This manuscript was accepted for publication in Drug and Alcohol Dependence on 6 Dec 2021

TITLE PAGE

Exploring Televend, an innovative combination of cryptomarket and messaging app technologies for trading prohibited drugs

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Running head: Exploring Televend, a new digital drug market

Word count: 3797 (maximum of 4000)

Declaration of competing interests: ARW is the founder and owner of Global Drug Survey. There are no other relevant interests to declare.

ABSTRACT

Background. Digital technologies continue to facilitate drug trading. Televend was an innovative combination of multiple digital technologies, with its backend hosted on the darknet, while purchases were made through the messaging app Telegram. Here, we provide an initial characterisation of this nascent market. Methods. Televend and White House Market (WHM) were scraped (Jun–Jul 2021) and a global cross-sectional web survey of 15,513 drug buyers (Global Drug Survey; GDS) was conducted (Dec 2020–Mar 2021). Results. Televend was 10% of the size of WHM, the largest drug cryptomarket (4,515/44,830 listings per week). Both markets predominantly contained drug-related listings covering similar drug categories, with similar country of origin and destination. Very few GDS drug buyers reported use of Televend (0.73%). Most Televend buyers (68/114) reported buying cannabis, then cocaine (20), MDMA (17), and LSD (12). The Televend and darknet groups had similar demographic and drug use characteristics; whereas compared with app purchasers, older age increased the odds of Televend use (aRRR=1.06, $p<.001$), identifying as a cisgender woman decreased the odds (aRRR=0.43, $p=.004$), while last-year use of a greater number of drug types (aRRR=1.20, $p<.001$) and less frequent drug use (aRRR=0.998, $p=.032$) increased the odds of Televend purchase. Conclusions. While smaller, Televend was not noticeably different in its drug offerings to its largest cryptomarket competitor, and it attracted a cohort more similar to darknet than to app drug buyers. Future Televend-like markets may be attractive to people with less specialised technical knowledge who already routinely scroll through social media feeds.

Word count for abstract: 248 (maximum 250)

Keywords: drug market, cryptomarket, darknet market, social media, messaging app (maximum 6)

1 INTRODUCTION

Digital communication technologies have facilitated the trade of illegal drugs for many decades, with the first reported example occurring in 1971 between university students using their institutions' Apranet accounts (predecessor to email) (Markoff, 2005). In the intervening years, new digital technologies have been adopted by drug buyers and sellers alike, including pagers and mobile phones (May and Hough, 2004). From the 2000s, clear or surface websites (Barratt et al., 2018) sold semi-illegal psychoactive products—including pharmaceutical drugs without prescription and novel substances advertised as 'research chemicals', 'spice' or 'plant food' (Hohmann et al., 2014; Littlejohn et al., 2005; Schifano et al., 2006). But it was not yet feasible to buy illegal drugs through the web. In 2011, this changed when the first darknet market or cryptomarket (Silk Road) began trading (Barratt, 2012; Martin, 2014). Cryptomarkets host multiple sellers, provide participants with anonymity via their location on the dark web (Barratt et al., 2018) and use of cryptocurrencies for payment, and aggregate and display customer feedback ratings and comments (Barratt and Aldridge, 2016; Martin, 2014). Over the last decade, cryptomarkets have offered cannabis, MDMA, heroin, cocaine and many other illegal substances in plain sight of law enforcement (e.g., see Pedersen et al., 2021). Law enforcement initiatives have removed some marketplaces, but the cryptomarket ecosystem remains active, with administrators responding to threats by innovating their services (Horton-Eddison et al., 2021; Shortis et al., 2020). Concurrently, other important changes in the digital media and communications landscape were occurring. Messaging apps, in particular those that offered encrypted messaging services and real-time mobile group messaging (Baulch et al., 2020; Ling, 2017; Nobari et al., 2021), as well as social media services that facilitated interaction and the sharing of user-generated content (McCay-Peet and Quan-Haase, 2016), afforded new possibilities for drug trading (Blankers et al., 2021; Childs et al., 2021; Demant et al., 2019; Li et al., 2019; McCulloch and Furlong, 2019; Moyle et al., 2019; Oksanen et al., 2021; Shah et al., 2021; van der Sanden et al., 2021), alongside the dramatic rise in social media use (Auxier and Anderson, 2021).

Despite offering advantages when compared with in-person drug sourcing methods—identified by cryptomarket buyers as wider range, better quality, convenience, and predictability (Bancroft and Scott Reid, 2016; Barratt et al., 2014)—the specialised knowledge required to successfully complete a cryptomarket drug purchase restricts its appeal to specific sub-populations (Childs et al., 2021; Kowalski et al., 2019). This specialised knowledge—accessing the darknet, acquiring and managing cryptocurrencies, and learning to use encryption software—is not required for participation in app markets (McCulloch and Furlong, 2019; Moyle et al., 2019). App-mediated markets offer additional innovations, including increased immediacy through facilitating in-person exchanges, greater convenience, location-based features, advertising products (images or video) via social media feeds and 'suggest friend' functions (Demant et al., 2019; McCulloch and Furlong, 2019; Moyle et al., 2019; van der Sanden et al., 2021). App-mediated drug trading may include joining broadcast-type groups or following public profiles of drug sellers, then using one-to-one messaging to broker a deal, followed by an in-person exchange or postal delivery (Li et al., 2019; McCulloch and Furlong, 2019; Moyle et al., 2019). Public data from app-mediated drug selling groups have been assessed across multiple platforms (e.g., Telegram (Blankers et al., 2021) and Instagram (Li et al., 2019; Shah et al., 2021)), with these studies confirming seller advertisement posts predominate with buyers directed to encrypted chat apps for purchase.

Televend was first reported in October 2020 (Power, 2020). Televend administrators described their service as "a direct deal platform which uses Telegram bots to interface with customers via a shop front inside the app and a Tor based .onion vendor panel for vendors to manage orders and customers, completely automated" (see Figure 1). Televend's backend wass accessible through the darknet; however, unlike a typical cryptomarket, items could not be purchased there. Instead, a specific vendor's Telegram-hosted "shopbot" handled the purchase. The shopbot was pre-programmed to automate the entire sales process. Cryptomarkets have long suffered from server downtime problems, for example, via distributed denial of service (DDOS) attacks instigated by competitors or law enforcement (Moeller et al., 2017). Televend's appropriation of the Telegram service minimised this risk of downtime as the shopbots could be consistently accessed through the app (Horton-Eddison et al., 2021; Power, 2020). Telegram itself has been identified as a messaging app that people who use drugs already utilise, for example, for harm reduction outreach services (Davitadze et al., 2020). Telegram's founders have resisted attempts to censor its content or share information with authorities (Wijermars, 2021). As a result it is one of the preferred platforms for sharing information about censored or illegal activities (Rogers, 2020). For further detail on how Telegram works, see (Nobari et al., 2021).

[Insert Figure 1]

To our knowledge, Televend has been only briefly mentioned in the scientific literature. It was included in a longer list of cryptomarkets that hosted listings for COVID-19 vaccines and fabricated proofs of vaccination (Bracci et al., 2021) and was described in a report about the future of drug cryptomarkets (Horton-Eddison et al., 2021). Televend is the first combination of a cryptomarket and app-mediated market, making it a unique phenomenon worthy of study. It is important to characterise this new marketplace in terms of its similarities or differences to existing cryptomarkets and to determine whether it attracted similar or different buyers.

1.1 Aims

This exploratory study has the following aims:

1. How similar are the number and characteristics of listings and vendors on Televend to the most popular cryptomarket in 2021, White House Market (WHM) (Pedersen et al., 2021)?
2. Using a global survey of people who buy illegal drugs (derived from the Global Drug Survey; GDS):
    a. Is Televend used to purchase drugs? If so, for which drug types?
    b. How does the use of Televend compare to the use of other drug sources?
    c. What are the demographic and drug use characteristics of groups that report use of different digital sourcing methods, including Televend, darknet markets and app-mediated markets?

