How accurate are drug cryptomarket listings by content, weight, purity and repeat purchase?

Monica J. Barratt, Ross Coomber, Michala Kowalski, Judith Aldridge, Rasmus Munksgaard, Jason Ferris, Aili Malm, James Martin and David Décary-Hétu

(Information about the authors can be found at the end of this article.)

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Erratum: It has come to the attention of the publisher that the article, Barratt, M.J., Coomber, R., Kowalski, M., Aldridge, J., Munksgaard, R., Malm, A., Martin, J. and Décary-Hétu, D. (2024), "How accurate are drug cryptomarket listings by content, weight, purity and repeat purchase?", *Drugs, Habits and Social Policy*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/DHS-11-2023-0043, omitted the author Jason Ferris. This error was introduced during the production process and has now been corrected in the online version. The publisher sincerely apologises for this error and any inconvenience caused.

Abstract

Purpose – *Drug cryptomarkets increase information available to market actors, which should reduce information asymmetry and increase market efficiency. This study aims to determine whether cryptomarket listings accurately represent the advertised substance, weight or number and purity, and whether there are differences in products purchased from the same listing multiple times.*

Design/methodology/approach – *Law enforcement drug purchases – predominantly cocaine, methamphetamine, MDMA and heroin – from Australian cryptomarket vendors (n = 38 in 2016/2017) were chemically analysed and matched with cryptomarket listings (n = 23). Descriptive and comparative analyses were conducted.*

Findings – *Almost all samples contained the advertised substance. In most of these cases, drugs were either supplied as-advertised-weight or number, or overweight or number. All listings that quantified purity overestimated the actual purity. There was no consistent relationship between advertised purity terms and actual purity. Across the six listings purchased from multiple times, repeat purchases from the same listing varied in purity, sometimes drastically, with wide variation detected on listings purchased from only one month apart.*

Research limitations/implications – *In this data set, cryptomarket listings were mostly accurate, but the system was far from perfect, with purity overestimated. A newer, larger, globally representative sample should be obtained to test the applicability of these findings to currently operating cryptomarkets.*

Originality/value – *This paper reports on the largest data set of forensic analysis of drug samples obtained from cryptomarkets, where data about advertised drug strength/dose were obtained.*

Keywords *Drug checking, Drug market, Drug adulteration, Drug purity, Illicit drug trade, Harm reduction, Darknet market, Cryptomarket, Unregulated supply*

Paper type *Research paper*

Introduction

Information asymmetry is an enduring problem within illegal drug markets. Most people who buy drugs will not know whether they have purchased what they had expected until the point of consumption (Ben Lakhdar *et al.*, 2013; Caulkins, 2007). Even after consumption, buyers may still have imperfect knowledge of the content and strength/dosage of the drugs. Economists label goods of this type "experience goods" (Andersson and Andersson, 2013), with the classic example being a restaurant meal, which has to be tasted and eaten before it can be rated by the consumer. Prohibited drugs have been termed "double experience goods" because not only do those who buy them have imperfect information prior to consumption, but most people who sell them also have imperfect knowledge of their product's content (Caulkins, 2007).

One promise of drug cryptomarkets has been to increase market information available to all drug market actors, which should reduce information asymmetry and increase market efficiency. Cryptomarkets are marketplaces that host multiple sellers, or “vendors”; that provide participants with anonymity via their location on the hidden or dark web (Barratt *et al.*, 2018) and use of cryptocurrencies for payment; and that aggregate and display customer feedback ratings and comments (Barratt and Aldridge, 2016; Martin, 2014). Since Silk Road in 2011 (Barratt, 2012), cryptomarkets have provided a public platform for the trade of various illicit substances – cannabis, MDMA, heroin, cocaine – and many other prohibited items (Christin and Thomas, 2019; Man *et al.*, 2023). Bringing multiple vendors together on one platform facilitates direct comparisons of vendors and their offerings, including reputation scores and sales statistics, allowing buyers to choose from a variety of sellers (Cox, 2016). In contrast, face-to-face drug markets have higher search costs (the effort and risk involved in switching suppliers) (Galenianos *et al.*, 2012; Wilkins, 2001) due to comparatively limited seller information. Furthermore, the escrow option found on cryptomarkets (where funds are held by the market administrator until goods are received) (Tzanetakis *et al.*, 2016) provides the buyer with leverage not typically available in face-to-face markets: if the product is considered inferior upon delivery, the buyer can dispute the transaction and can leave negative feedback or ratings. In practice, this feature results in vendors carefully managing negative feedback by asking people to contact them first to resolve the issues before going public. Customer service is therefore of greater focus in cryptomarkets than it is in face-to-face drug markets (Martin *et al.*, 2020).

