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Understanding and preventing the advertisement and sale of illicit drugs to young people through social media: A multidisciplinary scoping review

Ashly Fuller[1,2] | **Marie Vasek**[3] | **Enrico Mariconti**[2] | **Shane D. Johnson**[1,2]

[1]Dawes Centre for Future Crime, University College London, London, UK

[2]Jill Dando Institute of Security and Crime Science, University College London, London, UK

[3]Department of Computer Science, University College London, London, UK

Correspondence
Ashly Fuller, 35 Tavistock Square, London WC1H 9EZ, UK.
Email: ashly.fuller.16@ucl.ac.uk

Abstract

Issues: The sale of illicit drugs online has expanded to mainstream social media apps. These platforms provide access to a wide audience, especially children and adolescents. Research is in its infancy and scattered due to the multidisciplinary aspects of the phenomena.

Approach: We present a multidisciplinary systematic scoping review on the advertisement and sale of illicit drugs to young people. Peer-reviewed studies written in English, Spanish and French were searched for the period 2015 to 2022. We extracted data on users, drugs studied, rate of posts, terminology used and study methodology.

Key Findings: A total of 56 peer-reviewed papers were included. The analysis of these highlights the variety of drugs advertised and platforms used to do so. Various methodological designs were considered. Approaches to detecting illicit content were the focus of many studies as algorithms move from detecting drug-related keywords to drug selling behaviour. We found that on average, for the studies reviewed, 13 in 100 social media posts advertise illicit drugs. However, popular platforms used by adolescents are rarely studied.

Implications: Promotional content is increasing in sophistication to appeal to young people, shifting towards healthy, glamourous and seemingly legal depictions of drugs. Greater inter-disciplinary collaboration between computational and qualitative approaches are needed to comprehensively study the sale and advertisement of illegal drugs on social media across different platforms. This requires coordinated action from researchers, policy makers and service providers.

KEYWORDS
adolescent, harm reduction, illicit drugs, scoping review, social media

1 | INTRODUCTION

The online sale of illicit substances has been happening on the dark web for some time [1–4], but commercial activity is now emerging on Snapchat, Instagram, TikTok and other social media platforms that are commonly frequented by young people [5,6]. In a few clicks, social media posts advertising the sale of cannabis, cocaine or ecstasy can be found, and media coverage argues that this has the potential to normalise consumption among young people [7–9]. This ease of access also may put adolescents at a greater risk of consuming lethal concentrations of drugs as some cases of teenage overdose coincide with drugs being sourced through social media [10]. Agencies including EUROPOL, the European Monitoring Centre for Drugs and Drugs Addiction and the United Nations Office on Drug and Crime have recognised this and have highlighted the aggravating effects of the COVID-19 pandemic on the criminogenic landscape. Preliminary evidence points towards the increased use of social media to buy drugs as these facilitate contactless deliveries to end-consumers [11,12]. In addition, exposure to risky online content has been found to correlate with viewers' own risk-taking behaviour offline [13–15].

Research that provides insight into this problem and how to prevent it would be timely given activity underway to regulate social media and ensure users' safety, such as the UK's Online Safety Bill [16]. Although in its infancy, the existing literature offers some insights to address this growing phenomenon. However, there does not currently exist a comprehensive review of this literature. To that end, we present a systematic scoping review of the advertisement and sale of illicit drugs to young people through social media. The objective of the review was to establish the state of the literature on the sale, purchase and advertisement of drugs across platforms as well as potential solutions to the problem. In contrast to ad-hoc literature reviews, systematic scoping reviews employ a transparent search strategy, are highly replicable and involve steps to minimise bias [16,17]. The research questions that this review aimed to answer are: *What is the state of the literature on the advertisement and sale of drugs on social media towards young people (e.g., methods used, types of data)? In what ways are social media platforms used to advertised illicit drugs and how does this vary across countries? What are the characteristics of users that purchase and sell illicit drugs through social media? What is the rate of posts advertising the sale of illicit drugs?* Finally, *what interventions (technical or otherwise) exist or could be implemented by social media platforms to address this issue?*

The remainder of the paper is organised as follows. The next two sections describe the methodology employed and the findings of the review. The discussion then provides key conclusions outlining directions for future research, for academia and policymakers alike.

2 | METHODS

This research follows an overall top-down (or deductive) approach given the systematic nature of reviews [18], but also incorporates bottom-up (or inductive) elements including an iterative process to adjusting the search to optimise results, and a thematic approach to analysis. More details of these processes are provided below.

2.1 | Scoping review protocol

A protocol adhering to the PRISMA Extension for Scoping Reviews [18] was developed and independently reviewed by three researchers, an external working group and an academic librarian. Scoping reviews tend to have a broader research scope than systematic reviews and do not require a formal quality assessment, but otherwise are very similar in execution [19]. This research was deemed exempt from ethics committee oversight by the UCL Department of Security and Crime Science's Ethics Committee.

2.2 | Databases

The following multidisciplinary electronic databases were searched: PscyInfo, ProQuest and Scopus. Collectively, these search engines index over 30 databases. For example, ProQuest alone indexes over 20 databases. The Rutgers Law Library and National Criminal Justice Reference Service databases were searched to provide coverage of the criminological literature, and the ACM digital library and IEEE Xplore databases were searched to provide more detailed coverage of the computer science and information security literature. The CAIRN and LILACS databases were searched to provide coverage of the French and Latin and American and Caribbean research literature, respectively. Finally, the Arxiv.com and Open Grey databases identify research not yet published and otherwise 'unpublished' research.

2.3 | Search strategy

A preliminary literature search was conducted to develop and refine the search terms. Three key concepts were then used to search the academic databases. These encompass the target population of the study (young people), the phenomenon studied (illicit drug advertisement and sale) and the medium through which it is advertised (social media). Illicit drugs include illegal drugs including ecstasy, LSD and cocaine but also controlled prescription drugs such as Valium or Xanax which may be used illicitly. The inclusion of the latter was (inductively) informed by literature in the field of computer science concerned with illicit drugs, which mostly focuses on (the illegal sale of) prescription drugs. Specific platforms were also included in the search terms (see Table A1) to cover the range of platforms popular among adolescents [20]. Hand searches were conducted to complement the search strategy, especially for grey literature publications such as government reports or legal bills. Backward and forward searches* were also carried out by identifying relevant articles in the studies identified through the systematic searches. Forward searches were based on three seminal papers [21–23] on the topic of young people using social media to purchase illicit drugs.

The reference software *Zotero* was used to manage the literature database while *Rayyan* was used to screen and select relevant articles. The search was carried out from January to March 2022 and updated in August 2022. It became apparent that the searches conducted using the IEEE Xplore and ACM digital library databases retrieved only two records when the search string was applied to the 'abstract' field but retrieved a disproportionately high number of studies when using the 'full-text' one. This was likely due to disciplinary specificities related to the keywords used within these two databases. Despite the identification of many false positives using automated 'full-text' searches, these databases were included because the papers retrieved were highly relevant to the review from a technical perspective. The struggle to accurately encapsulate keywords from the search string across databases is here representative of the disciplinary challenges encountered when examining issues of this nature. The specific search string ultimately used for these two databases can be found in Table S1, Supporting Information.

TABLE 1 Summary of inclusion criteria for screening and eligibility assessment phases of the scoping review using the PICOS(T) format.

Criteria	Inclusion	Exclusion
Population(s)	Human	Non-human
Intervention(s)	The advertisement and sale of illicit drugs to young people through social media and mobile application platforms	Other types of crime committed through social media
Comparator	Not applicable	Not applicable
Outcome(s)	Data on users, drugs, terminology and social media platforms; Perceptions and drug search strategies; Interventions and solutions	
Study design	Peer-reviewed studies, academic theses, conferences proceedings; Industry reports; Government or institutional publications	Opinion pieces; Commentaries; News articles; Book reviews
Time	2015–2022	Prior to 2015
Language	English; French; Spanish; Other if a translation was available	Other than English, French and Spanish