2 MATERIAL AND METHODS

We utilised two data sources for this cross-sectional study: (1) web scrapes of Televend and a comparison cryptomarket, WHM; and (2) a web survey of drug buyers, via the GDS 2021. The GDS received ethics approval from University College London (11671/001), which was registered at RMIT University (2020-23913-11758) and The University of Queensland (2017001452). Market scrape data collection was approved by the Mahidol University Social Sciences Institutional Review Board (2021/090). The STROBE checklist for cross-sectional studies (von Elm et al., 2007) guided our reporting (see S1).

2.1 Part 1 – Web scrapes

Listing data were collected weekly over eight weeks from the Televend darknet end (4 June to 24 July 2021) and WHM cryptomarket (7 June to 26 July 2021) using custom web crawlers that automatically collect all information of interest from a website. The raw HyperText Markup Language files (HTML) of drug advertisements were then parsed using a dedicated parser to extract information regarding advertised product, vendor unique name, country/region of shipment origin, and potential shipment destination country/region.

Listings sharing the same ID number for WHM or the exact same information for Televend collected during the same crawling session were discarded from further analysis. The advertisement texts were processed using an extended version of the eDarkTrends-dedicated Named Entity Recognition (NER) algorithm to detect relevant entities (for further detail see Lamy et al., 2020; Lamy et al., 2021). The NER encompasses 5,707 terms associated with 19 psychoactive substance classes (e.g., cathinone, opioid, tryptamine). Manual checks were performed on advertisement data to remove inconsistencies and limit false positive identifications (e.g., "Versace" appears in advertisements for cannabis strains, MDMA pill logos and luxury brand markings on counterfeit items). Individual listings that advertised several substances (e.g., "PARTYPACK - 1G - HEROIN - 1G - MDMA") were discarded. Listings that did not provide specific information regarding their shipment origin (e.g., "Worldwide") were removed from frequency analysis of shipment origin.

2.2 Part 2 – Survey of drug buyers

The GDS is an independent research organisation that collects data on drug use patterns worldwide. GDS2021 launched on December 1, 2020 and ran until March 16, 2021. It was translated into 11 languages (German, English, French, Dutch, Hungarian, Spanish, Finnish, Portuguese, Danish, Romanian and Italian). Respondents were recruited via media partners and collaborating institutions worldwide, such as Vice, Mixmag, The Guardian, Fairfax Media, and global social platforms, such as Facebook and Twitter. Respondents provided informed consent by viewing the information sheet, then ticking a box to indicate that they are over the age of 16 and agree to participate. There were no financial incentives for taking part. The survey was anonymous: no IP addresses or other potentially identifying information were collected. The survey took between 20 to 40 minutes to complete. A fake drug was included, and responses from people who reported using this drug were excluded. While web surveys such as GDS are not necessarily representative of the general population, they can offer a timely and realistic picture of new emerging trends in drug use and are able to better reach hidden populations (Barratt et al., 2015; Barratt et al., 2017). Further detail on GDS methodology is available elsewhere (Barratt et al., 2017).

2.2.1 Drug sourcing

Drug sourcing was measured for the following drug types: cannabis, LSD, mushrooms, cocaine, MDMA, methamphetamine, GHB, ketamine, heroin, synthetic cannabinoid receptor agonists (SCRAs), other new/novel substances and prescribed opioids used nonmedically. Respondents were asked where they had purchased each drug type from in the last 12 months and could select multiple options from a defined list. Drugs sourced from darknet markets purchased directly and purchased indirectly were combined into a single darknet market or cryptomarket category. These data are presented for cannabis separately then combined for all drug types excluding cannabis.

2.2.2 Demographics

Country of residence, age, gender (with 3 levels; measurement and derivation described in S2) and level of education were included in the regression.

2.2.3 Drug use characteristics

Use of each drug type in the last 12 months and frequency of use during that time were measured. Composite variables were created from these including total number of drug types used in the last 12 months and the maximum frequency of use of any drug type during that period (minimum 1 to maximum 365 days of use). Refer to S2 for all questions.

2.2.4 Case selection

33,269 responses were retained after cleaning for missing age, gender or drug screen, and reports of using a fake drug. For the current analysis, we only included respondents who answered the drug sourcing questions. These questions were only displayed to respondents that reported use in the last 12 months of any of the drug types of interest. Respondents who only chose ‘I didn’t pay / it was free’ or ‘another source’ were excluded from analysis. These exclusions led to an analytic sample of N=15,513.

2.2.5 Analysis

The first two aims used descriptive statistics, while the final aim utilised a multivariable multinomial logistic regression to determine how demographic and drug use variables (modelled as main effects only) were associated with three mutually exclusive groups: (1)

Televend, (2) Darknet only, (3) Apps only. Due to empty and small cell numbers for older ages, the regressions were conducted on a subsample aged 16–50 years. Complete case analysis was used throughout (see S3 which shows percentage missing for regression analyses was 2.8%).

3 RESULTS

3.1 Part 1 – Listing and vendor characteristics

36,122 Televend listings were collected through eight weekly crawl sessions for an average of 4,515.25 ads (min=4,173, max=4,851) per crawl. The number of listings advertised on Televend increased by 4.9% during the study period (4,406.5 ads on average for the four crawling sessions of June compared to 4,624 on average for the four crawling sessions of July). Out of these 36,122 listings, 18,860 listings (58.7%) contained at least one term identified as a substance of interest by the NER. 2,357.5 drug related listings were identified on average at each crawling session (min=2,097, max=2,592) (see Table 1). In contrast, 358,636 listings were crawled from WHM through eight weekly crawl sessions for an average of 44,829.5 ads (min=43,177, max=45,781) per crawl. During the study period, the number of listings advertised on WHM decreased by 2.6% (45,416 ads on average during the month of June to 44,243 ads on average for July). Out of these 358,636 listings, the NER identified at least one substance of interest in 255,090 listings (71.1% of the total listings). On average, 31,886.3 drug-related listings were identified at each crawling session (min=30,773, max=32,939) (see Table 2).

[Insert Tables 1 & 2]

With 40.2% (n=7,591/18,860) of listings, cannabinoids was the most frequent category of substance advertised on Televend. Eight different SCRAs (e.g., 5F-MDA-19, MAM-2201) were advertised in 52 listings (0.7% of cannabinoid listings), with the remaining cannabinoid listings advertising plant-based cannabis products (e.g., flower, concentrates, edibles, etc.). Anxiolytics represented 8.9% (n=1,637/18,860) of listings with 25 different molecules listed. The third most common category appearing on Televend was psychedelics, with 8.4% (n=1,589/18,860) of total listings, followed by the opioid category with 8.3% (n=1,569/18,860) of total listings (Table 1). Similarly, cannabinoids were the most frequent category of substances advertised on WHM with 34.2% (n=87,338/255,090). Sixteen different types of SCRAs were advertised on WHM, for a total of 966 listings (1.1% of cannabinoid listings). Psychedelics was the second most common category with 11.4% (n=29,147/255,090) of listings with 33 different molecules offered, followed by MDMA-and-cathinone-type substances and anxiolytics with, respectively, 9.8% (n=24,885/255,090) and 9.0% (n=22,950/255,090) of the total listings identified as advertising drugs.

Overall, 76.5% (n=14,422/18,860) of the drug-related listings on Televend displayed origin information ("Ships from") at the nation level. Of these, 46.9% (n=6,758/14,422) of the drug listings with nation-level shipment location were advertised as shipped from the United Kingdom, followed by the United States with 23.6% (n=3,405/14,422) and Germany with 7.7% (n=1,117/14,422) (Table 1). In comparison, 91.4% (n=245,181/255,090) of WHM drug-related listings displayed nation-level origin information. Overall, 29.9% of drug listings with nation-level shipment information were shipped from the United States (n=73,324/245,181), followed by the United Kingdom with 24.6% (n=60,386/245,181) and Germany with 14% (n=34,442/245,181) (Table 2).