An important question, therefore, from the perspectives of market actors and drug market scholars, is: How accurate are the drug listings published on cryptomarkets? The open and independent review and rating systems on cryptomarkets might be expected to incentivise accuracy among vendors, who may be held to account more readily by an independent marketplace. However, drugs being “double experience goods” reminds us that vendors may give honest reports in connection to imperfect information about the content of their supply. In addition, part of building trust in supply is buying from a reputable vendor and choosing a listing from which others have purchased multiple times that comes with high ratings (Munksgaard and Tzanetakis, 2022; Bakken *et al.*, 2018); however, this practice is based on an untested assumption that goods sold by the same vendor through the same listing are indeed similar in content and purity. Furthermore, from the perspective of scholars who use digital trace analysis (e.g. web scrapes of cryptomarkets) to understand these markets (Enghoff and Aldridge, 2019), it should be noted that almost all digital trace research on cryptomarkets relies solely on digital trace data with no additional data sources for cross-checking and validating information accuracy. Therefore, a clear limitation is that scholarship using digital trace analysis relies on listings representing what is actually being traded in terms of what they contain, their purity and their weight, number or volume, as well as numerical and textual feedback from consumers, which acts as a proxy for *perceived* rather than objective content and purity.

What evidence currently exists on the question of accuracy of cryptomarket listings? Some studies have analysed the contents of drugs submitted by anonymous individuals for testing. The first study to report on adulteration rates of submitted drugs from an international sample (purportedly sourced via cryptomarkets) reported that for 91% of the 219 samples “the main result of analysis matched the advertised substance” (Caudevilla *et al.*, 2016). This study did not have access to the cryptomarket listings from which these substances were purchased and therefore could not test whether purity claims in the listings matched the actual purity of substances received. Other studies by the same group identified instances of adulteration among purported cryptomarket-sourced drugs – in particular, heroin adulterated with fentanyl analogues (Quintana *et al.*, 2017; Caudevilla *et al.*, 2018). A further study reported that a significant proportion (34%) of cocaine samples purportedly purchased from cryptomarkets contained “a component not ordinarily part of that substance” (an adulterant) (Torre Arce, 2020).

Only two studies have been published where the research teams purchased psychoactive substances directly from cryptomarket listings for the purposes of chemical analysis

(Rhumorbarbe *et al.*, 2016; Jurásek *et al.*, 2021). Rhumorbarbe *et al.* (2016) received legal authority to purchase drugs from Swiss-based cryptomarket vendors. They purchased an order of cocaine from two individual vendors, an order of cannabis concentrate and a repeat order of their first cocaine purchase (a total of four samples). They found that while all samples contained the advertised substance, the advertised purity was exaggerated. Although Rhumorbarbe *et al.* did not report advertised versus received weights in their paper, they did provide this information via personal communication to Aldridge *et al.* (2018), noting that the samples slightly exceeded their advertised weight. Rhumorbarbe *et al.* (2016) found the products purchased from the same listing were of similar purity. Jurásek *et al.* (2021) purchased nine samples of new psychoactive substances (NPS; that at the time of purchase were not yet illegal) from six vendors on one market. The research team analysed the contents of the samples and found that only one sample contained the advertised substance. NPS purchased from clearnet (non-cryptomarket) websites regularly contain substances that are different than those that are advertised (Brunt *et al.*, 2017), so Jurasek *et al.*'s study shows that cryptomarkets did not offer relatively more transparency or accurate information to the buyer than would be expected when purchased from the clearnet.