2.4 | Eligibility criteria

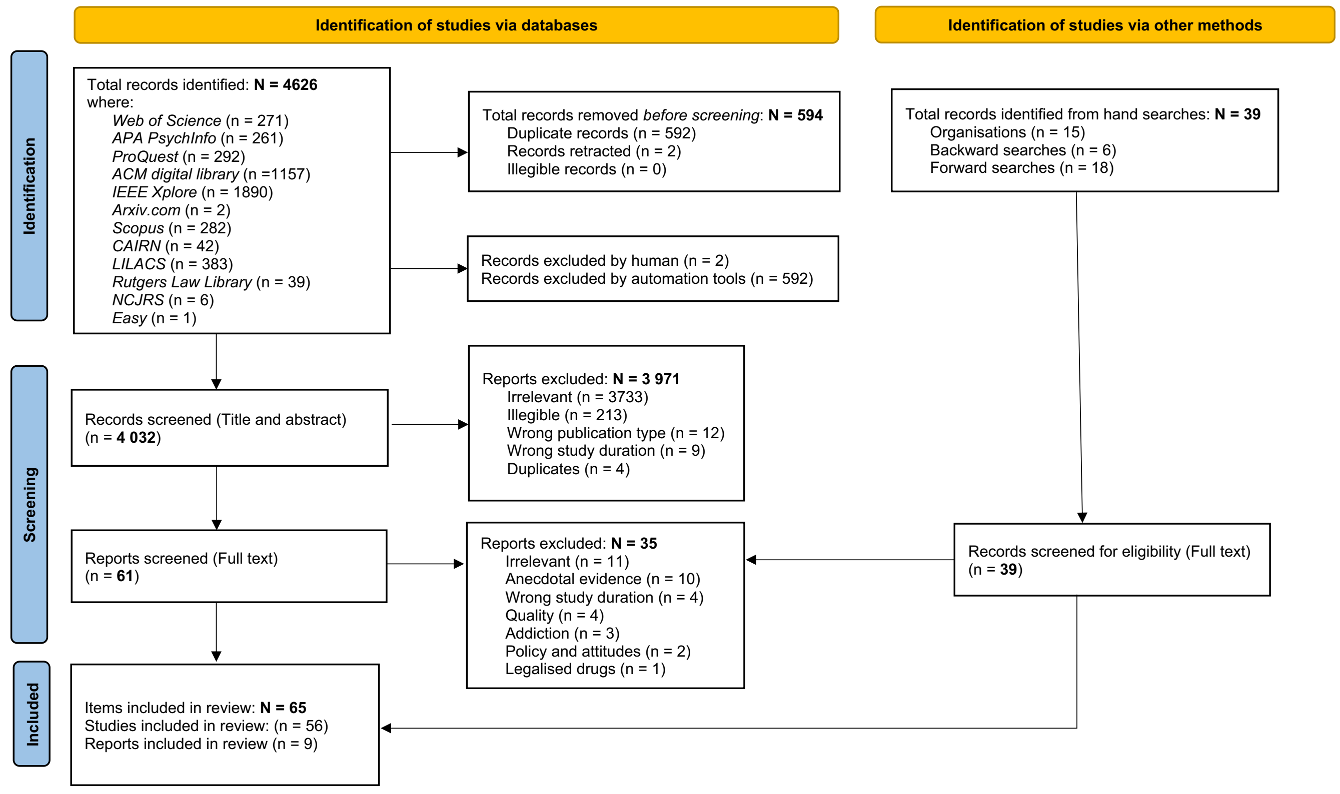
We use the PICOS(T) framework to specify the eligibility criteria for study selection [24,25] (Table 1). All types of study design were included, but opinion pieces, news articles, book reviews and commentaries were excluded. Grey literature including conference proceedings, industry reports, government and institutional publications were also included. The population of interest are children and young people but given the infancy of the literature, no specific age restrictions were employed. Publications written in English, French and Spanish were included. Searches were limited to papers published between 2015 and 2022. To be included, publications had to clearly discuss the advertisement and sale of illicit drugs through social media platforms and provide empirical evidence. We considered social media in this review as mobile applications (in contrast with web-based forums) that: are popular with young people [20], are known to facilitate drug supply [22] and that mainly focus on the provision of video/image-based content [26].

This research excluded papers that examined posts from jurisdictions where the drugs studied were considered legal. This criterion was applied to ensure the focus of the research and avoid confusion or the conflation of results relating to legalisation status. Publications about other crimes committed through social media were excluded. Where interventions were discussed, no restrictions were applied to the approach taken.

2.5 | Data extraction and analysis

To address the key research questions and provide a broader understanding of the strengths, limitations and

TABLE 2 PRISMA 2020 flow diagram for new systematic reviews which included searches of databases, registers and other sources.



coverage of the existing literature, data were systematically extracted from each study about: (i) country of study; (ii) design and methods; (iii) main results of the study; (iv) identified limitations; (v) sample sizes; (vi) reliability checks; and (vii) existence of an ethical review and suggested future research. When available, the following variables were also extracted: (i) policy implications; (ii) rate of posts advertising drugs; (iii) types of drugs advertised and their terminology[†]; (iv) social media platforms used; (v) user characteristics; (vi) user search strategies (*modus operandi*); (vii) perceptions of drug advertisements; (viii) types of interventions discussed; (ix) exposure to drug-related content; and (x) expected time horizon of the issue. A thematic approach [27] was used to identify the main themes discussed across the included studies.

Inter-rater reliability was monitored during the screening of titles and abstracts. Two researchers screened the titles and abstracts of 100 articles, guided by a decision tree (Figure S1). The computed Cohen's kappa score for the sample of papers was 0.82, indicating almost perfect agreement (97%) [28]. The small number of disagreements were resolved through discussion.

3 | RESULTS

3.1 | Descriptive characteristics of studies

Table 2 shows the number of papers identified, screened, assessed and excluded at each stage of the review, along with the reasons for exclusions [29]. From an initial search query of 4626 records, 594 were removed before screening (592 were duplicates and 2 were retracted studies). Of the 4032 records reviewed during the screening of titles and abstracts, 61 met the criteria for full text screening. Hand searches (including forward and backward) yielded an additional 39 records which were also screened. From these 100 records, 35 were excluded leaving 63 records included in the final review. Of these, 56 were peer-reviewed studies and 9 were grey literature reports. Only one of the latter [30] provided novel empirical evidence. The others discussed relevant issues but did not contribute additional data and hence were omitted from the analysis that follows.

Researchers from 18 countries were involved in the 56 studies. More than half were from the United States ($N = 33$), 3 were from Denmark, 13 were cross-national collaborations and 7 were from other countries (Italy, Chile, India, Canada, Mexico, Australia and Ecuador). Authors spanned eight unique disciplines with computer science being the most represented ($N = 20$). This was followed by multidisciplinary projects ($N = 15$), health-related disciplines ($N = 10$), psychology ($N = 4$), sociology ($N = 4$), communication ($N = 2$) and crime science ($N = 1$). The research methods employed were diverse, ranging from the application of machine learning (ML), statistical analysis, interviews, content analysis, ethnography, ad-hoc literature reviews, focus groups and surveys.

A total of 30 unique social media platforms were studied across the studies with Twitter ($N = 28$) and Instagram ($N = 26$) being clearly overrepresented, followed by Facebook ($N = 14$) and Snapchat ($N = 10$) (Figure S2). Most studies used quantitative methods ($N = 35$), but 16 adopted a qualitative approach and 3 used mixed methods. Qualitative papers tended to look at more than one platform whereas quantitative studies focused on one platform given the constrains posed by data collection methods (interviews and surveys can be more flexible than web scrapping).

The 56 reviewed studies examined 30 different types of unique drugs, although opioids and cannabis represented 40% of the drugs considered (Figure S3). The extraction and coding of drug names proved challenging as there were many inconsistencies in reporting across studies: some using chemical names (e.g., Lorazepam), some using brand names (e.g., Ativan), while others used the drug family group (e.g., Benzodiazepines). To minimise this, drug names were extracted as written and subsequently classified into the most prevalent categories. For example, specific prescription drugs were grouped under 'opioids'.

3.2 | Rates and sample sizes

The rates of posts advertising drugs on social media was measured in two ways across studies. First, as the proportion of social media posts selling/advertising drugs and second, as the proportion of user accounts/individuals buying and/or selling drugs. Studies conducted by computer scientists typically collected and scraped social media posts and used these as the unit of analysis, while qualitative studies by researchers from other fields typically surveyed or interviewed users. The total sample sizes of the reviewed studies can be found in Tables S2 and S3. Only one study [31] examined video-based metrics and provided viewership numbers. Other metrics such as incidence (*new posts in period of time t*) virality (*posts viewed in a period of time t*) or engagement rates (*interactions of content per follower*) were not examined in the reviewed studies.

For each study that extracted a representative sample of social media posts, we extracted data on, and calculated the proportion of illicit drug posts and their confidence intervals[‡] (Formulae S1). We also calculated the overall mean and associated confidence intervals for each platform (Table S4). The latter were calculated using the inverse variance weighted approach and a random effects model [33] which are commonly used in statistical meta-analyses [34,35].

Figure 1 shows the proportion and confidence intervals of illicit drug advertisement posts found by studies and the weighted mean proportion across platforms for the 23 studies for which data were available. For clarity, studies are grouped by platform. There is variation in the estimated percentage across studies, but on average, just over 13% of all posts sampled in the reviewed studies advertised illicit drugs. We note that for the overall estimate, the confidence intervals are very small. This is explained by some studies having very large samples (see Table S2: six studies had millions of observations). The calculations were re-computed excluding the studies with the largest samples, which produced a slightly higher overall proportion of 0.15 (with confidence intervals of 0.013–0.170). Across the platforms examined, the average proportion of illicit drug advertisements was highest for Instagram (0.19, 95% confidence interval 0.12–0.25). Overall, these rates seem high, although it is worth noting that it is difficult to say what 'high' is in the absence of a meaningful baseline or comparison (e.g., what is the occurrence for advertisements of vitamins?).

In the first quarter of 2022, Meta (which includes Facebook and Instagram) reported that they had found 5 per 10,000 posts relating to illicit and regulated goods [36]. In contrast, in its latest transparency report, Twitter reports that illegal or regulated goods or services made up 11.20% of the total content removed (571,902 of 5 million posts) [37]. This is in line with the proportion of illicit drugs posts found in the reviewed studies for Twitter (11%, 95% confidence interval 2.5–19.3). However, Twitter's categorisation for illegal goods includes other items such as firearms which might inflate that number. Overall, these comparisons are useful to provide a picture of the rate of occurrence of illicit drug advertisement posts on social media but should be carefully considered given the variation in sample sizes.