Concerning destination ("Ships to"), 90.7% (n=17,108/18,860) of Televend drug-related listings displayed information about potential shipment destination. 39.3% listings (n=6,718/17,108) were advertised as shipping "Worldwide", 23.1% (n=3,949/17,108) as shipped solely to the United Kingdom and 18.8% (n=3,208/17,108) to the United States (Table 1). All WHM drug-related listings displayed destination information with 34.2% (n=87,295/255,090) of listings shipping worldwide, 26.2% (n=66,801/255,090) listed as shipped only to the United States and 16.1% (n=40,979/255,090) to Europe (Table 2).

For Televend, 313 vendor unique names have advertised at least one drug-related product during the study period (Table 1) compared to 1,418 on WHM (Table 2). On average, Televend vendor unique names advertised 60.25 (min=1, max=868) drug-related listings during the study period, compared with 178.5 (min=1, max=2,823) for WHM vendor unique names.

3.2 Part 2 – Buyer characteristics and trends

While around 1/10 GDS drug buyers reported sourcing from darknet markets (11.3%) or apps (9.0%), very few reported use of Televend (0.73%). Most Televend buyers (68/114) reported buying cannabis, with other drug types purchased via Televend including cocaine (20), MDMA (17), LSD (12), psilocybin mushrooms (6), ketamine (6), prescription opioids (3), methamphetamine (2), heroin (2), GHB (1) and new/novel drugs (1).

Figure 2 charts all drug sources utilised in the last 12 months for all drugs, cannabis only, and all drugs excluding cannabis. Over 90% of respondents reported some kind of in-person sourcing. While there were no differences in the rates of Televend use between cannabis and other drugs, cryptomarket and open website procurement were more readily reported for other drugs while apps were more commonly reported for accessing cannabis. Among the 18.9% (2,926/15,513) of the sample that reported use of the three digital trading methods that we focused on for this paper (see Figure 3), 60% reported darknet access, 48% apps and 4% Televend. Around half of the Televend group (46% of 114) also reported use of one or both of the other two digital sources, with little difference in the proportion reporting dual use of apps versus darknet.

[Insert Figures 2 & 3]

Table 3 compared the Televend group (n=114) with app only (n=1,110) and darknet only (n=1,444) groups. The Televend group was older than both the darknet and app groups (median ages 26 v 24 v 23 years, respectively, p<.001). The Televend group was more similar in gender distribution to the darknet group, with the app group containing a greater relative proportion of cisgender women (26% v 15% in the Televend group, p<.001). The most common countries of residence for the Televend group were Germany, UK, Australia and Switzerland; for the darknet group, Germany, US, UK and Finland; for the app group, US, Mexico, France and Australia. In terms of drug use patterns, the Televend group appeared more similar to the darknet group than the app group. The Televend and darknet groups both reported a median of 4 drug types used in the last 12 months compared with 3 for the app group (p<.001); however, the app group reported a higher maximum frequency of use (155 days in the last 365) compared with the darknet group (80) and the Televend group (120; p<.001).

When comparing Televend and darknet groups by multinomial logistic regression (see Table 4), there were no statistically significant differences in demographic variables. In both univariable regressions and the adjusted model, greater frequency of use of any drug type over the last 12 months increased the odds of Televend use, compared with the darknet group (aRRR=1.002, p=.033). When comparing the Televend group with the app group by univariable multinomial logistic regression, older age (RRR=1.05, p<.001), obtaining a university degree (RRR=1.64, p=.014), and greater numbers of drug types used in the last 12 months (RRR=1.13, p=.006) increased the odds of using Televend, while identifying as a woman (RRR=0.49, p=.010) decreased the odds. Controlling for covariates, education was no longer a significant predictor, while frequency of use become significant. In the multivariable model, older age increased the odds of Televend use (aRRR=1.06, p<.001) (also see Figure S4), identifying as a woman decreased the odds (aRRR=0.43, p=.004), while last-year use of a greater number of drug types (aRRR=1.20, p<.001) and less frequent drug use (aRRR=0.998, p=.032) increased the odds of Televend purchase, compared with app purchasers.

[Insert Tables 3 & 4]

4 DISCUSSION

Televend innovatively combined multiple digital technologies with its backend hosted on the darknet, while purchases were made through the messaging app Telegram. Although both Televend and White House Market had shut down only months after our data collection finished (Chatterjee, 2021; DNetSEO, 2021), the Televend model—through the addition of an automated shopfront using a surface web app—has extended the normal reach of traditional cryptomarkets that are usually limited to the dark web environment.

In this paper, we provided the first systematic characterisation of the Televend drug market. Measured in number of listings, the nascent marketplace was 10% of the size of the largest drug cryptomarket (WHM). The total number of Televend listings increased slightly, while WHM listing totals decreased slightly over the same 8-week period. Both markets contained predominantly drug-related listings covering broadly similar drug categories. Origin and destination information was also broadly similar between the two markets, with Televend slightly more oriented toward the UK market and WHM toward the US market. To summarise, while being considerably smaller in size, Televend was not noticeably different in its drug listing offerings to its largest drug cryptomarket competitor.

When surveying drug buyers from the GDS, very few reported use of Televend (0.73%); with in-person sourcing methods continuing to dominate (92%) and more established digital sourcing methods like darknet markets (11%) and apps (9%) reported by around 1/10 drug buyers. Cannabis, cocaine, MDMA and LSD were the drug types most commonly purchased on Televend. The Televend and darknet groups had similar demographic and drug use characteristics, whereas when compared to the app group, Televend buyers were older and less likely to identify as women, while also reporting last-year use of a greater number of different drug types which they used less often over the last 12 months. To summarise, Televend's reach was small, and it attracted a cohort that was more similar to other drug cryptomarket buyers.

4.1 Limitations

This exploratory analysis has limitations. We measured characteristics of drug-related listings on Televend and WHM. These do not represent actual sales volumes, as each listing may result in anything from no sales to 1000s of sales. Future work using feedbacks/reviews left by customers can be used to approximate sales volume (Christin and Thomas, 2019). The GDS uses convenience sampling and therefore cannot be used to indicate prevalence in the population (Barratt et al., 2017). However, the focus of this paper is not to estimate general population behaviour but to understand digital technology engagement with respect to novel drug-related transactions— something no representative survey currently addresses. Surveying people about drug purchasing necessarily relies on self-report which may be unreliable; however, anonymous web surveys with no material incentives at least provide a more optimal setting for people to disclose information on sensitive topics (Kays et al., 2013). We were unable to implementing country clustering because the number of GDS participants who reported use of Televend was small (n=114); this also limited the power of statistical analyses.

4.2 Conclusions

What did the emergence of Televend mean for the future of digital drug trading? Is the Televend-like platform the 'new generation of DW [dark web] market place' (see Figure 1)? Our initial analysis does not indicate widespread uptake of a service that offers similar wares at a smaller scale to its cryptomarket competitors, but further monitoring is required. Competitors may adopt a similar configuration of technologies, and we may see a broadening of appeal of Televend-like markets to people who are otherwise deterred from using cryptomarkets due to the specialised knowledge required to access them (Kowalski et al., 2019), and for whom scrolling through social media feeds is already an everyday routine (Lupinacci, 2020). Furthermore, the relative stability of the Telegram app, compared with darknet marketplaces that suffer from regular downtime, is likely to hold appeal to buyers and sellers alike (Horton-Eddison et al., 2021; Power, 2020). If this innovative digital drug marketplace configuration does start to appeal to a broader population, digital drug buying may move further from the fringes towards the mainstream, with complex effects on drug use prevalence and harms (Aldridge et al., 2018). Conversely, Telegram may change its policies supporting free information exchange, a move that could threaten the existence of Televend-like services. In addition to continued monitoring of messaging apps such as Telegram for emerging Televend-like markets, additional research should more fully investigate the relative appeal of Televend-like markets compared with other digital sourcing modes, as well as strategies buyers use to mitigate perceived risks.