Aims

Our aim was to explore whether cryptomarket vendors (on one of the leading cryptomarket sites at the time of study) accurately represented their drug listings by comparing drug seizure data matched with scraped cryptomarket listings. We report on the extent of discrepancies between:

1. advertised versus actual content;
2. advertised versus actual weight (or number of pills);
3. advertised versus actual purity (or dosage per pill); and
4. Finally, we examined differences in purity between multiple purchases from the same listing.

Methods

Design and measures

Two data sets were used in the analysis: a bespoke data set of Australian Federal Police (AFP) drug seizures from cryptomarket vendors and a data set of web scrapes from cryptomarket listings. The data set of AFP drug seizures contained both information gathered from the cryptomarket listings police proceeded to purchase from and results from chemical analysis of the received substance. Between April 2016 and June 2017, AFP officers executed 38 controlled buys as part of active investigations of 10 Australian vendors (defined as advertising shipping from Australia to Australia) trading on one (anonymised) cryptomarket active at the time. The samples were tested by the AFP National Forensic Rapid Laboratory and the Australian Forensic Drug Laboratory at the National Measurement Institute using gas chromatography – mass spectrometry, Fourier transform infrared spectroscopy and colorimetric tests. The AFP provided the research team with the results of their chemical analysis containing the following variables: month of purchase, a persistent but randomly assigned vendor number, advertised drug, advertised weight (or number of tablets), price in Bitcoin (BTC), actual weight (or actual number of tablets), actual (primary) drug, actual purity (%) or mg per pill and the presence and list of adulterants (including contaminants, adulterants and diluents, see Cole *et al.* (2010)], where tested and found (while we list these adulterants, they were not used in comparative analysis because the data were incomplete). Our data processing generated additional variables, including advertised drug present or absent, milligrams of MDMA per tablet and difference scores between advertised and received weights (or numbers of tablets).

Law enforcement were unable to provide us with copies of the listings from which their purchases were made. Using our data set of listings in Australia that covered the buying period (DATACRYPTO; Décary-Hétu and Aldridge, 2015), we were able to match the purchases to a single listing for 23 of 38 samples. The matching process used all available information: month of purchase/listing, advertised substance, advertised weight (g) or number of tablets, matching of listing price and combinations of listings available from unique vendors (that is, ruling in or out possible matches based on knowledge of the menu of drug types available from the 10 vendors profiled in the AFP data set). Matches on BTC price were fuzzy to account for the volatility of the BTC market. A match occurred if the listing price was between 10% lower and 10% higher than the price reportedly paid by the AFP. Once a listing was sufficiently matched to an analysed substance, we manually extracted any qualitative (e.g. "top shelf") and/or numeric (e.g. "95% pure") information from the listing that could signify purity of the drug. The remaining 15 of the 38 drug sales were not able to be uniquely matched to a listing. Typically, this was because there were multiple possible matches. When this occurred, we did not feel confident knowing which listing to choose, and as such, these purchases were removed from the analysis for aims 3 and 4.

Analysis

For aims 1 and 2, we used only the police-provided data set ($n = 38$ for aim 1 and $n = 35$ for aim 2, as 3 cases were removed where the advertised drug did not match the detected drug). For aims 3 and 4, we used a reduced data set ($n = 23$) of the analysed substances that were able to be matched with the DATACRYPTO listings. Descriptive comparisons were calculated. Inferential statistics were not appropriate due to low numbers. Qualitative comparisons were conducted individually for each matched forensic and market listing/s. Stata SE 16 and Microsoft Excel were used. These analyses were not pre-registered; therefore, this study can be considered exploratory only.