3.3 | A multifaceted approach

The studies reviewed captured different aspects of the issue researched, providing unique perspectives. They also used different methods and data to understand the advertisement and sale of drugs through social media. Figure 2 illustrates how the methodological design

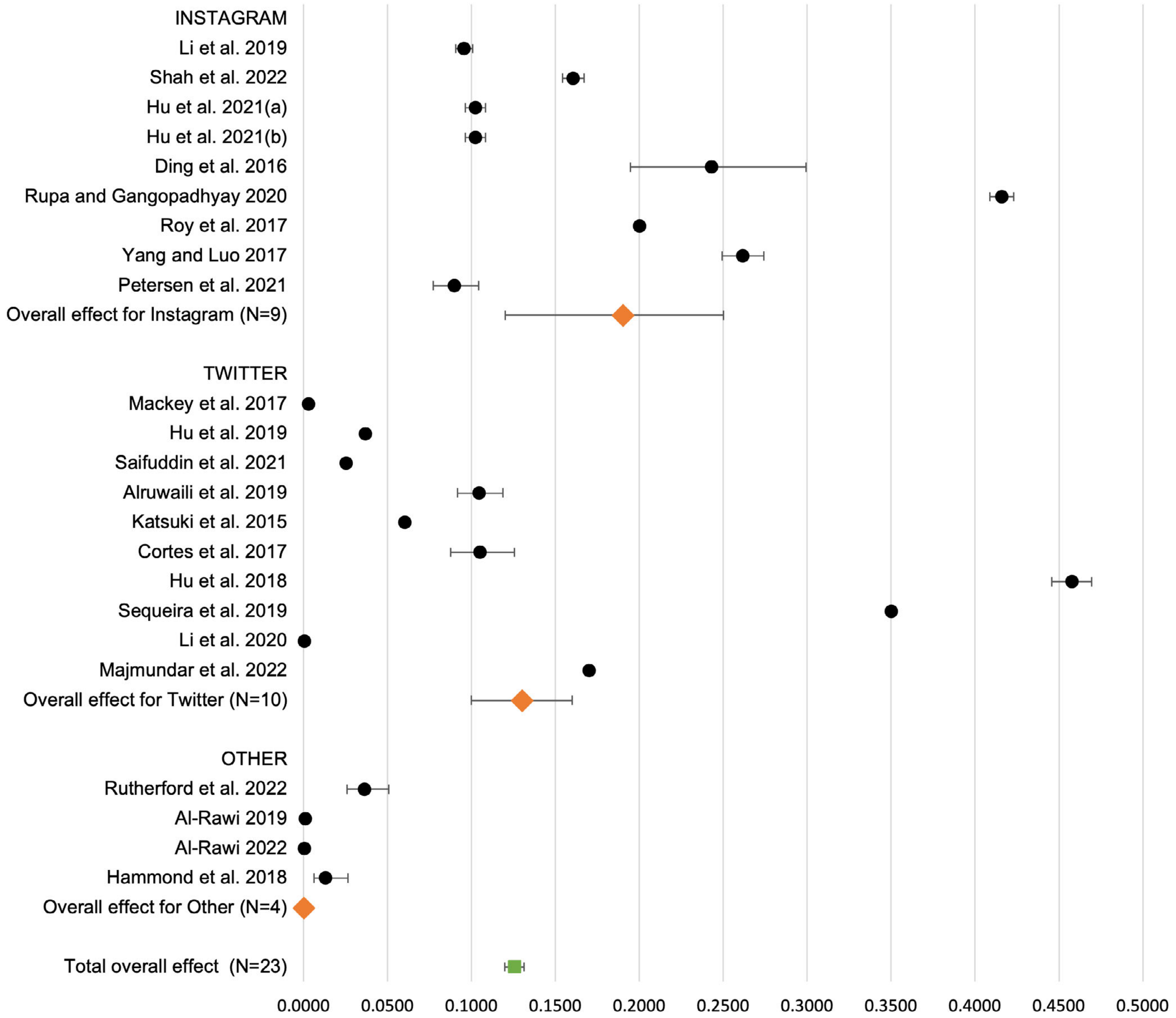


FIGURE 1 Forest plot of the average proportion of illicit drug posts found by individual studies and across platforms ($N = 23$ studies) and their 95% confidence intervals.

adopted by studies varied according to the social media platforms studied. This diversity is inherent to the multidisciplinarity of this review where technical and solution-oriented studies complement and inform existing public health and drug research approaches. Table 3 summarises how the 56 studies were classified under the four general themes of research that emerged. The sections that follow discuss these themes and key findings in more detail.

3.4 | Qualitative research on drug markets and social media platforms

Papers focusing on drug markets and social media platforms [21,22,31,38–44] tended to use qualitative and in-depth approaches to investigate social media. The modus operandi to sell, advertise and purchase drugs on social media was broadly similar across countries and platforms. Drugs were found to be advertised on open platforms where dealers posted images of their product and their contact details to private or encrypted channels of communication. This information was either embedded within the picture, the caption, or comments of the post. After agreeing to a price and a delivery method (postal or face to face), payment was then sent either online (through a platform such as PayPal) or paid in cash during pickup. Despite a high presence of illicit drug advertisements on social media, studies acknowledged that most dealing through platforms (notably the encrypted ones) emanate from a pre-established contact with a drug dealer, a form of social supply.

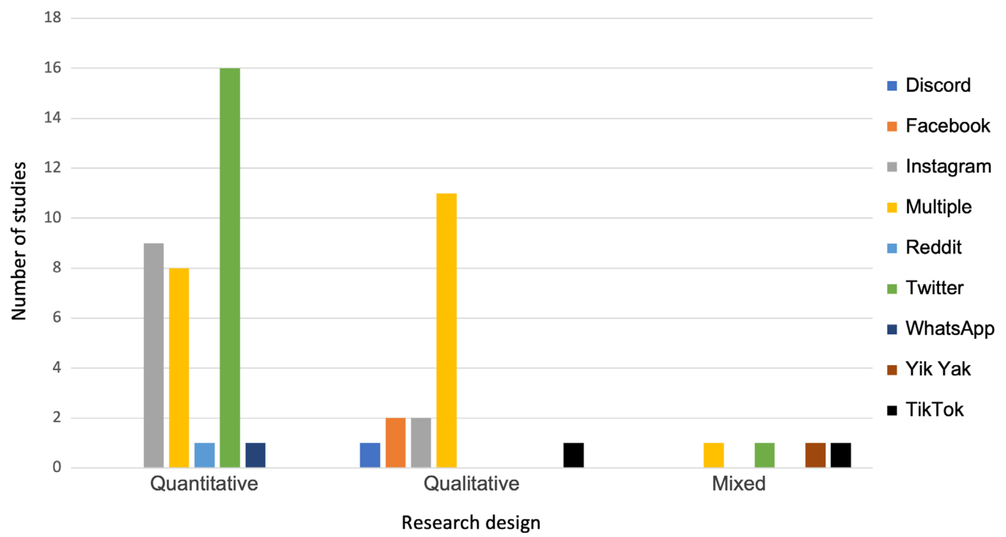


FIGURE 2 Number of studies researching types of social media platform by their methodological design ($N = 56$).

The convenience, expediency and relative security attributed to social media drug dealing were recurring themes across studies [21,22,39,40,43,44,77,79,83–84] which are also noted in studies comparing social media with cryptomarkets [90,91]. These findings attest that users can easily open several accounts to sell or buy, making their products always available and findable despite efforts to remove them by platforms. Emojis, hashtags, comments, search bars and stories are all used by dealers to actively promote their accounts, often by spamming. This content is used to create positive sentiments towards illicit drugs [38,75], integrating humour (for example) to explicitly sell their products and to create memorable advertising [31,76]. This is further accentuated by the sense of personal proximity that social media yields, as users can relate to drug dealers as individuals [30] and are therefore more likely to engage with their content [38].

A concurrent finding between studies related to the movement of users between platforms when purchasing or selling drugs. Advertisements are typically placed on platforms such as Instagram or Facebook whereas discussions around transactions were found to occur on platforms such as Snapchat or Wickr. This distinction is already observed in Demant's et al. [21] and Bakken and Demant's [78] comparative studies which adapt the public/private market divide from the drug literature [92,93] to classify social media into public, semi-private or private digital markets. Thinking of platforms in terms of degrees of 'openness' is valuable for analysing differences in drug advertisement and sale across countries and social media applications. For instance, public platforms are favoured in Denmark, Iceland and Sweden whereas in Norway and Finland, there is more widespread use of encrypted messaging platforms such as Telegram [21]. Similarly, findings show variation in the popularity of platforms between the United Kingdom and Australia, where Snapchat and Instagram were found to be used more in the United Kingdom [22] and Facebook in Australia [84].

Besides cross-national preferences, the unique structures of platforms make their usage inherently different. For example, Snapchat provides self-destructing messages and pictures, QR 'snapcodes' to connect to exclusive content and interactive 'snapmaps' which indicate the location of contacts in real time [94]. Navigating the sale of drugs on Snapchat is fundamentally different to Facebook, the latter being seen as more of a forum [40], or to Twitter where hashtags can yield large amounts of openly accessible results, including illicit advertisements sponsored by bots [39]. This underlines the relevance of examining specific social media platforms and the context in which drugs are sold. The latest evidence suggests that choice of platform may not rest on national preferences identified in the literature but rather, it is shaped by the relationships established between individual buyers and sellers, such as perceived closeness or friendship [44]. Researching the behaviours of users will be crucial to explore how these intersect with existing organisations of online drug distribution [95] and assess their porosity with darknet markets.