ACKNOWLEDGEMENTS

We would like to thank all participants in the GDS who volunteered their time to complete the survey. In addition, we would like to thank everyone who helped translate and promote the GDS, in particular, our global media partners.

FUNDING

This research did not receive grants from any funding agency in the public, commercial or not-for-profit sectors.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the joint lead authors, MJB and FRL, upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

S1 – Supplementary Material – STROBE checklist for cross-sectional studies

S2 – Supplementary Material – Questionnaire items (GDS)

S3 – Supplementary Material – Missing data analysis (GDS)

S4 – Supplementary Material – Relationship between digital sourcing method and age (GDS)

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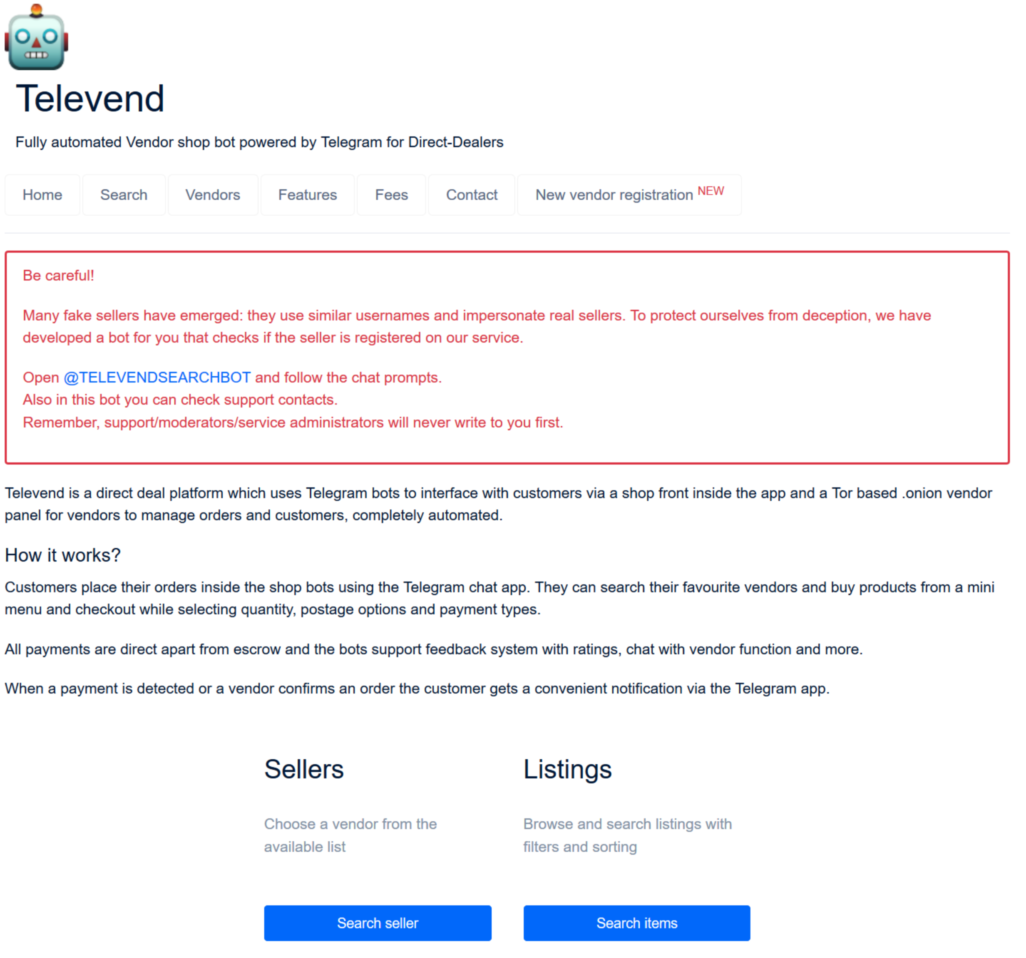
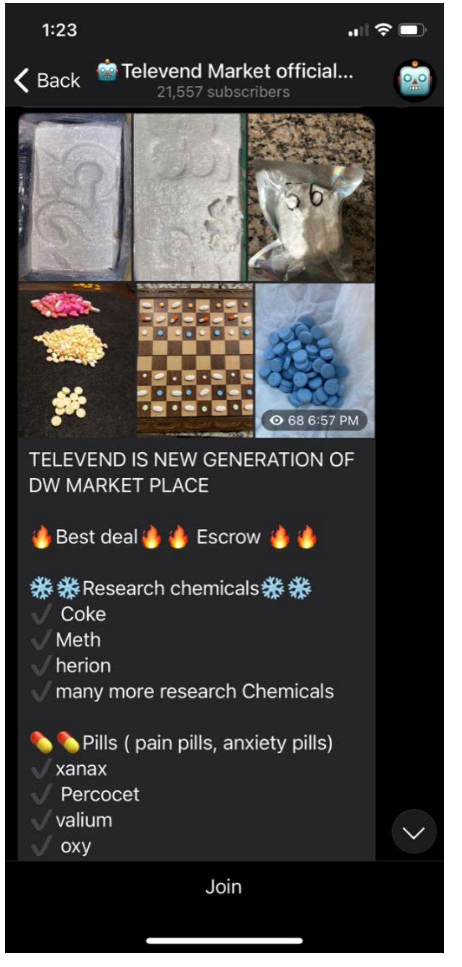
Figure 1. Screenshots of the Televend marketplace: Darknet backend (left) and Telegram frontend (right)





Note: Screenshots taken by authors in May 2021

Table 1. Total numbers of listings, average number of listings, proportion of total number of listings, total number of substances, associated unique vendor counts, main origins and potential destinations per substance category on Televend (4 June 2021–24 July 2021).

Substance category	Total number of ads	Average ads per crawl	Proportion of drug-related ads	Number of substances advertised	Vendors	Shipment Origin	Shipment Destination
Cannabinoids	7,591	948.9	40.2%	10	183	United Kingdom (50.9%), United States (24.4%), Canada (6.6%)	United Kingdom (29.2%), Worldwide (26.6%), Europe (21%)
Anxiolytic	1,673	209.1	8.9%	25	68	United Kingdom (71%), Germany (9.8%), United States (9.5%)	Worldwide (57.5%), United Kingdom (28.1%%), United States (6.9%)
Psychedelics	1,589	198.6	8.4%	12	94	United Kingdom (42.9%), United States (24.4%), Netherlands (8%)	Worldwide (39.4%), United Kingdom (21.6%), United States (14.8%)
Opioids	1,569	196.1	8.3%	23	65	United Kingdom (41%), United States (25.2%), Germany (18.6%)	Worldwide (48.6%), United Kingdom (20.9%), United States (19.7%)
MDMA/Cathinone	1,276	159.5	6.8%	18	98	Netherlands (27%), United Kingdom (25%), Germany (18.1%)	Worldwide (45.6%), Europe (17.7%), United States (15.1%)
Cocaine	1,153	144.1	6.1%	1	112	United Kingdom (42.1%), United States (26.7%), Netherlands (13.4%)	Worldwide (37%), United States (25%), United Kingdom (17.8%)
Steroid	1,016	127.0	5.4%	30	8	United Kingdom (68.1%), United States (29.4%), Germany (2.3%)	Worldwide (54.5%), United States (31.8%), United Kingdom (13.7%)