Results

Aim 1 – testing advertised versus actual content

Over 90% (92%; 35/38) of samples contained the advertised substance (see Table 1). The most substituted drug was "MDMA": two of the five samples advertised as MDMA primarily contained *n*-ethyl-pentylone and did not contain MDMA. These two substituted cases were both in powder/crystal form, whereas the remaining three MDMA cases that did contain MDMA were pressed pills. Only one other sample was completely substituted: a single case where methamphetamine was sold as cocaine. Synthetic cocaine was advertised four

Table 1 Number of samples where drug was advertised and/or detected ($n = 38$)

Drug type	*Advertised (n)*	*Detected (n)*
Alprazolam	2	2
Cocaine	12	11
Diazepam	1	1
Flephedrone[a]	1	1
Heroin	4	4
MDMA	5	3
Methamphetamine	9	9
"Synthetic cocaine"	4	4
Total	38	35

Notes: Substances that were detected but not advertised included: 4-fluoromethylphenidate, benzocaine, caffeine, dimethylsulfone, levamisole, lignocaine, methorphan, n-ethylpentylone and procaine. This is an incomplete list as the AFP reported only routinely testing for adulterants when samples were >1g. [a]Also known as 4-fluoromethcathinone times, and in each case, a combination of benzocaine and 4-fluoromethylphenidate was detected. This combination is consistent with expectations of the ingredients of "synthetic cocaine" (Luethi *et al.*, 2018).

Aim 2 – testing advertised versus actual weight (or number)

Across all drug types, in most cases (74%; 26/35) the received weight or number was within 10% of the weight or number that was advertised (see Figure 1). The remaining samples were more than 10% underweight or number (5/35) or more than 10% overweight or number (4/35). The most underweight drug was heroin (50%; 2/4), although the most underweight sample was cocaine, which was nearly 40% less weight than advertised. None of the drugs that were in tablet form were supplied under the advertised amount, with one shipment of MDMA tablets arriving with 20% more tablets than purchased.

Aim 3 – testing advertised versus actual purity

Of the 23 AFP drug purchases matched with cryptomarket listings, nine were for cocaine, six were for methamphetamine, four were for heroin, three were for MDMA (all in tablet form) and one was for flephedrone (not discussed below as no purity indicators were apparent on the matched listing) (see Table 2).

Cocaine. The nine cocaine samples were purchased from four different vendors and matched to one listing per vendor. There was a mix of congruence between indicators of purity in the listing and actual analysed purity of the samples. In one sample (ID 2/6) [1], the listing aligned with "pure cocaine" tested at 95%. However, for the samples purchased from vendor #4 (ID 4/2), the advertised purity of 95% was actually found to be between 72 and 74%. Similarly, three purchases from vendor #6 who advertised cocaine as "pure uncut" (ID 6/11) were analysed to contain 58–66% cocaine. The final samples purchased from vendor #3 (ID 3/1) were described in the listing as "pretty euphoric" with no other purity indicators – these were analysed to contain 56–68% cocaine.

Methamphetamine. The six methamphetamine samples were purchased from two different vendors and matched to one listing per vendor (IDs 2/8 and 6/12). All six listings described

Figure 1 How different were the advertised weights or numbers from the weights or numbers received? (*n*)

% Change in weight or number	–39	–33	–20	–9	0	10	17	20	90	Total
Alprazolam					1	1				2
Cocaine	1			3	6			1		11
Diazepam					1					1
Flephedrone					1					1
Heroin		2			1		1			4
MDMA					2			1		3
Methamphetamine			1		7				1	9
Synthetic cocaine			1		2	1				4
Total	1	2	2	3	21	2	1	2	1	35

Legend
Underweight/fewer amount by >10%
weight/number within ±10% of advertised
Overweight/more amount by >10%

Note: Only substances where the expected substance was detected were included in this table (*n* = 35)

Table 2 Analysis of actual versus listed quality indicators for police drug purchases that were matched with DATACRYPTO listings, sorted by vendor ($n = 23$)