3.5 | Computational approaches to detecting and monitoring patterns of advertisements

Most of the reviewed literature concerned the detection and analysis of drug advertisements on social media.

TABLE 3 Summary of four groups in which the 56 peer-reviewed studies were classified according to their respective objectives and characteristics.

	Qualitative research on drug markets and social media platforms	Computational approaches to detecting and monitoring patterns of advertisements	Characteristics of users: buyers and sellers	Interventions on social media to prevent the sale and advertisement of drugs
Description	Studies that map out the structures of drug markets on social media and the mechanisms through which platforms are used	Studies that focus solely on the detection of drug advertisements on social media and the analysis of its related patterns (posts, users or comments)	Studies that investigate the profiles and characteristics of users that witness, buy or sell drugs on social media	Studies that explore the use of potential strategies to prevent young people to engage with drug advertisements on social media
References	[21,22,31,38–44] ($N = 10$)	[45–74] ($N = 30$)	[75–85] ($N = 12$)	[86–89] ($N = 4$)
Main disciplines	Multidisciplinary, sociology	Computer science	Health, psychology	Multidisciplinary
Design	Qualitative	Quantitative	Qualitative/quantitative	Quantitative
Main method	Interviews, content analysis, ethnography	Machine learning, automated detection	Focus groups, surveys, ethnography, interviews, regression analysis	Focus groups, machine learning, regression analysis, content analysis
Drugs studied	Prescription and illicit	Prescription and illicit	Mainly illicit	Mainly illicit
Main platforms	Facebook and Instagram (multiple)	Twitter and Instagram	Facebook, Instagram and Snapchat (multiple)	Instagram, Twitter and Snapchat (multiple)
Ethics	Mainly approved (Yes = 7/No = 3)	Mainly missing (Yes = 2/No = 28)	Mainly approved (Yes = 9/No = 3)	Mainly missing (Yes = 1/No = 3)
Limitations	• Challenges of data collection: asynchronous interviews or time-consuming manual collection; • Cross national differences in platform uses	• Lack of inter-rater reliability for data labelling; • Tendency for imbalanced datasets	• Difficulty to access participants and disclose truthful information; • Self-selection bias, disparity in ages of participants; • Cross-sectional and small samples: lack of representative findings	• Self-selection bias, participants already in harm reduction/drug education programs; • Studies only discuss the potential effectiveness of social media interventions or the lack of thereof: no evaluations of existing social media strategies
Future research	• Diversify research across social media platforms; • Measure and evaluate the effects of drug exposure on social media on drug consumption behaviour and attitudes; • Empirical studies on individual drugs to understand their specificities; • Research on the intersection between dark markets and social media markets	• Move towards improving data collection speed and quality (capacity to process emojis and characters); • Improving the accuracy and precision of detection models; • Understanding and detecting behaviour: fine-grained demographics, sentiment analyses, geolocation, network analysis	• Investigate the psychosocial determinants and motivations to engage in drug advertisements on social media; • Investigate the existence of causal relationships with longitudinal studies across cultural settings; • Understand the effectiveness of messaging strategies to deter users; • Establishing the role of gender in interacting, buying, or selling drugs on social media	• Outline the main barriers in young people's engagement in drug prevention campaigns on social media; • Use of randomised-controlled trials designs to estimate the effectiveness of interventions in schools; • Developing iOS version of parental control applications to detect risky content in online conversations

TABLE 3 (Continued)

	Qualitative research on drug markets and social media platforms	Computational approaches to detecting and monitoring patterns of advertisements	Characteristics of users: buyers and sellers	Interventions on social media to prevent the sale and advertisement of drugs
Policy implications	• Introduce clear policy frameworks to hold social media companies accountable; • Authorities and health professionals to be more present on social media: video-based prevention campaigns	• Limited awareness of policy implications beyond detection; • Use of detection tools by service providers but also regulatory agencies; • Importance of collaboration across disciplines and between academia and industry	• Educational stakeholders and law enforcement: increase drug education to young people and their media literacy skills; • Need differentiated policies across countries and foster collaboration across stakeholders	• Harm reduction messaging campaigns on social media: demystify the safety of online drugs; • Peer-to-peer prevention messaging; • Parental control features or monitoring applications may result in privacy and security breaches

These papers were mainly written by US Computer Science scholars where insights from Health, Social Networks or Linguistics complemented the use of ML techniques. Twitter was by far the most prominent social media platform used to carry out these types of studies ($N = 19/30$), due to the accessibility of its application programming interface. Instagram was also used, yielding vital insights on drug advertisement on social media from a ML point of view. However, data sets tended to be relatively small and restricted in the information that could be extracted. This is representative of the difficulty researchers experience in accessing representative data from popular platforms, given companies' data policies around sharing their user's information and surrounding privacy debates [45,47].

Drug advertisements can be detected by ML algorithms with different rates of accuracy and using different input sources, which are then analysed by the model to output a prediction. With respect to methods, ML algorithms can be supervised or unsupervised. Supervised ML refers to when the algorithm is trained by the researchers to recognise patterns (i.e., the data is given labels) whereas for unsupervised ML the algorithm trains itself, sifting through the data to infer patterns (i.e., the algorithm assigns labels to data). Some studies [45,46,49,58,63] used natural language processing models and unsupervised techniques to detect and predict the use of specific keywords that characterise drug-related content. For example, Simpson et al. [49] used word-vector embeddings[§] to analyse Twitter data to generate previously unknown terms for illicit drugs and compared these to lists of terms generated by drug experts. Of 200 candidate terms, 115 correctly related to cannabis. Of these, 30 were previously unknown, thus uncovering new terminology. Ding et al. [58] and Ginart et al. [63] employed topic modelling and support vector machine analysis to disambiguate false negative drug-related keywords (e.g., 'dabbing' as a dance vs. as a cannabis consumption practice). Their classifiers exhibited relatively high precision and accuracy scores, suggesting that they could improve the detection of new and relevant hashtags on social media related to illicit drugs.

Other studies focused on the detection of illicit drug content using all the available text data within a post, not just keywords [47,51,52,54–56,59,60,62]. This included full sentences, metadata (e.g., the number of times a post had been retweeted), the comments of the post and user information. Most papers used supervised or semi-supervised approaches. Posts were studied in their relative context, analysing geographic metadata [55,56,62] or the co-occurrence of drug names [59].

However, a group of papers [48,50,53,57,61,64–66,70–74] distinguished themselves by extending existing models by adding increasingly granular layers of input. This included not only text information but also images, the timing of posts and the relationships between them. The detection of content was here elevated to the detection of behaviour associated with drug advertisement and sale on social media. Datasets used to train these models require the aggregation of these various sources of data to extract plausible behavioural patterns. For instance, Hu et al. [57] constructed a dataset using multiple Instagram sources such as post images, comments and the homepage bio and used deep learning models to identify likely drug dealing profiles. Some papers [50,61,66,71,72] explored the relationships between comments and the posts of users through network analysis and integrated images in their ML algorithms (computer vision) to estimate the age and gender of users [72]. In addition to creating richer datasets to increase the predictive power of detection algorithms, these studies provided further data to analyse the features and patterns of drug-related posts. For example, posts relating to cannabis tended to peak at 4 and 9 pm on Thursdays and Fridays and were associated with previously unknown words connoting 'luxury lifestyle' (high society) [36]. Posts were predominantly from male users between the ages of 20 and 40 but included teenagers as young as 15. Network analysis revealed that most drug users shared common interests based on the accounts they followed and that they formed a more centralised community than non-drug users [36]. Furthermore, Li et al. [73] and Majmundar et al. [74] examined the intersections between types of users (verified or suspended Twitter accounts) and topics (posts including cannabis, e-cigarettes and tobacco). Suspended Twitter accounts mostly posted advertisements and promotions of illicit drugs but coincided with regular users in the topic of recreational usage of drugs: cannabis retail constituted 20.6% of the five most discussed topics for regular users [54]. One important finding was the interest of verified users in the cannabis industry and the legalisation of related products, such as cannabis-based social media brands promoting match-making services based on cannabis consumption [54]. Furthermore, tagging other users in posts and discussing illicit products was a common behaviour in Twitter for posts at the intersection of e-cigarettes, combustible tobacco and cannabis [60]. These strands of research seem the most promising in terms of detection accuracy and align with social media's attempts to leverage big data to target more precisely those behaviours that violate their community guidelines [36,96].

Weaknesses of this body of literature are inherent to methodological issues of using ML to identify a rarely occurring phenomenon. Detecting posts is challenging due to the amount of noise in social media data sets and the 'hidden' nature of drug dealing. Many studies did not provide tests of inter-rater reliability rates and used imbalanced data sets to train their algorithms. Evaluation metrics used to assess the quality of predictive models were also selectively reported, with Recall being the most frequent, and receiver operating characteristic analysis the least.[¶] The processing of text used for ML often involved filtering data by removing emojis and special characters. While this is necessary to convert raw data into coherent features, including them in future research will be important given their role in signalling drug advertisements [21,22,30,40,77,86]. The removal of non-English words was also common in the processing stages, restricting posts by language. Only two papers did not focus on English but used text-classifications to detect tweets selling drugs in Arabic [52] and Spanish [61]. This signals the need for research from non-anglophone countries, to broaden understandings of diverse drug markets, social media platform structures and user behaviour, particularly given evidence of differentiated patterns across countries. A lack of heterogenous training data sets can further deepen the gap of research between western and non-western settings, putting young people in those countries at risk of less effective solutions.