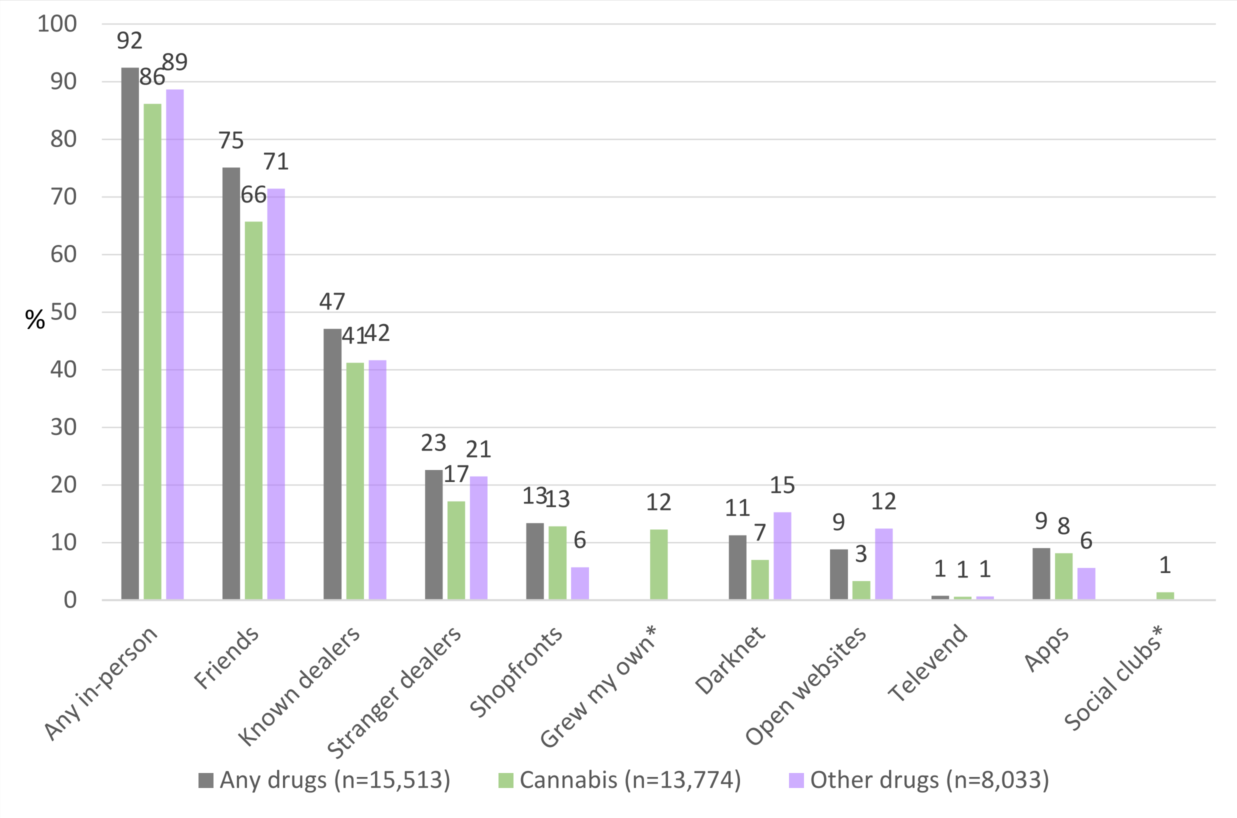
Phenylamine	997	124.6	5.3%	15	84	United States (41.9%), United Kingdom (19%), Germany (14.7%)	Worldwide (39.8%), United States (32.5%), United Kingdom (11.9%)
PDE5-inhibitor	841	105.1	4.5%	4	28	United States (45.5%), United Kingdom (31.8%), France (15%)	United States (54.6%), Worldwide (36%), United Kingdom (8%)
Dissociative	760	95.0	4.0%	8	78	United Kingdom (42.1%), Germany (17.4%), Netherlands (14.7%)	Worldwide (40.7%), Europe (22.5%), United Kingdom (16.1%)
Others (Antihistamine, Hydroxybutyrates, Quinazolinone, Sleeping pills)	202	25.3	1.1%	7	22	United Kingdom (65.9%), Germany (20.8%), France (5.2%)	Worldwide (58.6%), United Kingdom (27.6%), United States (11%)
Antidepressant	193	24.1	1.0%	13	10	France (57.1%), United Kingdom (31.7%), United States (6.2%)	Worldwide (93.8%), United States (.25%), Canada (1%)
Total	18,860	2,357.5		166	313	United Kingdom (46.9%), United States (23.6%), Germany (7.7%)	Worldwide (39.3%), United Kingdom (23.1%), United States (18.8%)

Table 2. Total numbers of listings, average number of listings, proportion of total number of listings, total number of substances, associated unique vendor counts, main origins and potential destinations per substance category on White House Market (7 June 2021-26 July 2021).

Substance category	Total number of ads	Average ads per crawl	Proportion of drug-related ads	Number of substances advertised	Vendors	Shipment Origin	Shipment Destination
Cannabinoid	87,338	10,917.3	34.2%	17	627	United States (42.9%), United Kingdom (29.3%), Germany (10.4%)	United States (36.8%), Worldwide (20.4%), United Kingdom (17.5%)
Psychedelic	29,147	3,643.4	11.4%	33	399	United States (26.3%), Germany (19.3%), United Kingdom (16.8%)	Worldwide (40%), United States (22.5%), Europe (19.7%)
MDMA/Cathinone	24,885	3,110.6	9.8%	18	317	Netherlands (30.3%), Germany (23.8%), United Kingdom (16.6%)	Worldwide (38.2%), Europe (27.5%), United Kingdom (9.8%)
Anxiolytic	22,950	2,868.8	9.0%	33	291	United Kingdom (42.3%), United States (35.3%), Australia (3.6%)	Worldwide (42.9%), United States (34.1%), United Kingdom (9%)
Amphetamine-type	22,363	2,795.4	8.8%	30	436	United States (26.7%), Germany (25.3%), Netherlands (16.5%)	Worldwide (30.2%), United States (24.6%), Europe (22.6%)
Cocaine	21,774	2,721.8	8.5%	2	344	United Kingdom (24.8%), United States (198%), Germany (17%)	Worldwide (39.9%), Europe (17.2%), United States (17.0%)
Opioid	15,446	1,930.8	6.1%	30	302	United States (25.9%), United Kingdom (18.2%), Netherlands (18%)	Worldwide (48.0%), United States (24.2%), Europe (11.5%)

Dissociative	12,391	1,548.9	4.9%	16	230	Germany (26.2%), Netherlands (24.6%), United Kingdom (18.6%)	Worldwide (33.1%), Europe (34.7%), United States (9.4%)
PDE5-inhibitor	8,427	1,053.4	3.3%	3	87	India (31.1%), United Kingdom (25.4%), United States (18.8%)	Worldwide (68%), United States (16.6%), Europe (6.9%)
Steroid	8,152	1,019.0	3.2%	65	64	United States (34.1%), United Kingdom (32.4%), Netherlands (9.5%)	Worldwide (56.8%), United States (26.4%), Europe (6.9%)
Others (Antihistamine, Hydroxybutyrates, Quinazolinone, Sleeping pills)	1,326	165.8	0.5%	9	46	United States (29.6%), United Kingdom (22.6%), India (9.4%)	Worldwide (32.7%), United States (32.6%), Europe (15.4%)
Antidepressant	891	111.4	0.3%	26	35	India (29.4%), United Kingdom (19.8%), France (18.9%)	Worldwide (75.5%), Europe (9.7%), United Kingdom (7.5%)
Total	255,090	31,886.3		282	1418	United States (29.9%), United Kingdom (24.6%), Germany (14%)	Worldwide (34.2%), United States (26.2%), Europe (16.1%)

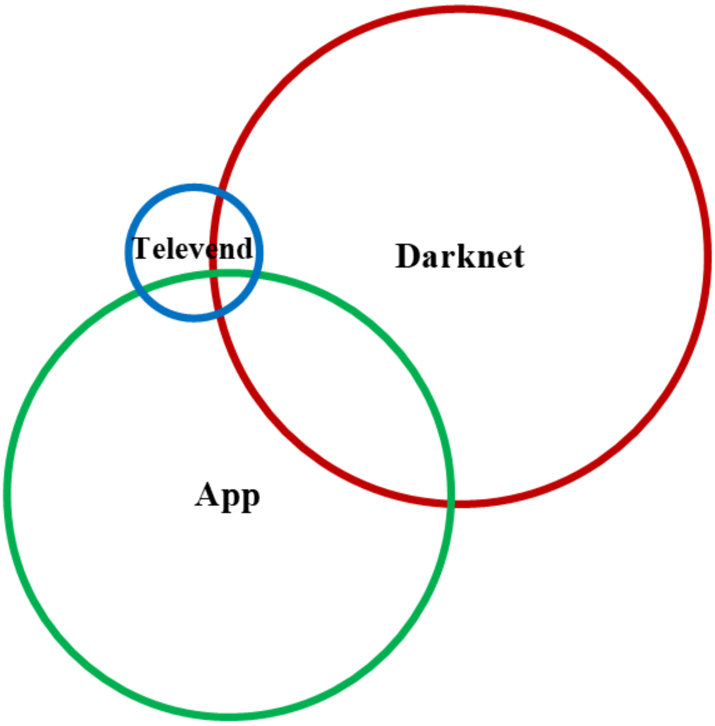
Figure 2: Sources of drugs obtained in the last 12 months by cannabis and other drugs (%) (N=15,513)



Source: Global Drug Survey 2021.