Month	*ID*[a]	*Advertised drug*	*Actual purity % (or mg per pill)*	*Listed purity % (or mg per pill)*	*% less drug than advertised*	*Qualitative indicators of quality (quotations extracted from vendor listings)*	*Comment comparing listed purity with actual purity*	*Comment on purity from different purchases from same matched listing*
Matched	*Pol/Web*	*Matched*	*Police*	*Web*	*Derived*	*Web*	*Interpretation*	*Aggregation of same ID*
Apr-16	1/3	Heroin	73%	NA	NA	As pure as pure heroin #4 can be	73% is high strength – consistent with quality indicators "heroin #4" (refers to China White) and "pure"	Range 18–73%
May-16	1/3	Heroin	18%	NA	NA	As pure as pure heroin #4 can be	but 18% is relatively weak for the same quality indicators	Range 18–73%
Feb-17	2/6	Cocaine	95%	NA	NA	free base pure cocaine. It is from the best cocaine in the world	At 95% this was indeed very pure cocaine (crack/ freebase)	NA
Jul-16	2/9	Heroin	48%	NA	NA	raw. warn people you are selling to that this is pure	low purity when compared with claim by vendor that the product is "raw" and "pure"	Range 46–48%
Aug-16	2/9	Heroin	46%	NA	NA	raw. warn people you are selling to that this is pure	low purity when compared with claim by vendor that the product is "raw" and "pure"	Range 46–48%
Apr-16	2/10	MDMA	104 mg	250 mg	58%	worlds best pill. Stupidly insane. utmost high quality and purity to provide a truly pure mdma experience	58% less mg MDMA per tab than advertised. Qualitative language not aligned with purity measurement	NA
May-16	2/7	MDMA	70 mg	130 mg	46%	A good strong roll. High quality MDMA	46% less mg MDMA per tab than advertised	NA
Jul-16	2/8	Methamphetamine	80%	NA	NA	top shelf. Very very high quality	less than average purity of street methamphetamine (>90%)[b]	Range 69–80%
Feb-17	2/8	Methamphetamine	80%	NA	NA	top shelf. Very very high quality	less than average purity of street methamphetamine (>90%)[b]	Range 69–80%
Mar-17	2/8	Methamphetamine	80%	NA	NA	top shelf. Very very high quality	less than average purity of street methamphetamine (>90%)[b]	Range 69–80%
Apr-17	2/8	Methamphetamine	71%	NA	NA	top shelf. Very very high quality	lower relative purity	Range 69–80%
May-17	2/8	Methamphetamine	69%	NA	NA	top shelf. Very very high quality	lower relative purity	Range 69–80%
Apr-16	3/1	Cocaine	68%	NA	NA	pretty euphoric	while "pretty euphoric" is a quality indicator, it's not too convincing – aligns with the 56–68 purity	Range 56–68%

(*continued*)

Table 2

Month	ID[a]	Advertised drug	Actual purity % (or mg per pill)	Listed purity % (or mg per pill)	% less drug than advertised	Qualitative indicators of quality (quotations extracted from vendor listings)	Comment comparing listed purity with actual purity	Comment on purity from different purchases from same matched listing
Matched	Pol/Web	Matched	Police	Web	Derived	Web	Interpretation	Aggregation of same ID
May-16	3/1	Cocaine	56%	NA	NA	pretty euphoric	while "pretty euphoric" is a quality indicator, it's not too convincing – aligns with the 56–68 purity	Range 56–68%
Jun-16	4/2	Cocaine	73%	95%	24%	NA	greater than 20% less purity than advertised	Range 72–74%
Jun-16	4/2	Cocaine	74%	95%	23%	NA	greater than 20% less purity than advertised	Range 72–74%
Jun-16	4/2	Cocaine	72%	95%	24%	NA	greater than 20% less purity than advertised	Range 72–74%
Aug-16	6/11	Cocaine	66%	NA	NA	purest cocaine available. Pure uncut	Quality language is misaligned with 58–66% purity	Range 58–66%
Feb-17	6/11	Cocaine	59%	NA	NA	purest cocaine available. Pure uncut	Quality language is misaligned with 58–66% purity	Range 58–66%
Feb-17	6/11	Cocaine	58%	NA	NA	purest cocaine available. Pure uncut	Quality language is misaligned with 58–66% purity	Range 58–66%
Aug-16	6/12	Methamphetamine	80%	NA	NA	purest meth available. Pure uncut	less than average purity of street methamphetamine (>90%)[b]	NA
Sep-16	7/5	Flephedrone	83%	NA	NA	recommended dose 100 mg (but purity of the product not described)	NA	NA
Sep-16	7/4	MDMA	196 mg	220 mg	11%	If you have a low tolerance to MDMA please be careful to take it easy on this and not be a hero. Lab tested. Marquis reagent tested turned directly to deep purpleblack	While being 11% less mg MDMA per pill than advertised, it was still relatively strong and aligned with qualitative quality indicators	NA