3.6 | Characteristics of users: Buyers and sellers

Studies that examined social media users and drug advertisements tended to use a mixture of quantitative and qualitative methods for data collection such as surveys [81,83,85], interviews/focus groups [76,77,79,80] and ethnographies [78,85]. Methods of data analysis ranged from content analysis [83] to the use of logistic regression to analyse survey data [23,81].

Individuals who saw or engaged with drug advertisements and sales online were predominantly young[**] [76–79,84], correlating with their increased use of social media [97,98]. Living in a city, having lower educational attainment and risk-taking behaviours were positively associated with the purchase of drugs from social media [81,83,84]. Few studies solely focused on sellers. However, an Australian study that used police data revealed that drug suppliers were more likely to use social media to sell their products, due to the security features provided, than buyers were to buy from them.

Rather than exploring advertisement and sale strategies, some studies focused on contextual information such as the purposes for which drugs were used by young people. While most authors typically assume that illicit drugs are purchased for recreational purposes, there is growing interest in understanding how drugs are generalised on social media for study/work performance [38], body enhancement or sexual practices [77]. These approaches investigated the 'cultural' aspect of social media drug posting and their different characterisations according to specific drugs or the social context in which they were sold. The ways in which drugs are marketed varied by and within platforms. Significant research [85] on this included an exploration of the gendered approach to cannabis sales on Instagram. By comparing the user profiles of Swedish illicit drug dealers and US-based cannabis influencers, Bakken and Harder [85] demonstrated how the portrayal of drugs on social media can transform accepted traditional perceptions of it. Whereas the Swedish dealer accounts were either attached to masculine conceptions of 'illegality' or void of any possible gender identification, the US influencers highlighted their identities as women and mothers, displaying cannabis as empowering and fashionable. This highlights how the line between legality and illegality is murky: influencers may be selling legal products, but which are prohibited to minors. Despite their profiles being accompanied by age limit disclaimers, the responsibility is nevertheless shifted to viewers to avoid such content. Further empirical and gendered research [99] on the motivations, habits and roles of influencers in drug advertising on social media is needed to bridge existing knowledge gaps.

3.7 | Interventions on social media to prevent the sale and advertisement of drugs

The four studies that examined intervention strategies used various data collection strategies such as focus groups [87] and surveys [89], and data analysis techniques such as content analysis [86] and ML [88]. Online prevention campaigns on social media were the most cited types of interventions recommended across the studies reviewed. Targeted public health messaging and educational content on social media delivered by public health bodies, charities, schools, celebrities or influencers were suggested as approaches to change young people's behaviours.

However, rigorous evaluations of such campaigns are in short supply. Evans et al. [89] evaluated the effectiveness of a US-based program aimed at reducing drug use in young people through the peer-to-peer promotion of prevention messages on social media. It was found to have a significant protective effect against drug use intentions among students [89]. However, this study used a self-report measure of outcomes, as opposed to a behavioural measure and no control group was used to estimate the counterfactual, something that the authors acknowledge as a limitation of their study. Moreover, the potential success of these initiatives should not be generalised as the influence of peers may decrease over time [100]. Further, a problem with media campaigns is that many people may not engage with them. Dunn et al. [87] examined the reasons for this and found that most adolescents opted for limited online engagement when interacting with harm reduction content on social media. Young people's desire for privacy was a common challenge identified when implementing these campaigns [87–89], as adolescents tend to use social media platforms that provide the most autonomy from their parents. This speaks to the social cost of young people engaging with and sharing prevention messages condemning substance use, as adolescents fear the judgement of their own peers. Adolescents stated that virality, humour and the strikingness of content were key to attracting their attention, and that short video-based formats were preferred to lengthy posts [87]. While social media campaigns delivered 'by and for young people' require contextual design and rigorous evaluation, the literature seemed to agree on the importance of using the same tools and platforms from where illicit advertisements emanate to address the problem. Authors argued (but have not shown empirically) that social media is central to breaking down the predominant misconception of safety when purchasing drugs online.

One paper proposed the implementation of parental controls for WhatsApp as an intervention to prevent the sale and advertisement of drugs [88]. Using a text-classifying algorithm, the parental control application scanned messages and detected content that could be flagged as harmful for the categories of drugs, sex or bullying. While seemingly effective, these types of approaches need to be installed by parents and adolescents alike, echoing the issue of realistically considering to what extent young people are likely to willingly concede their privacy and the challenges of developing solutions such as this. Instagram's recent parental control 'Family Centre' allows parents and teens to share the same interface, enabling parents to see their children's followers, screen time and reports submitted [101]. Adolescents need to be proactive in this activity by 'inviting' their parents to supervise their account. There is no direct oversight of content for parents, which instead relies on Instagram's *sensitive content control* tool which limits posts that promote the use of certain regulated goods [102]. There was no evidence as to the effectiveness of such approaches in the reviewed literature.

4 | DISCUSSION

The 56 studies included in this scoping review reveal that a variety of disciplines and methods have been used to study the advertisement and sale of illicit drugs. The literature focused on four main areas of study: how drug markets vary across social media platforms, the development of detection techniques, user characteristics and social media interventions to address the problem. In the sections that follow, we discuss the implications of findings, the limitations of this review and directions for future research.

4.1 | Towards an integrated approach to detection

Evidence offered by the computer science papers provide a solid understanding of the state of detection of illicit drug advertisements on social media. To improve detection models, research should aim to increase the quality of data sets and their speed of collection. This is especially relevant to compare platforms and to reduce the data and knowledge asymmetries between them.

On average, for the studies reviewed, more than 1 in 10 social media posts were found to advertise illicit drugs. Unfortunately, while most existing studies provided data concerning rates of occurrence, they failed to measure exposure rates which can be significant when assessing the virality of content and its potential viewership. To illustrate this, we considered a study of TikTok content that promoted cannabis [31]. In this study, while only 3.6% of the 881 sampled videos advertised cannabis, these had been viewed 27 million times and received 5 million likes. These figures exceed the engagement rates of macro-influencers with 100,000 to 1 million followers, which research estimates receive an average of 38,000 views per post [103]. It is therefore important that future work considers other measures of engagement such as rates of incidence, virality and viewership as only considering the overall occurrence of content may not provide the true picture of the problem.

However, the most significant narrative constructed by existing studies is the rapid move towards complex detection, integrating the detection of behaviour through ML (Figure S4). Models which use multiple data sources to inform predictions would appear to be essential moving forwards. As illicit drug advertisements become more complex in the race to avoid detection, the tools used to effectively identify violating content need to become more granular in their analysis of data to increase their predictive power. Therefore, algorithms would benefit from studies analysing longitudinal data from a diverse set of samples (countries, platforms, age of users). This also applies to integrating different kinds of drugs in models as the popularity of synthetic drugs are on the rise [6,12,104] but rarely focused on in the literature. Illicit drugs have been found to be advertised differently if they are presented as 'study', 'mental health' or 'wellness' drugs [38,77,85]. This highlights the necessity for future research on detection to integrate the behaviour of users. The dynamics of the networks of young people, the types of drugs they consume and the cultural and linguistic context within which they are sold are all elements which will need to be considered when devising detection methods. This reinforces the importance of fostering interdisciplinary collaboration, as ML increasingly combines qualitative data using insights from the behavioural sciences such as linguistics and psychology. For example, Zhou et al. [72] suggested further complementing fine-grained mining analysis techniques with network analysis to understand how communities differ between drug and non-drug related networks. These computational advances inscribe themselves within the broader monitoring of drug markets through online research [105] by institutions like the European Monitoring Centre for Drugs and Drugs Addiction, World Health Organization or Interpol. Social media detection software should therefore be leveraged as a complimentary tool for longitudinal surveillance of trends instead of ad-hoc research.

4.2 | The need to diversify research

The disciplinary differences highlighted in this review are reflected in the variation in focus on drugs, platforms and policy implications formulated by each discipline and group. If this can be explained by specific constraints intrinsic to a field or method, it is vital for future research to attempt to move beyond these boundaries. Papers on detection focused on opioids while studies investigating users emphasised 'typical' illicit drugs. These differences could be due to researchers' preconceptions when selecting drugs and their keywords according to previous work, availability heuristics, or contextual biases. The severity of the opioid crisis in the United States may explain why the computer science studies (mainly from the United States) focused their research on potentially abusable prescription drugs, whereas qualitative studies from six continents investigating sellers indirectly elicited typical perceptions of drug dealers supplying illicit drugs. It is important for researchers to consider these biases when selecting their keywords or target drugs, as the models developed to detect this content may have limited generalisability.

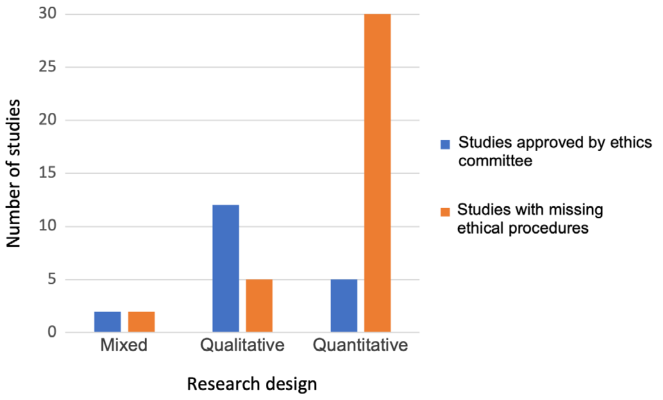


FIGURE 3 Number of studies with or without ethical approval according to research design ($N = 56$).