Notes. * denotes option only available for cannabis. Other drug category included all other drugs where sourcing was measured by the survey, see S2. Any in-person includes friends, known dealers and dealers who were strangers. Shopfronts included the following examples: adult stores, head shops, coffee shops, smoke shops, cannabis dispensaries. Darknet markets included purchased directly or through an intermediary. Open websites were defined as not darknet markets. Apps were defined as 'social and messaging apps, e.g. WhatsApp, SnapChat, Instagram, Wickr, Facebook Messenger, etc.'.

Figure 3: The intersection of three digital drug sourcing methods (n) (N=2926)



Darknet (D)	1,750
Televend (T)	114
App (A)	1,399
T and D	38
T and A	31
D and A	284
T, D, and A	16
Total	2,926

Table 3. Demographic and drug use characteristics by digital drug trading group

	Televend (all) n=114	Darknet (only) n=1,444	Apps (only) n=1,100	p value
Age (median, IQR)	26 (21-33.5)	24 (20-32)	23 (19-29)	<.001
Gender (%)				
Cis man	77	80	68	<.001
Cis woman	15	13	26	
Trans, non-binary or intersex	8	7	6	
Highest qualification (%)				
University degree	43	34	32	.059
Country of residence (%)				
Germany	33	22	8	<.001
United States	4	14	11	
United Kingdom	11	12	8	
France	4	5	9	
Australia	9	5	9	
Finland	2	10	2	
Mexico	4	0	11	
Ireland	4	5	5	
Denmark	0	1	8	
New Zealand	0	2	5	
Brazil	2	0	6	
Austria	0	3	1	
Sweden	0	3	1	
Netherlands	0	2	2	
Switzerland	8	2	1	
Other country	19 *	12	12	
Total no. drug types (median, IQR) [a]	4 (2-5)	4 (2-6)	3 (2-5)	<.001
Max. freq. of most used drug type (median, IQR) [b]	120 (26-340)	80 (20-250)	155 (45-320)	<.001

Source: Global Drug Survey 2021.

Notes. See S2 for questionnaire items and how variables were derived. * Other countries that reported use of Televend included Israel (6), Argentina (2), Iceland (2), Spain (2), 1 each for Andorra, Aruba, Belgium, Canada, Italy, Latvia, Portugal, Russian Federation, Ukraine, Zimbabwe. [a]Total number of drug types used in the past 12 months. [b]The number of days in the past 12 months that respondent reports using their most used drug type; e.g. 12=monthly; 365=daily.

Table 4. Multinomial logistic regression predicting sourcing group (Televend (all), Darknet (only), Apps (only)) for subsample aged 16-50 years

	Univariable				Multivariable			
Variable	Televend vs Darknet		Televend vs Apps		Televend vs Darknet		Televend vs Apps	
	RRR (95% CI)	p value	RRR (95% CI)	p value	aRRR (95% CI)	p value	aRRR (95% CI)	p value
Age [a]	1.02 (1.00-1.04)	.099	1.05 (1.02-1.07)	<.001	1.01 (0.99-1.04)	.257	1.06 (1.03-1.09)	<.001
Gender								
Cisgender man [#]								
Cisgender woman	1.15 (0.66-2.00)	.626	0.49 (0.28-0.84)	.010	1.08 (0.61-1.93)	.782	0.43 (0.24-0.77)	.004
Trans, non-binary or intersex	1.19 (0.58-2.44)	.630	1.10 (0.53-2.27)	.807	1.17 (0.55-2.51)	.678	1.09 (0.50-2.36)	.835
Highest qualification								
University degree	1.47 (0.99-2.18)	.054	1.64 (1.10-2.45)	.014	1.34 (0.88-2.04)	.176	1.28 (0.83-1.97)	.261
Total no. drug types [b]	0.98 (0.90-1.07)	.685	1.13 (1.04-1.24)	.006	1.00 (0.92-1.10)	.961	1.20 (1.09-1.31)	<.001
Max. freq. of most used drug type [c]	1.002 (1.000-1.003)	.013	0.999 (0.998-1.000)	.284	1.002 (1.000-1.003)	.033	0.998 (0.996-1.000)	.032

Source: Global Drug Survey 2021.

Notes. N=2,539. Televend (all) n=108; Darknet (only) n=1,374; Apps (only) n=1,057. Analyses exclude n=46 respondents aged over 50 years. [#]Reference group. [a]Given that non-linear relationships between age and drug use are common, polynomial age terms were included in the model (not shown), but the linear term provided the best fit (shown). [b]Total number of drug types used in the past 12 months. [c]The number of days in the past 12 months that respondent reports using their most used drug type; e.g. 12=monthly; 365=daily.

S1 – STROBE Statement—checklist of items that should be included in reports of observational studies.
Barratt et al. ‘Exploring Televend, an innovative combination of cryptomarket and messaging app technologies for trading prohibited drugs’

	Item No.	Recommendation	Page No.	Relevant text from manuscript
Title and abstract	1	(*a*) Indicate the study’s design with a commonly used term in the title or the abstract	2	Televend and White House Market (WHM) were scraped (Jun–Jul 2021) and a global cross-sectional web survey of 15,513 drug buyers (Global Drug Survey; GDS) was conducted (Dec 2020–Mar 2021).
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	2	See Findings and Conclusions of Abstract
Introduction				
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	3-5	See introduction section, including “To our knowledge, Televend has been only briefly mentioned in the scientific literature… Televend is the first combination of a cryptomarket and app-mediated market, making it a unique phenomenon worthy of study. It is important to characterise this new marketplace in terms of its similarities or differences to existing cryptomarkets and to determine whether it attracted similar or different buyers.”
Objectives	3	State specific objectives, including any prespecified hypotheses	5	This exploratory study has the following aims: 1. How similar are the number and characteristics of listings and vendors on Televend to the most popular cryptomarket in 2021, White House Market (WHM) (Pedersen et al., 2021)? 2. Using a global survey of people who buy illegal drugs (derived from the Global Drug Survey; GDS): a. Is Televend used to purchase drugs? If so, for which drug types? b. How does the use of Televend compare to the use of other drug sources? c. What are the demographic and drug use characteristics of groups that report use of different digital

				sourcing methods, including Televend, darknet markets and app-mediated markets?
Methods				
Study design	4	Present key elements of study design early in the paper	5	"We utilised two data sources for this cross-sectional study: (1) web scrapes of Televend and a comparison cryptomarket, WHM; and (2) an online survey of drug buyers, via the GDS 2021."
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	5-6	Web scrapes: "Listing data were collected weekly over an eight-week period from the Televend darknet end (4 June to 24 July 2021) and WHM cryptomarket (7 June to 26 July 2021) using custom web crawlers that automatically collect all information of interest from a website." GDS: "GDS2021 launched on December 1, 2020 and ran until March 16, 2021."
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up *Case-control study*—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls *Cross-sectional study*—Give the eligibility criteria, and the sources and methods of selection of participants	6-7	Web scrapes: "Listings sharing the same ID number for WHM or the exact same information for Televend collected during the same crawling session were discarded from further analysis. The advertisement texts were processed using an extended version of the eDarkTrends-dedicated Named Entity Recognition (NER) algorithm to detect relevant entities (for further detail see Lamy et al., 2020; Lamy et al., 2021). The NER encompasses 5,707 terms associated with 19 psychoactive substance classes (e.g., cathinone, opioid, tryptamine). Manual checks were performed on advertisement data to remove inconsistencies and limit false positive identifications (e.g., "Versace" appears in advertisements for cannabis strains, MDMA pill logos and luxury brand markings on counterfeit items). Individual listings that advertised several substances (e.g., "PARTYPACK - 1G - HEROIN - 1G - MDMA") were discarded. Listings that did not provide specific information regarding their shipment origin (e.g., "Worldwide") were removed from frequency analysis of shipment origin." GDS: "Respondents were recruited via media partners and collaborating institutions worldwide, such as Vice, Mixmag,

