)	4.39 (1.10)	.52 (0.25-1.06)	.078
Effective size	2.56 (1.23)	2.26 (1.21)	1.58 (0.81-3.33)	.195
Efficiency	0.56 (0.26)	0.53 (0.26)	.05 (0.01-2.10)	.131
Constraint	0.56 (0.18)	0.61 (0.20)	.11 (0.01-1.43)	.096
LSD (n=1,384)	Recent cryptomarket drug purchase (n=258)	No recent cryptomarket drug purchase (n=1,126)	AOR (95% CI)	p
Degree	4.03 (1.33)	4.11 (1.27)	.88 (0.57-1.35)	.545
Effective size	2.13 (1.16)	2.38 (1.24)	1.32 (0.88-1.99)	.174
Efficiency	0.57 (0.27)	0.60 (0.27)	1.40 (0.19-10.45)	.744
Constraint	0.65 (0.21)	0.62 (0.22)	2.60 (0.56-12.38)	.223

Note: All variables were measured over the last 12 months, described here as 'recent'.

Table 4
Descriptive statistics and binary logistic regressions examining associations between adverse drug events from MDMA, cocaine, LSD and combined drugs with cryptomarket drug purchase, network characteristics degree, effective size, efficiency, and constraint after controlling for covariates (age, gender and frequency of drug use) in the last 12 months*

Combined adverse drug events # (n=7,746)	Adverse event % (n=491)	No adverse event % (n=7,255)	AOR	p
Recent cryptomarket drug purchase	6.8%	5.6%	.75 (0.54-1.05)	.094
Degree (M/SD)	4.48 (1.00)	4.36 (1.10)	1.15 (0.80-1.65)	.458
Constraint (M/SD)	0.60 (0.20)	0.62 (0.20)	1.15 (0.28-4.05)	.931
Effective size (M/SD)	2.36 (1.21)	2.25 (1.21)	.98 (0.69-1.39)	.891
Efficiency (M/SD)	0.54 (0.26)	0.54 (0.26)	1.33 (0.20-8.48)	.766
Age (median, IQR)	21 (19-26)	23 (20-29)	.95 (0.93-0.96)	< .001
Female	47.6%	35.6%	1.44 (1.19-1.74)	< .001
Adverse MDMA events (n=4,074)	**Adverse event % (n=173)**	**No adverse event % (n=3,901)**	**AOR**	**p**
Recent cryptomarket drug purchase	8.4%	8.3%	1.29 (0.71-2.21)	.374
Degree (M/SD)	4.58 (0.86)	4.42 (1.10)	1.06 (0.55-2.04)	.854
Constraint (M/SD)	0.60 (0.20)	0.62 (0.19)	1.89 (0.16-22.99)	.613
Effective size (M/SD)	2.30 (1.14)	2.21 (1.19)	1.14 (0.62-2.24)	.674
Efficiency (M/SD)	0.51 (0.24)	0.52 (0.26)	.79 (0.02-22.39)	.894
Age (median, IQR)	20 (18-24)	23 (20-28)	.90 (0.87-0.93)	< .001
Female	53.8%	37.1%	1.87 (1.36-2.59)	< .001
Frequency of drug use (median, IQR)	12 (6-30)	6 (3-12)	1.02 (1.01-1.03)	< .001
Adverse Cocaine events (n=2,094)	**Adverse event % (n=123)**	**No adverse event % (n=1,971)**	**AOR**	**p**
Recent cryptomarket drug purchase	7.4%	5.6%	1.20 (0.56-2.40)	.619
Degree (M/SD)	4.66 (0.81)	4.39 (1.10)	1.19 (0.49-2.88)	.689
Constraint (M/SD)	0.56 (0.18)	0.61 (0.20)	.25 (0.01-4.16)	.339
Effective size (M/SD)	2.56 (1.23)	2.26 (1.21)	.98 (0.41-2.48)	.957
Efficiency (M/SD)	0.56 (0.26)	0.53 (0.26)	1.12 (0.01-23.15)	.963
Age (median, IQR)	25 (20-30)	26 (22-31)	.97 (0.94-0.99)	.015
Female	47.2%	35.8%	1.61 (1.11-2.36)	.013
Frequency of drug use (median, IQR)	40 (20-100)	10 (4-30)	1.01 (1.01-1.02)	< .001
Adverse LSD events (n=1,353)	**Adverse event % (n=54)**	**No adverse event % (n=1,299)**	**AOR**	**p**
Recent cryptomarket drug purchase	30.6%	17.4%	1.86 (0.99-3.51)	.049
Degree (M/SD)	4.03 (1.33)	4.11 (1.27)	1.60 (0.68-4.10)	.297
Constraint (M/SD)	0.65 (0.21)	0.62 (0.22)	1.41 (0.05-46.15)	.840
Effective size (M/SD)	2.13 (1.16)	2.38 (1.24)	.50 (0.22-1.13)	.840
Efficiency (M/SD)	0.57 (0.27)	0.60 (0.27)	8.89 (0.14-60.34)	.292
Age (median, IQR)	20 (17.75-23)	23 (19-28)	.88 (0.82-0.94)	< .001
Female	17.5%	22.2%	1.00 (0.48-2.01)	.999
Frequency of drug use (median, IQR)	5 (3-12)	6 (3-12)	1.00 (0.98-1.01)	.857