These differences are even more significant for the social media apps studied. While research on new platforms such as Discord [43] is to be welcomed, we find a glaring omission of some. Only two studies [31,42] explored the existence of illicit drugs on TikTok, despite it being the second most popular social media platform among 13- to 17-year-olds [98]. The recency of these papers and the authors' statements that they were the first to examine TikTok, illustrates the need for research on all platforms. Evidenced by the move towards research that recognises the role of cultural and social analyses on advertisement and sale strategies, a variety of platforms that may not have previously been thought of as social media must be examined. This includes gaming platforms such as Twitch or Roblox, or apps that sell clothes such as Depop.

As Twitter was clearly overrepresented (Figure 2) in the literature, it is vital for future studies to investigate social media apps that have not been researched within their discipline: for example, advances in detection might only be effective and applicable to Twitter and Instagram. Similarly, studies using multiple designs focused on a wider range of platforms including Wickr, Grindr or Tumblr, but overlooked the use of Twitter. It is acknowledged that fostering research across social media does not equate to greater generalisability of findings as these may be unique to some platforms. However, a holistic approach to this issue has the potential to reveal useful patterns that may otherwise go unnoticed. The challenge for future research will be to balance the applicability of findings across all social media while catering to the specificities of each platform and its unique solutions. Further cross-examinations of social media drug markets with darknet or street markets [106] would allow for the triangulation of data and the bridging of information from different sources and methods.

Out of the reviewed papers, 66% had no disclosure of ethical review, a figure close to what Winter and Gundur [107] find (72.5%) in their review of criminological studies with digital methodologies. There seemed to be an observable pattern between the design of the study and whether ethical approval had been obtained (Figure 3). A chi-square test of independence was performed to determine whether there was a significant relationship between paper type and ethical review. There was ($X^2(2, N = 56) = 16.7$, $p = 0.0002$). Specifically, qualitative studies (see Figure 3) were more likely to undergo appropriate ethical review than were quantitative studies (mostly from computer science) which lacked ethical approval or failed to acknowledge ethical concerns. The justification for this was that the research used 'public' information available on social media platforms and that it did not involve primary data collection [108]. This is representative of debates within the field of digital research on what constitutes open-source data or public/private spaces online and how these should be researched [109,110]. However, this line of argument does not account for issues relating to self-disclosure of social media users. That is, the availability and accessibility of data should not equate to an exemption of ethical consideration [111–113]. In some instances, screenshots and the usernames of drug dealers included in a published paper were not anonymised. While these studies were mostly published 'early' in the study period (2015–2016), some users could still be found on social media as of June 2022. The ethical disparities found in this review underline the importance of understanding the 'critical intersections of ethical review and digital methodologies' [105] to foster better ethical considerations in illicit drug advertisement studies.

4.3 | Implementing evaluation strategies

While studies examining potential or existing interventions offer important first insights into preventive solutions, they are, for now, only exploratory. These papers suffer from self-selection bias, whereby participants are usually those already involved in drug prevention programs or those who demonstrate a pre-existing interest in them. Academic studies also tended to rely on self-reported measures of drug use to estimate the potential effectiveness of social media interventions or the lack of thereof. These studies did not examine whether interventions actually affected behaviour (e.g., by examining click through rates) and did not employ randomised control designs, which weakens their internal validity (i.e., the ability to establish causality). Moreover, none of the studies reported findings that examined the current solutions implemented by social media platforms.

If the efforts to increase the presence of drug prevention campaigns on social media and educational workshops in schools are to be sustained, these need to be complemented with other solutions. Despite platforms generating labels and warning messages to combat misinformation or protect users from sensitive content, the use of these for illicit drugs is not yet widespread. An example is Snapchat's 'Heads Up' campaign, which is a partnership with the drug education charity With You. It redirects users searching for illicit drugs to the substance harm reduction website 'Talk to Frank'. However, Rutherford et al.'s [31] study on TikTok reveals that while the platform flags potential fake news and graphic content, no such banners were found when performing searches on cannabis at the time of the study.

Another issue is how these interventions can be implemented by platforms across different jurisdictions or countries (e.g., the United States vs. the Netherlands) where the legal status of drugs might differ. The evolving policy landscape around decriminalisation requires policymakers, health practitioners and social media platforms to strike a balance between the lawful advertisement and sale of substances and harm reduction measures. While beyond the scope of this review, the effects of legal drug marketing practices on young people's behaviour [114,115] warrants further examination, especially on social media.

4.4 | Limitations

Carrying out a multidisciplinary review is time consuming and requires a detailed understanding of the methods used to rigorously extract and synthesise evidence. While the expertise of the authors in their respective fields helped to bridge disciplinary divides, nuances and technicalities may have been unintentionally simplified. As discussed, different strategies were needed to search IEEE Explore and the ACM Digital Library compared to the databases used to archive social science literature. This reiterates the struggle for researchers in different disciplines to access work in other fields, and systematically review the entire multidisciplinary research space. Finally, to capture the most recent literature, it was necessary to repeat the searches throughout the research process. It is acknowledged that relevant studies may have been published since our last search and hence not included.

5 | CONCLUSIONS AND FUTURE TRENDS

The advertisement and sale of drugs through social media is likely to increase, especially targeting young people [22,31,43,73,78]. The global rise in smartphone usage by young people coupled with the popularity and growing appeal of apps makes plausible a (future) shift from 'social dealing' as the dominant method of drug supply to one through social media [84]. With 227 million new social media users in 2022 [116] the potential for illicit and harmful content to expand on these applications is evident. Environmental changes and the ease of sending parcels quickly also provide new opportunities for offenders: the acceleration of the sale of drugs through social media during the COVID-19 pandemic [12] is a telling example.

Greater presence of illicit content on social media has been suggested as contributing to the normalisation of substance use in the future [30,117,118], while also increasing the visibility not only to consumers, but also to researchers. This trend was particularly suggested with cannabis, as its growing marketisation on social media feeds into movements and online communities of 'wellness' and 'healthy lifestyles' which may encourage drug seeking behaviours among young people [31,43,85]. The influencer and social media culture era brings new challenges as the expansion of new products within the boundaries of legal concentrations or marketised as 'safe' add to the complexity of an existing legal grey area. The blurriness of the law and its international disparities are likely to afford greater opportunities for sellers to market their goods in new spaces, such as social media or other apps [73,85]. This echoes suggestions that anonymous location-based apps may flourish, facilitating drug commercialisation [75]. Finally, the shift to social media use for wider-scale drug trafficking has also been outlined as a potential cause for a change in drug market structures, as occasional sellers, including adolescents, may be encouraged to move into higher level retailing operations [40].

The implications of the studies reviewed motivate the urgency of mitigating the risks for young people posed by the proliferation of harmful substances on social media. Adopting a 'what works' approach [119,120] to this problem is not only an obligatory step within the policy cycle but will also be essential to fostering inter-agency cooperation between researchers, regulators, law enforcement, charities and technology companies [47]. We believe that knowledge sharing will be crucial to the move towards proactively addressing illegal and harmful content on social media [16,36,121].

AUTHOR CONTRIBUTIONS

Ashly Fuller: Conceptualisation, methodology, formal analysis, writing-draft and editing. Shane D. Johnson: Supervision, methodology, formal analysis, writing-review-and editing. Marie Vasek: Supervision, methodology,

writing-review and editing. Enrico Mariconti: Supervision, methodology, writing-review and editing. Each author certifies that their contribution to this work meets the standards of the International Committee of Medical Journal Editors.

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CONFLICT OF INTEREST STATEMENT

None to declare.

ORCID

Ashly Fuller https://orcid.org/0000-0002-6603-8138

ENDNOTES

* Backwards searches refer to the search of references or works cited in an article while forward searches refer to identifying articles that cite an original article or work after its publication.

† The full list of terms and keywords is available to be shared on request.

‡ We use the command *Metaprop* in STATA to perform analysis of binomial data [32]. Details of the approach used can be found in Formulae S1.

§ Word embeddings are a way to represent words for machine learning analysis. They use real-valued vectors where words that are closer in the vector space are expected to be similar in meaning.

¶ Recall refers to the true positive rate of detected posts while receiver operating characteristic analysis represents graphically the ratio between true positives and false positives.

** As discussed in Section 2, given the infancy of the literature no specific age restrictions were employed and most studies included users of all ages.