				The Guardian, Fairfax Media, and global social platforms, such as Facebook and Twitter… For the current analysis, we only included respondents who answered the drug sourcing questions. These questions were only displayed to respondents that reported use in the last 12 months of any of the drug types of interest. Respondents who only chose 'I didn't pay / it was free' or 'another source' were excluded from analysis."
		(*b*) *Cohort study*—For matched studies, give matching criteria and number of exposed and unexposed *Case-control study*—For matched studies, give matching criteria and the number of controls per case		N/A
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	6-7	Web scrapes: "The raw HyperText Markup Language files (HTML) of drug advertisements were then parsed using a dedicated parser to extract information regarding advertised product, vendor unique name, country/region of shipment origin, and potential shipment destination country/region…. The advertisement texts were processed using an extended version of the eDarkTrends-dedicated Named Entity Recognition (NER) algorithm to detect relevant entities (for further detail see Lamy et al., 2020; Lamy et al., 2021). The NER encompasses 5,707 terms associated with 19 psychoactive substance classes (e.g., cathinone, opioid, tryptamine)." GDS: "Drug sourcing was measured for the following drug types: cannabis, LSD, mushrooms, cocaine, MDMA, methamphetamine, GHB, ketamine, heroin, synthetic cannabinoid receptor agonists (SCRAs), other new/novel substances and prescribed opioids used nonmedically. Respondents were asked where they had purchased each drug type from in the last 12 months and could select multiple options from a defined list. Drugs sourced from darknet markets purchased directly and purchased indirectly were combined into a single darknet market or cryptomarket category. These data are presented for cannabis separately

				then combined for all drug types excluding cannabis. Demographics. Country of residence, age, gender (with 3 levels; measurement and derivation described in S2) and level of education were included in the regression. Drug use characteristics. Use of each drug type in the last 12 months and frequency of use during that time were measured. Composite variables were created from these including total number of drug types used in the last 12 months and the maximum frequency of use of any drug type during that period (minimum 1 to maximum 365 days of use). Refer to S2 for all questions.”
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	5-6	“We utilised two data sources for this cross-sectional study: (1) web scrapes of Televend and a comparison cryptomarket, WHM; and (2) an online survey of drug buyers, via the GDS 2021… Listing data were collected weekly over an eight-week period from the Televend darknet end (4 June to 24 July 2021) and WHM cryptomarket (7 June to 26 July 2021) using custom web crawlers that automatically collect all information of interest from a website… The GDS is an independent research organisation that collects data on drug use patterns worldwide.”
Bias	9	Describe any efforts to address potential sources of bias		N/A
Study size	10	Explain how the study size was arrived at		N/A
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why		N/A
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	7-8	“The first two aims used descriptive statistics, while the final aim utilised a multivariable multinomial logistic regression to determine how demographic and drug use variables (modelled as main effects only) were associated with three mutually exclusive groups: (1) Televend, (2) Darknet only, (3) Apps only. Due to empty and small cell numbers for older ages, the regressions were conducted on a subsample aged 16–50 years.”

		(*b*) Describe any methods used to examine subgroups and interactions		N/A
		(*c*) Explain how missing data were addressed	7-8	"Due to empty and small cell numbers for older ages, the regressions were conducted on a subsample aged 16–50 years. Complete case analysis was used throughout (see S3 which shows percentage missing for regression analyses was 2.8%)."
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed *Case-control study*—If applicable, explain how matching of cases and controls was addressed *Cross-sectional study*—If applicable, describe analytical methods taking account of sampling strategy	7-8	"The first two aims used descriptive statistics, while the final aim utilised a multivariable multinomial logistic regression to determine how demographic and drug use variables (modelled as main effects only) were associated with three mutually exclusive groups: (1) Televend, (2) Darknet only, (3) Apps only."
		(*e*) Describe any sensitivity analyses		N/A
Results				
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	7-8	Web scrapes: "36,122 Televend listings were collected through eight weekly crawl sessions for an average of 4,515.25 ads (min=4,173, max=4,851) per crawl." GDS: "33,269 responses were retained after cleaning for missing age, gender or drug screen, and reports of using a fake drug. For the current analysis, we only included respondents who answered the drug sourcing questions. These questions were only displayed to respondents that reported use in the last 12 months of any of the drug types of interest. Respondents who only chose 'I didn't pay / it was free' or 'another source' were excluded from analysis. These exclusions led to an analytic sample of N=15,513."
		(b) Give reasons for non-participation at each stage		N/A
		(c) Consider use of a flow diagram		N/A
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	9	"Table 3 compared the Televend group (n=114) with app only (n=1,110) and darknet only (n=1,444) groups. The Televend group was older than both the darknet and app groups (median ages 26 v 24 v 23 years, respectively, p<.001). The Televend group was more similar in gender

				distribution to the darknet group, with the app group containing a greater proportion of cisgendered women (26% v 15% in the Televend group, p<.001). The most common countries of residence for the Televend group were Germany, UK, Australia and Switzerland; for the darknet group, Germany, US, UK and Finland; for the app group, US, Mexico, France and Australia.”
		(b) Indicate number of participants with missing data for each variable of interest	Table S3	See Supplementary Table 3.
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)		
Outcome data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time		
		Case-control study—Report numbers in each exposure category, or summary measures of exposure		
		Cross-sectional study—Report numbers of outcome events or summary measures	8-9	Televend: “36,122 Televend listings were collected through eight weekly crawl sessions for an average of 4,515.25 ads (min=4,173, max=4,851) per crawl. The number of listings advertised on Televend increased by 4.9% during the study period (4,406.5 ads on average for the four crawling sessions of June compared to 4,624 on average for the four crawling sessions of July).” GDS: “While around 1/10 GDS drug buyers reported sourcing from darknet markets (11.3%) or apps (9.0%), very few reported use of Televend (0.73%). Most Televend buyers (68/114) reported buying cannabis, with other drug types purchased via Televend including cocaine (20), MDMA (17), LSD (12), psilocybin mushrooms (6), ketamine (6), prescription opioids (3), methamphetamine (2), heroin (2), GHB (1) and new/novel drugs (1).”
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	Table 4 and S2, p3.	Table 4 provides unadjusted and adjusted estimates with confidence intervals. Confounders are listed in Table 4. Text in S2 indicating why drug use confounders were chosen: “Composite variables were created from Use in the last 12

				months and Frequency of use in the last 12 months including total number of drug types used in the last 12 months and the maximum frequency of use of any drug type during that period (minimum 1 to maximum 365 days of use). Both of these variables were included in the analysis as indicators of level of engagement with drugs, and therefore with drug markets.”
		(*b*) Report category boundaries when continuous variables were categorized		N/A – continuous variables were not categorised.
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period		N/A
Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses		N/A
Discussion				
Key results	18	Summarise key results with reference to study objectives	11	“Measured in number of listings, the nascent marketplace was 10% of the size of the largest drug cryptomarket (WHM). The total number of Televend listings increased slightly, while WHM listing totals decreased slightly over the same 8-week period. Both markets contained predominantly drug-related listings covering broadly similar drug categories. Origin and destination information was also broadly similar between the two markets, with Televend slightly more oriented toward the UK market and WHM toward the US market. To summarise, while being considerably smaller in size, Televend was not noticeably different in its drug listing offerings to its largest drug cryptomarket competitor.”
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	12	“This exploratory analysis has limitations. We measured characteristics of drug-related listings on Televend and WHM. These do not represent actual sales volumes, as each listing may result in anything from no sales to 1000s of sales. Future work using feedbacks/reviews left by customers can be used to approximate sales volume