Notes: [a]ID format = researcher assigned vendor ID/ID of matched listing; [b]See Figure 3, Salouros, H. 2022. Synthetic origin of illicit methylamphetamine in Australia: 2011–2020. Drug Testing and Analysis, 14, 427–438. Three of the matched samples were purchased by the AFP in August 2016, which was a month where Web scrapes of the markets were unavailable. These matches were conducted using data from July and September 2016 instead. Five of the matched samples were reportedly purchased as unusual quantities, including 0.33, 0.9 and 1.1 g amounts. No such listings were located, but we were able to match the samples to listings for 0.3 and 1.0 g amounts instead the methamphetamine available as “top shelf”, “very high quality” or “pure uncut”. Most of the samples (4/6) were found to contain 80% methamphetamine; the remaining two samples were of lower purity (69–71%). All methamphetamine samples could be considered lower purity than advertised, given that Australian police seizures of methamphetamine in 2016–2017 had an average purity of over 90% (Salouros, 2022).

Heroin. The four heroin samples were purchased from two different vendors and matched to one listing per vendor (IDs 1/3 and 2/9). All four listings described the heroin on offer using high purity indicators: “as pure as pure heroin #4 can be” (heroin #4 is also known as “China White”, a high purity grading) (see also Friedman *et al*., 2022) and “raw”, “this is pure”. However, there was wide variability in the actual purity of the samples. While one sample was 73% heroin, two were 46–48% and one was 18%.

MDMA. The three MDMA samples were purchased from two different vendors and matched to three separate listings (IDs 2/10, 2/7 and 7/4). All three listings advertised the expected amount of MDMA per tablet in mg as well as used indications of purity in the text of the listing. For all three samples, the MDMA amounts advertised were less than the MDMA mg actually detected in the tablets (advertised 250 mg but contained 104 mg, 58% less than advertised; advertised 130 mg but contained 70 mg, 46% less than advertised; and advertised 220 mg but contained 196 mg, 11% less than advertised).

Aim 4 – how similar in purity are repeat purchases from the same listing?

Cocaine. There were three cocaine listings from which drugs were purchased multiple times in this study (see the final column of Table 2). These ranged from 56% to 68% (ID 3/1, $n =$ 2), 72% to 74% (ID 4/2; $n = 3$) and 58% to 66% (ID 6/11; $n = 3$). For ID 3/1, two samples were purchased one month apart from the same listing, but there was a 12% difference in the cocaine purity detected. For ID 4/2, three samples were purchased in the same month from the same listing, and these had the smallest range of purity, perhaps indicating they came from the same wholesale purchase batch. Conversely, for ID 6/11, one sample was purchased many months before the other two and looked to be from a different wholesale purchase batch.

Methamphetamine. For methamphetamine, there was only one listing from which multiple purchases occurred (ID 2/8). In this case, purchases were made over five different months, and while the first three purchases appeared identical (80%), the last two were of relatively lower purity (69–71%).

Heroin. For heroin, there were two listings, from which two purchases were made. In both cases, the purchases were made only one month apart. For the first listing (ID 1/3), there was a very large discrepancy between the purity of the two samples – 18–73%, whereas for the second listing (ID 2/9) the two samples ranged 46–48%.