REFERENCES

1. Barratt MJ, Ferris JA, Winstock AR. Use of silk road, the online drug marketplace, in the United Kingdom, Australia and the United States. Addiction. 2014;109:774–83.
2. Aldridge J, Décary-Hétu D. Hidden wholesale: the drug diffusing capacity of online drug cryptomarkets. Int J Drug Policy. 2016;35:7–15.
3. Nurmi J, Kaskela T, Perälä J, Oksanen A. Seller's reputation and capacity on the illicit drug markets: 11-month study on the Finnish version of the Silk Road. Drug Alcohol Depend. 2017;178:201–7.
4. Martin J, Munksgaard R, Coomber R, Demant J, Barratt MJ. Selling drugs on darkweb cryptomarkets: differentiated pathways, risks and rewards. Br J Criminol. 2020;60:559–78.
5. Marengo D, Angelo Fabris M, Longobardi C, Settanni M. Smartphone and social media use contributed to individual tendencies towards social media addiction in Italian adolescents during the COVID-19 pandemic. Addict Behav. 2022; 126:107204.
6. European Monitoring Centre for Drugs and Drug Addiction. European drug report 2021: trends and developments. [Internet]. LU: Publications Office; 2021. https://doi.org/10.2810/18539
7. BBC. Teens found selling drugs on snapchat and Instagram, BBC three investigation finds. BBC News [Internet]. 2017 [cited 9 December 2021]. Available from: https://www.bbc.com/news/newsbeat-40601036
8. Marsh S. Youth workers warn of rise in drugs purchases through social media. The Guardian [Internet]. 2017 [cited 9 December 2021]. Available from: https://www.theguardian.com/society/2017/dec/31/youth-workers-warn-of-rise-in-drugs-purchases-through-social-media
9. Howard S. 'My son was groomed into drug dealing by gangs on snapchat'. The Telegraph [Internet]. 2018 [cited 9 December 2021]. Available from: https://www.telegraph.co.uk/family/parenting/son-groomed-drug-dealing-gangs-snapchat/
10. VICE. Buying Drugs Over Snapchat | High Society [Internet]. 2020 [cited 18 February 2022]. Available from: https://www.youtube.com/watch?v=1Ki7d_R-t60
11. Carrez R, Lopez F. Entre confinement et répression: comment les usagers de cannabis se sont organisés. Psychotropes. 2020; 26:165.
12. United Nations. World drug report 2021 [Internet]. Vienna: United Nations: Office on Drugs and Crime; 2021 [cited 15 January 2022]. Available from: www.unodc.org/unodc/en/data-and-analysis/wdr2021.html
13. Branley DB, Covey J. Is exposure to online content depicting risky behavior related to viewers' own risky behavior offline? Comput Hum Behav. 2017;75:283–7.
14. Brunborg GS, Andreas JB, Kvaavik E. Social media use and episodic heavy drinking among adolescents. Psychol Rep. 2017;120:475–90.
15. AlSayyari A, AlBuhairan F. Relationship of media exposure to substance use among adolescents in Saudi Arabia: results from a national study. Drug Alcohol Depend. 2018;191:174–80.
16. House of Commons. Online Safety Bill—Hansard—UK Parliament [Internet]. 121 2022. Available from: https://hansard.parliament.uk//commons/2022-07-12/debates/942C54C4-D672-492E-BAD9-195E3BB63724/OnlineSafetyBill
17. Gough D, Oliver S, Thomas J. An introduction to systematic reviews [Internet]. 2nd ed. London: SAGE Publications Ltd; 2017 [cited 28 September 2022]. Available from: https://uk.sagepub.com/en-gb/eur/an-introduction-to-systematic-reviews/book245742
18. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Ann Intern Med. 2018;169:467–73.

19. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. Int J Soc Res Methodol. 2005;8:19–32.
20. Auxier B, Erson M. Social media use in 2021 [Internet]. Washington: Pew Research Center: Internet, Science & Tech; 2021 [cited 9 December 2021]. Available from: https://www.pewresearch.org/internet/2021/04/07/social-media-use-in-2021/
21. Demant J, Bakken SA, Oksanen A, Gunnlaugsson H. Drug dealing on Facebook, Snapchat and Instagram: a qualitative analysis of novel drug markets in the Nordic countries. Drug Alcohol Rev. 2019;38:377–85.
22. Moyle L, Childs A, Coomber R, Barratt MJ. #Drugsforsale: an exploration of the use of social media and encrypted messaging apps to supply and access drugs. Int J Drug Policy. 2019; 63:101–10.
23. Oksanen A, Miller BL, Savolainen I, Sirola A, Demant J, Kaakinen M, et al. Illicit drug purchases via social media among American young people: International Conference on Social Computing and Social Media, held as part of the 22nd International Conference on Human-Computer Interaction, HCII 2020. In: Meiselwitz G, editor. Cham: Social Computing and Social Media; 2020. p. 278–88.
24. Schardt C, Adams MB, Owens T, Keitz S, Fontelo P. Utilization of the PICO framework to improve searching PubMed for clinical questions. BMC Med Inform Decis Mak. 2007;7:16.
25. Shamseer L, Moher D, Clarke M, Ghersi D, Liberati A, Petticrew M, et al. Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015: elaboration and explanation. BMJ. 2015;349:g7647.
26. Gretzel U. The visual turn in social media marketing. Tourismos. 2016;12:3.
27. Braun V, Clarke V. Thematic analysis. APA handbook of research methods in psychology. Research designs: Quantitative, qualitative, neuropsychological, and biological. Volume 2. Washington, DC, US: American Psychological Association; 2012. p. 57–71. (APA Handbooks in Psychology).
28. Higgins J, Green S. Cochrane handbook for systematic reviews of interventions [Internet]. 2011 [cited 8 January 2022]. Available from: https://training.cochrane.org/handbook
29. PRISMA. PRISMA [Internet]. PRISMA Flow Diagram. 2021 [cited 3 November 2021]. Available from: http://www.prisma-statement.org/PRISMAStatement/FlowDiagram.aspx
30. McCulloch L, Furlong L. DM for details: selling drugs in the age of social media [Internet]. Volteface. 2019 [cited 19 October 2021]. Available from: https://volteface.me/publications/dm-details-selling-drugs-age-social-media/
31. Rutherford BN, Sun T, Johnson B, Co S, Lim TL, Lim CCW, et al. Getting high for likes: exploring cannabis-related content on TikTok. Drug Alcohol Rev. 2022;41:1119–25.
32. Nyaga VN, Arbyn M, Aerts M. Metaprop: a Stata command to perform meta-analysis of binomial data. Arch Public Health. 2014;72:39.
33. Tufanaru C, Munn Z, Stephenson M, Aromataris E. Fixed or random effects meta-analysis? Common methodological issues in systematic reviews of effectiveness. Int J Evid Based Healthc. 2015;13:196–207.
34. Lipsey M, Wilson D. Practical meta-analysis [Internet]. Los Angeles: SAGE Publications Ltd; 2001 [cited 18 February 2023]. (Applied Social Research Methods Series; vol. 49). Available from: https://us.sagepub.com/en-us/nam/practical-meta-analysis/book11092
35. Schwarzer G, Rücker G. Meta-analysis of proportions. In: Evangelou E, Veroniki AA, editors. Meta-research: methods and protocols [Internet]. New York, NY: Springer US; 2022. p. 159–72. [cited 28 February 2023]. (Methods in Molecular Biology). https://doi.org/10.1007/978-1-0716-1566-9_10
36. Meta. Detecting violations | Transparency Centre [Internet]. 2022 [cited 27 September 2022]. Available from: https://transparency.fb.com/en-gb/enforcement/detecting-violations/
37. Twitter transparency. Rules Enforcement—Twitter Transparency Center [Internet]. 2021 [cited 6 February 2023]. Available from: https://transparency.twitter.com/en/reports/rules-enforcement.html
38. Petersen M, Petersen I, Poulsen C, Norgaard L. #studydrugs-persuasive posting on Instagram. Int J Drug Policy. 2021;95: 103100.
39. Al-Rawi A. The fentanyl crisis & the dark side of social media. Telemat Inform. 2019;45:101280.
40. Demant J, Bakken SA, Hall A. Social media markets for prescription drugs: platforms as virtual mortars for drug types and dealers. Drugs Alcohol Today. 2020;20:36–49.
41. Jain P, Zaher Z, Mazid I. Opioids on Twitter: a content analysis of conversations regarding prescription drugs on social media and implications for message design. J Health Commun. 2020;25:74–81.
42. Garimella AL, Kerr B, Hyzer R, Moreno M. Hallucinogens on TikTok. J Adolesc Health. 2022;70:S96.
43. van der Sanden R, Wilkins C, Rychert M, Barratt MJ. The use of discord servers to buy and sell drugs. Contemp Drug Probl. 2022;49:453–77.
44. van der Sanden R, Wilkins C, Rychert M, Barratt MJ. 'Choice' of social media platform or encrypted messaging app to buy and sell illegal drugs. Int J Drug Policy. 2022;108:103819.
45. Adams N, Artigiani EE, Wish ED. Choosing your platform for social media drug research and improving your keyword filter list. J Drug Issues. 2019;49:477–92.
46. Mackey TK, Kalyanam J, Katsuki T, Lanckriet G. Twitter-based detection of illegal online sale of prescription opioid. Am J Public Health. 2017;107:1910–5.
47. Li J, Xu Q, Shah N, Mackey TK. A machine learning approach for the detection and characterization of illicit drug dealers on Instagram: model evaluation study. J Med Internet Res. 2019; 21:e13803.
48. Hu H, Phan N, Chun SA, Geller J, Vo H, Ye X, et al. An insight analysis and detection of drug-abuse risk behavior on twitter with self-taught deep learning. Comput Soc Netw. 2019;6:10.
49. Simpson SS, Adams N, Brugman CM, Conners TJ. Detecting novel and emerging drug terms using natural language processing: a social media corpus study. JMIR Public Health Surveill. 2018;4:e2.
50. Shah N, Li J, Mackey TK. An unsupervised machine learning approach for the detection and characterization of illicit drug-dealing comments and interactions on Instagram. Subst Abus. 2022;43:273–7.
51. Saifuddin KM, Islam MIK, Akbas E. Drug Abuse Detection in Twitter-sphere: Graph-Based Approach. 2021 IEEE International Conference on Big Data (Big Data). New York: IEEE; 2021. p. 4136–45.
52. Alruwaili W, Protano B, Sirigiriraju T, Alhoori H. Using Arabic tweets to understand drug selling behaviors. Procedia Comput Sci. 2019;164:559–64.