				(Christin and Thomas, 2019). The GDS uses convenience sampling and therefore cannot be used to indicate prevalence in the population (Barratt et al., 2017). However, the focus of this paper is not to estimate general population behaviour but to understand digital technology engagement with respect to novel drug-related transactions— something no representative survey currently addresses. Surveying people about drug purchasing necessarily relies on self-report which may be unreliable; however, anonymous web surveys with no material incentives at least provide a more optimal setting for people to disclose information on sensitive topics (Kays et al., 2013). We were unable to implementing country clustering because the number of GDS participants who reported use of Televend was small (n=114); this also limited the power of statistical analyses."
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	11-13, final paragraph quoted here.	"What did the emergence of Televend mean for the future of digital drug trading? Is the Televend-like platform the 'new generation of DW [dark web] market place' (see Figure 1)? Our initial analysis does not indicate widespread uptake of a service that offers similar wares at a smaller scale to its cryptomarket competitors, but further monitoring is required. Competitors may adopt a similar configuration of technologies, and we may see a broadening of appeal of Televend-like markets to people who are otherwise deterred from using cryptomarkets due to the specialised knowledge required to access them (Kowalski et al., 2019), and for whom scrolling through social media feeds is already an everyday routine (Lupinacci, 2020). Furthermore, the relative stability of the Telegram app, compared with darknet marketplaces that suffer from regular downtime, is likely to hold appeal to buyers and sellers alike (Horton-Eddison et al., 2021; Power, 2020). If this innovative digital drug marketplace configuration does start to appeal to a broader population,

				digital drug buying may move further from the fringes towards the mainstream, with complex effects on drug use prevalence and harms (Aldridge et al., 2018). Conversely, Telegram may change its policies supporting free information exchange, a move that could threaten the existence of Televend-like services. In addition to continued monitoring of messaging apps such as Telegram for emerging Televend-like markets, additional research should more fully investigate the relative appeal of Televend-like markets compared with other digital sourcing modes, as well as strategies buyers use to mitigate perceived risks.”
Generalisability	21	Discuss the generalisability (external validity) of the study results	11	“The GDS uses convenience sampling and therefore cannot be used to indicate prevalence in the population (Barratt et al., 2017). However, the focus of this paper is not to estimate general population behaviour but to understand digital technology engagement with respect to novel drug-related transactions— something no representative survey currently addresses.”
Other information				
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	12	“This research did not receive grants from any funding agency in the public, commercial or not-for-profit sectors.”

*Give information separately for cases and controls in case-control studies and, if applicable, for exposed and unexposed groups in cohort and cross-sectional studies.

Note: An Explanation and Elaboration article discusses each checklist item and gives methodological background and published examples of transparent reporting. The STROBE checklist is best used in conjunction with this article (freely available on the Web sites of PLoS Medicine at http://www.plosmedicine.org/, Annals of Internal Medicine at http://www.annals.org/, and Epidemiology at http://www.epidem.com/). Information on the STROBE Initiative is available at www.strobe-statement.org.

Supplementary material – S2 – GDS items used in Televend paper

DRUG SOURCING

Sources used in the last 12 months

Where did you purchase [drug type]* from in the last 12 months? Only include times when you received drugs in your own country.

- Friends or acquaintances
- Dealers that I know
- Dealers that I don't know/strangers
- Shopfronts (e.g. adult stores, head shops, coffee shops, smoke shops, cannabis dispensaries)
- Darknet markets (purchased by me directly)
- Darknet markets (purchased by someone else)
- Open websites (not darknet markets)
- Televend (direct deal platform using Telegram bots)
- Other social and messaging apps (e.g. WhatsApp, Snapchat, Instagram, Wickr, Facebook Messenger, etc.)
- Cannabis social clubs *[cannabis only]*
- Manufactured or grew my own *[cannabis only]*
- I didn't pay / it was free
- Another source *[note: no other specify text box was provided]*

* DRUG TYPES

For all sourcing questions, they were asked individually for each of the following drug types, using the exact wording below:

- Cannabis products containing THC (psychoactive)
- LSD
- Magic mushrooms (psilocybin)
- Cocaine (powder)
- Ecstasy/MDMA/Molly
- Crystal methamphetamine
- GHB/GBL/ 1.4 butanediol
- Ketamine
- Prescription opioids *[note: nonmedical use is mentioned in the section header]*
- Heroin
- Synthetic cannabinoids
- Novel drugs

DEMOGRAPHICS

Country

Which country do you currently live in?

A list of all countries is provided.

Age

How old are you?

Responses measured continuously from 16 to 85+.

Gender

Gender and sex are measured through three items which are then combined to make a composite variable:

What is your gender?

- Male
- Female
- Non-binary
- Different identity

What gender were you assigned at birth?

- Male
- Female

Are you intersex?

- Yes
- No
- Prefer not to say

The variable used in the analysis contains the following categories

- Cis-woman
- Cis-man
- Trans, non-binary, intersex

It is compiled using the following formula

Cis-woman = Female gender, assigned female at birth, not intersex

Cis-man = Male gender, assigned male at birth, not intersex

Trans = Male gender, assigned female at birth, or Female gender, assigned male at birth

Non-binary = non-binary or different identity

Intersex = indicates intersex

Where trans, non-binary and intersex are combined to facilitate statistic power in analysis

Education levels

Highest academic qualification attained?

- No formal schooling
- Primary school
- Lower secondary school/School certificate/Intermediate Certificate
- Technical or trade certificate
- Higher secondary school/ HSC/VCE/Leaving Certificate
- College certificate/diploma
- Undergraduate degree

- Postgraduate degree
- Don't know

The education variable was dichotomised into university degree or higher versus no university degree, removing ‘don’t know’ responses.

DRUG USE CHARACTERISTICS

Use in the last 12 months

When did you last use the following drugs?

Each drug type is listed alongside the following response options:

- Never
- In the last 30 days
- Between 31 days and 12 months
- More than 12 months ago

‘In the last 30 days’ and ‘Between 31 days and 12 months’ are combined to indicate use in the last 12 months.

Frequency of use in the last 12 months

For respondents who report use of a drug type in the last 12 months, the following question is asked:

During the last 12 months, on how many days have you used [drug type]? For example: Daily = 365, Twice weekly = 104, Weekly = 52, Monthly = 12

A text entry field is provided that is validated to receive responses between 1 and 365.

Composite variables were created from *Use in the last 12 months* and *Frequency of use in the last 12 months* including total number of drug types used in the last 12 months and the maximum frequency of use of any drug type during that period (minimum 1 to maximum 365 days of use). Both of these variables were included in the analysis as indicators of level of engagement with drugs, and therefore with drug markets.

Televend – S3 – Missing data analysis for multinomial regression (for Table 4)

Variables	N complete	Total possible N	Missing	Percentage missing
Age	2612	2612	0	0.0
Gender	2612	2612	0	0.0
Highest qualification	2559	2612	53	2.0
Total no. drug types	2612	2612	0	0.0
Max. freq. of most used drug type	2591	2612	21	0.8
Median percentage missing				0.0
Complete case analysis	2539	2612	73	2.8

Televend – S4 – Relationship between digital sourcing method and age