Note: All variables were measured over the last 12 months, described here as 'recent'.

* Adverse drug events included reporting seeking emergency medical treatment following the use of a drug and/or needing to seek medical treatment but not actually doing so.

Frequency of use was not included in the combined drugs regression as it was not able to be calculated accurately.

using network, supporting previous qualitative research (Barratt et al., 2016). Cryptomarkets can facilitate access to drugs for people who lack social connections to purchase from and consume with. The present study suggests people who use cryptomarket may also be at a slightly higher risk of reporting adverse cocaine and LSD events. The increased likelihood of adverse drug events could be due to the absence of protective contextual factors as well as inability to gauge their own drug use relative to others if they are alone, as theorised by Cooper et al., (1992). Alternatively, in the case of an adverse drug event, harms can be exacerbated by having no immediate physical assistance to seek treatment (Dietze et al., 2006; Moore, 2004). While this study does report an association between the risk of harm and use of cryptomarkets, it cannot confirm that this was mediated by the higher likelihood of no drug-using network. It cannot be certain that those who were using cryptomarkets were in fact alone during the adverse drug event. It also cannot discount the possibility of harm reducing mechanisms on cryptomarkets (Martin, 2014) such as feedback (Christin, 2013; Van Hout & Bingham, 2013) and discussion forums (Bancroft & Reid, 2016) that may be operational.

It should be noted that although some people who use cryptomarkets may be disadvantaged by not having a physical social network during drug consumption, they may instead be part of virtual networks providing advice on safer drug use (Bancroft & Reid, 2016; Boothroyd & Lewis, 2016). These networks could be beneficial for the consumer as much as information on drug use is communicated in physical drug-using networks. Misinformation could counter these benefits, but that effect applies to both physical and virtual networks.

The structural differences among those who do have a drug-using network were also investigated. The hypothesis that social network characteristics of those who do have a drug-using network were different for those who purchase drugs from cryptomarkets (H2a) was not supported. There were no network differences for people who recently used cryptomarkets compared with the remainder of the sample. The hypothesis that social network characteristics and the recent purchase of drugs from cryptomarkets will be associated with adverse drug events, after controlling for covariates was not supported (H2b). Recent cryptomarket use was however associated with adverse LSD events.

This result suggests cryptomarket use was associated with adverse LSD events even among those with a drug-using network (after controlling for covariates). This is contrary to expectations of cryptomarkets increasing harm for people who use drugs alone but otherwise reducing harm for those with a drug-using network. One possible explanation is that drugs like LSD sourced from cryptomarkets could be higher in strength relative to traditional drug markets. People who use cryptomarkets have access to a wide range of vendors competing for product quality and could be opting for products advertised to be high in strength. Therefore, higher strength substances may be consumed by people who use cryptomarkets and could be reporting more adverse drug events. The findings were restricted to adverse LSD events associated with cryptomarket use and not cocaine or MDMA. This could be due to the branding of LSD blotters that may be available for cryptomarket consumers to gauge strength. With a wider range of sellers, higher strength brands could be recognised, ordered and consumed by someone using cryptomarkets whereas a consumer in a traditional marketplace may have less choice (Barratt, Ferris, & Winstock, 2014). This is somewhat inconsistent with the finding (H1b) using a larger sample that people who recently used cryptomarkets were more likely to report not just adverse LSD events but adverse cocaine events as well, emphasising the need for further research. These findings lend support to the notion that people who use cryptomarkets could be at increased risk of drug-related harm, however these findings must be understood in light of the limitations of the study discussed below.