Discussion

In this sample of cryptomarket-purchased drugs matched with sales listings, over 9 in 10 purchases contained the advertised substance, and 6 in 7 purchases were either supplied as advertised weight or number or overweight or number. Regarding our first aim, we report similar results to Caudevilla *et al.* (2016) in that, like their study, over 90% of our cryptomarket-purchased drug samples contained the advertised substance. While our findings demonstrate generally accurate advertisement of content and weight or number, there was mixed congruence between indicators of product purity in sales listings compared with the actual analysed purity of the samples. All six listings that quantified purity (three cocaine and three MDMA) overestimated the actual purity, which varied from 11% to 58% less than advertised. It was unsurprising, given that most (if not all) vendors do not have access to reliable testing equipment to determine exact purity levels and that most listings did not provide exact purity indicators and instead used qualitative terms such as "top shelf" or "very high quality". There was no consistent relationship between advertised purity terms and actual purity (e.g. "free base pure cocaine" was 95% cocaine, whereas "purest cocaine available. pure uncut" was 58–66% cocaine).

There were six listings in our sample that were purchased multiple times. In all cases, repeat purchases contained the advertised substance but varied in purity; in most cases, by relatively small amounts, as would be expected even within the same wholesale batch, but in one case (ID 1/3), which was a listing advertising heroin and purchased one month apart, one sample contained 18% heroin while the other contained 73% heroin. There were instances where repeat purchases from the same listing diverged in purity levels following longer gaps between purchases, which may reflect greater likelihood of the vendor having obtained a different drug batch. Overall, though, we can conclude that buying from the same listing is no guarantee that the product will be consistently replicated.

Our findings support those of Rhumorbarbe *et al.* (2016), who found that the advertised purity of cocaine samples overestimated the analysed purity (although in our sample, we did have one listing advertised at 95% that was actually 95%, but this was an exceptional case). Adding our study to the overall body of evidence, we could conclude that this consistent overestimation may be a sales tactic that takes advantage of drugs being experienced goods as well as the consumer typically being unable to ascertain exact purity of the drug even post consumption. It may also represent a lack of purity knowledge on behalf of vendors, who nevertheless use specific language to signify higher purity to increase sales.

Our findings suggest that purity is not assured over time across any specific listing. This lack of consistency has potential implications for the use of ratings and detailed feedback as a guide to information about, or a proxy for, adulteration and purity. There are also significant harm potentials where individuals purchase from the same listing one month at low purity, then the next month at unexpectedly high purity if they expect consistency of product and apply consistent dosing, such as we found for heroin purchased from the same listing. Even recent positive feedback will not guarantee consistent purity – despite this being a promise of the cryptomarket system – and it is important for market actors and drug market scholars to be aware of the limitations of cryptomarkets in practice.

Chemical analysis of prohibited drug samples is costly and difficult to achieve from an ethical and governance perspective for most researchers. If our findings were to be considered representative (although there are significant limitations on representativeness; see below), then we would advise researchers that content and weight information presented in cryptomarket listings appear to be mainly accurate, while purity and dosage of individual listings and repeat listings are more liable to variation from advertisement. Subject to these limitations, these findings have international significance. For researchers, our findings underscore the utility of matching forensic results with web-scraped data, and when reporting on questions of purity and dosage, we advise that use of solely web-scrapes to answer these questions poses validity issues. For people who use drugs and purchase from cryptomarkets, our findings warn of the possibility of discrepancies between a vendor's advertisement and the actual products that are shipped and received, despite the promise of cryptomarket feedback systems to ameliorate this information asymmetry.

Strengths and limitations

Our data set is unique: while the numbers appear small, they are larger than those of Rhumorbarbe *et al.* ($n = 4$, Swiss cocaine listings only) (2016) and Jurásek *et al.* ($n = 9$, NPS only) (2021). While our numbers are smaller than those of Caudevilla *et al.* (2016) ($n = 219$), that study could only answer the question of advertised versus actual content: being based on drug checking service data, they did not have access to the cryptomarket listing from which to extract advertised weight or purity, nor to identify repeat purchases. For multiple reasons, this data set should not be considered representative of cryptomarket-sourced drugs more broadly. Sampling was not random, as the choice of vendor listings was made by police for operational reasons, which for security reasons remain unknown to the research team. The data set was also restricted to vendors that advertised shipping drugs from Australia, and the samples purchased were delivered to Australia. Australia has a unique drug market profile due to its relative global isolation (Cunliffe *et al.*, 2017). The AFP does not routinely test for adulterants in samples <1 g. Therefore, we could not reliably report on the types and ranges of adulterants in this data set. We were unable to access screenshots of the exact listings that the drugs were purchased from; instead, we used fuzzy matching to a separate data set of market scrapes. This process may have introduced error, and it also reduced our sample size for aims 3 and 4, as numerous samples were not matched with adequate certainty. The matching process was made more difficult by the lack of detail on the exact date of purchase, with this information being provided in month/year format only. Some of the samples that remained unmatched may have had listings that were uploaded and then removed between market scrapes, but it is also possible that vendors edited the text of their listings in between scrapes, which would remain uncaptured by our methods. Finally, these data are now dated, and it is unclear how more current data sets may compare with those collected in 2016–2017. While our findings should be interpreted with these conditions in mind, we are unaware of the existence of a more fulsome data set with similar features to the one presented here and therefore believe these analyses are worthwhile despite their limitations.

Conclusions and implications

In this data set, most drug listings were accurate to the extent that they contained the advertised substance at the advertised weight or number, but where listings advertised markers of purity, all products fell short. Repeat purchases from the same listing varied in purity, and while this was to be expected with long gaps between purchases, wide variation was also detected on listings purchased from only one month apart. Our study demonstrates that information asymmetry still remains in cryptomarkets, despite their capacity to aggregate and rank feedback on specific vendors and their listings. Being able to rate "double experience goods" after consumption and share those with potential buyers may have value, but with no guarantee that specific vendor listings will provide a similar product to those rated, the utility of these ratings is called into question.

Future research in this area could measure the impact of including specific purity descriptions in cryptomarket listings on their subsequent sales (adding to the work of Andrei and Veltri, 2024). Further research directions could also include systematic comparisons of labelling accuracy between other illegal markets as well as similar legal markets, for example, herbal food supplements (Esposito *et al.*, 2023). An additional line of inquiry could build on existing analyses of cryptomarket ads as cultural artefacts, where signals of drug purity are understood as "commodity-signs" that represent a hedonistic lifestyle (Craciunescu, 2021).

In terms of the practical implications of this work, we note that attempts by cryptomarket actors to self-regulate content and purity of drug listings have recently been reported (Barratt *et al.*, 2024; Logie *et al.*, 2023), whereby drug samples are sent to drug checking facilities and the results reported back to the market administration. If such a system were independent and implemented at scale, to the extent that vendors can control their supply, purity may become more consistent on cryptomarkets. Research into this phenomenon would be beneficial to replicate the findings we have reported here with more current data using a larger, less biased and globally representative sample.

Note

1. ID format = researcher assigned vendor ID/ID of matched listing (see Table 2).

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Author affiliations

Monica J. Barratt is based at the Social Equity Research Centre and Digital Ethnography Research Centre, RMIT University, Melbourne, Australia and National Drug and Alcohol Research Centre, UNSW, Sydney, Australia.

Ross Coomber is based at the Department of Sociology, Social Policy and Criminology, Faculty of Humanities and Social Sciences, University of Liverpool, Liverpool, UK.

Michala Kowalski is based at the Drug Policy Modelling Program, Social Policy Research Centre, University of New South Wales, Sydney, Australia.

Judith Aldridge is based at the Department of Criminology, The University of Manchester, Manchester, UK.

Rasmus Munksgaard is based at the Department of Sociology and Social Work, Aalborg Universitet, Aalborg, Denmark.

Jason Ferris is based at the Centre for Health Services Research, The University of Queensland, Herston, Australia.

Aili Malm is based at the School of Criminology, Criminal Justice, and Emergency Management, California State University Long Beach, Long Beach, California, USA.

James Martin is based at the School of Humanities and Social Sciences, Faculty of Arts and Education, Deakin University, Melbourne, Australia.

David Décary-Hétu is based at the School of Criminology, Universite de Montreal, Montreal, Canada.

Corresponding author

Monica J. Barratt can be contacted at: monica.barratt@rmit.edu.au