Limitations

While our measures of isolates and structural holes in the ego-centric networks were not significantly associated with outcomes in our models, this result could be due to limitations in network measurement. The study was limited by the social networks' maximum of five people they know by name in their drug-using network. Measurement of a greater range in the social network could allow greater discrimination of network characteristics, particularly given the majority of participants nominated the maximum of five peers in their drug-using network for each drug type. Another limitation of this study was the method of classification of no drug-using network. The item wording means being the only person in a network using one type of drug (e.g. cocaine) with other people using other substances or no substances at all would still be classified as having no drug-using network. Moreover, the study did not account for individuals who used one drug type alone and another drug with others, a factor that was only measured for one drug type per person. People socially connected and who do not use the same drugs if any, would not be included in the network. Additionally, only including people they know by name in their network does not account for people who are using drugs in public social settings (e.g. clubs and festivals) but do not know anyone by name. The network measure also did not distinguish between in person and digitally facilitated connections. It was assumed participants would only consider in-person networks, however this was not specified and remains a limitation. In terms of assisting during an adverse drug event, identifying this group in networks would be important to measure in future studies. It may have impacted the results by overestimating people without a drug-using network. Future research should measure all members of a network and their level of support (including digitally facilitated networks). The present study was also limited by not accounting for alters' connections to people outside the ego-centric network whereby information may traverse via "weak ties" to the ego. Future research should incorporate measurement of these external connections for a more complete picture of network structure. The present study was also limited by uncertainty around the adverse event itself. That is, how many people were around at the time, their support, the amount of drugs consumed, if alcohol or additional substances were consumed and other factors contributing to adverse drug events were not accounted for. The self-selection and self-reported substance use of the GDS represents limitations outlined by Winstock et al. (2022). Moreover, the study relies on the participants' self-reported experiences with a substance whose actual composition is uncertain. There are issues with high levels of poly-drug use, potential confounding effects from other substances, and the possibility of recall bias. Caution must be exercised when interpreting the data due to the relatively low number of individuals who are using these platforms for drug purchases. Despite the many limitations of this work, it is to our knowledge the largest dataset of social network data of this kind in existence, and despite its limitations, GDS is the only global survey to consistently measure purchase of drugs through cryptomarkets.

Conclusion

This study set out to investigate if the presence of a drug-using network, and social network characteristics of those who do have a drug-using network, were different for those who used cryptomarkets and those reporting adverse drug events. A drug-using network of zero (possibly solitary drug use) was more commonly reported among people who purchased drugs from cryptomarkets. However, the characteristics of these networks (when present) did not differ between people who used cryptomarkets and people who did not use cryptomarkets, nor between people reporting or not reporting adverse drug events. Our results support the notion that cryptomarket use increases drug-related harm, but further disentanglement of multiple complex mechanisms is needed. These findings can help inform decision makers to further public health and drug-related policy matters. Measures could be implemented to improve targeting of harm reduction interventions such as awareness campaigns for those at higher risk of adverse drug events, namely people who use cryptomarkets and use cocaine or LSD. With early intervention and access to harm reduction services, the impact of adverse drug events can be mitigated to reduce the overall public health burden. These findings also contribute to the evidence base on the overall harms associated with cryptomarket use that can inform policy makers developing cryptomarket-related policy decisions. Further research could examine the networks of people who use cryptomarkets more closely, specifically the influence of digitally facilitated networks on adverse drug events.

CRediT authorship contribution statement

Leigh Coney: Formal analysis, Writing – original draft, Writing – review & editing. **Amy Peacock:** Supervision, Writing – review & editing. **Aili Malm:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Rasmus Munksgaard:** Data curation, Software, Supervision, Writing – review & editing. **Judith Aldridge:** Writing – review & editing. **Jason A. Ferris:** Data curation, Funding acquisition, Resources, Writing – review & editing. **Larissa J. Maier:** Writing – review & editing. **Adam R. Winstock:** Conceptualization, Funding acquisition, Project administration, Resources, Writing – review & editing. **Monica J. Barratt:** Conceptualization, Data curation, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

ARW is the founder and owner of Global Drug Survey. AP has received untied educational grants from Seqirus and Mundipharma for study of opioid medications; these organisations had no role in study design, conduct or reporting. There are no other relevant interests to declare.

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Data availability statement

Data were collected from surveys with consenting participants. The data are not publicly available due to ethical constraints.

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Supplementary materials

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