53. Hu C, Yin M, Liu B, Li X, Ye Y. Detection of illicit drug trafficking events on Instagram: a deep multimodal multilabel learning approach. Proceedings of the 30th ACM international conference on Information & Knowledge Management [Internet]. New York: Association for Computing Machinery; 2021. p. 3838–46 [cited 19 May 2022]. Available from: http://arxiv.org/abs/2108.08920
54. Kalyanam J, Mackey T. Detection and characterization of illegal marketing and promotion of prescription drugs on Twitter. ArXiv E-Prints. 2017;1:1-5. arXiv:1712.00507.
55. Katsuki T, Mackey TK, Cuomo R. Establishing a link between prescription drug abuse and illicit online pharmacies: analysis of Twitter data. J Med Internet Res. 2015;17:e280.
56. Balsamo D, Bajardi P, Panisson A. Firsthand opiates abuse on social media: monitoring geospatial patterns of interest through a digital cohort. The world wide web conference [Internet]. New York, NY, USA: Association for Computing Machinery; 2019. p. 2572–9. (WWW '19). https://doi.org/10.1145/3308558.3313634
57. Hu C, Yin M, Liu B, Li X, Ye Y. Identifying illicit drug dealers on Instagram with large-scale multimodal data fusion. ACM Trans Intell Syst Technol. 2021;12:1–23.
58. Ding T, Roy A, Chen Z, Zhu Q, Pan S. Analyzing and retrieving illicit drug-related posts from social media. 2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). New York: IEEE; 2016. p. 1555–60.
59. Phan N, Chun SA, Bhole M, Geller J. Enabling Real-Time Drug Abuse Detection in Tweets. 2017 IEEE 33rd International Conference on Data Engineering (ICDE). New York: IEEE; 2017. p. 1510–4.
60. Tian Q, Lagisetty J, Li B. Finding needles of interested tweets in the haystack of Twitter network. 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). New York: IEEE; 2016. p. 447–52.
61. Cortés VD, Velásquez JD, Ibáñez CF. Twitter for Marijuana Infodemiology. Proceedings of the International Conference on Web Intelligence [Internet]. New York, NY, USA: Association for Computing Machinery; 2017. p. 730–6. (WI '17). https://doi.org/10.1145/3106426.3106541
62. Hu H, Moturu P, Dharan K, Geller J, Iorio S, Phan H, et al. Deep learning model for classifying drug abuse risk behavior in tweets. 2018 IEEE International Conference on Healthcare Informatics (ICHI). New York: IEEE; 2018. p. 386–7.
63. Ginart A, Das S, Harris JK, Wong R, Yan H, Krauss M, et al. Drugs or Dancing? Using Real-Time Machine Learning to Classify Streamed "Dabbing" Homograph Tweets. 2016 IEEE International Conference on Healthcare Informatics (ICHI). New York: IEEE; 2016. p. 10–3.
64. Paul Rupa A, Gangopadhyay A. Multi-modal deep learning based fusion approach to detect illicit retail networks from social media. 2020 International Conference on Computational Science and Computational Intelligence (CSCI). New York: IEEE; 2020. p. 238–43.
65. Roy A, Paul A, Pirsiavash H, Pan S. Automated detection of substance use-related social media posts based on image and text analysis. IEEE 29th International Conference on Tools with Artificial Intelligence (ICTAI). Baltimore, MD: IEEE; 2017. p. 772–9.
66. Yang X, Luo J. Tracking illicit drug dealing and abuse on Instagram using multimodal analysis. ACM Trans Intell Syst Technol [Internet]. 2017;8:1–5. https://doi.org/10.1145/3011871
67. Kalyanam J, Mackey TK. A review of digital surveillance methods and approaches to combat prescription drug abuse. Curr Addict Rep. 2017;4:397–409.
68. Sarker A, DeRoos A, Perrone J. Mining social media for prescription medication abuse monitoring: a review and proposal for a data-centric framework. J Am Med Inform Assoc. 2020;27:315–29.
69. Halevy A, Canton Ferrer C, Ma H, Ozertem U, Pantel P, Saeidi M, et al. Preserving integrity in online social networks. Communications of the ACM. 2020;65:92–98 arXiv:2009.10311.
70. Kalyanam J, Katsuki T, Lanckriet GRG, Mackey TK. Exploring trends of nonmedical use of prescription drugs and polydrug abuse in the Twittersphere using unsupervised machine learning. Addict Behav. 2017;65:289–95.
71. Sequeira R, Gayen A, Ganguly N, Dandapat SK, Chandra J. A large-scale study of the Twitter follower network to characterize the spread of prescription drug abuse tweets. IEEE Trans Comput Soc Syst. 2019;6:1232–44.
72. Zhou Y, Sani N, Luo J. Fine-grained mining of illicit drug use patterns using social multimedia data from Instagram. ArXiv161108351 Cs [Internet]. 24 November 2016 [cited 27 October 2021]. Available from: http://arxiv.org/abs/1611.08351
73. Li M, Kakani N, Li C, Park A. Understanding cannabis information on social media: examining tweets from verified, regular, and suspended users. 2020 IEEE International Conference on Healthcare Informatics (ICHI). New York: IEEE; 2020. p. 1–0.
74. Majmundar A, Allem J, Cruz T, Unger J, Pentz M. Twitter surveillance at the intersection of the triangulum. Nicotine Tob Res. 2022;24:118–24.
75. Hammond AS, Paul MJ, Hobelmann J, Koratana AR, Dredze M, Chisolm MS. Perceived attitudes about substance use in anonymous social media posts near college campuses: observational study. JMIR Ment Health. 2018;5:e52.
76. Montero-Dominguez F, Cruz-Juarez A, Tiburcio-Sainz M, Garcia-Gonzalez J. High school student's perception of contents related to alcohol and marijuana consumption on social networks. Cienciauat. 2018;13:50–64.
77. Tan RKJ, Wong CM, Chen MIC, Chan YY, Bin Ibrahim MA, Lim OZ, et al. Chemsex among gay, bisexual, and other men who have sex with men in Singapore and the challenges ahead: a qualitative study. Int J Drug Policy. 2018;61:31–7.
78. Bakken S, Demant J. Sellers' risk perceptions in public and private social media drug markets. Int J Drug Policy. 2019;73:255–62.
79. Adejoh SO, Adisa WB, Onome O, Anyimukwu C, Olorunlana A. The influence of social media on illicit drug sale and use among undergraduates in Lagos, Nigeria. J Alcohol Drug Educ. 2020;64:20–40.
80. Kurcevic E, Lines R. New psychoactive substances in Eurasia: a qualitative study of people who use drugs and harm reduction services in six countries. Harm Reduct J. 2020;17:94.
81. Oksanen A, Miller BL, Savolainen I, Sirola A, Demant J, Kaakinen M, et al. Social media and access to drugs online: a nationwide study in the United States and Spain among adolescents and young adults. Eur J Psychol Appl Leg Context. 2021;13:29–36.
82. Sullivan T, Voce A. Use of mobile phones to buy and sell illicit-drugs [Internet]. Canberra: Australian Institute of Criminology;

2020 [cited 19 August 2022]. Available from: https://www.aic.gov.au/publications/sb/sb22
83. Moureaud C, Hertig J, Dong Y, Muraro IS, Alhabash S. Purchase of prescription medicines via social media: a survey-based study of prevalence, risk perceptions, and motivations. Health Policy. 2021;125:1421–9.
84. van der Sanden R, Wilkins C, Romeo JS, Rychert M, Barratt MJ. Predictors of using social media to purchase drugs in New Zealand: findings from a large-scale online survey. Int J Drug Policy. 2021;98:103430.
85. Bakken S, Harder S. From dealing to influencing: online marketing of cannabis on Instagram. Crime Media Cult. 2022;19:135–57.
86. Al-Rawi A. The convergence of social media and other communication technologies in the promotion of illicit and controlled drugs. J Public Health (Oxf). 2022;44:e13–60.
87. Dunn HK, Pearlman DN, Beatty A, Florin P. Psychosocial determinants of teens' online engagement in drug prevention social media campaigns: implications for public health organizations. J Prim Prev. 2018;39:469–81.
88. Moreno EFC, Salazar GKC. Development of an application for parental control of WhatsApp on android mobile devices. 2019 p. 16–23. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85078184624&doi=10.1109%2fICI2ST.2019.00010&partnerID=40&md5=feb16ab85d10ad3d54ed5df278465828
89. Evans W, Andrade E, Pratt M, Mottern A, Chavez S, Calzetta-Raymond A, et al. Peer-to-peer social media as an effective prevention strategy: quasi-experimental evaluation. JMIR Mhealth Uhealth. 2020;8:e16207.
90. Moeller K, Munksgaard R, Demant J. Illicit drug prices and quantity discounts: a comparison between a cryptomarket, social media, and police data. Int J Drug Policy. 2021;91:102969.
91. Bancroft A. Potential influences of the darknet on illicit drug diffusion. Curr Addict Rep. 2022;9:671–6.
92. May T, Hough M. Drug markets and distribution systems. Addict Res Theory. 2004;12:549–63.
93. Sandberg S. The importance of culture for cannabis markets: towards an economic sociology of illegal drug markets. Br J Criminol. 2012;52:1133–51.
94. Snapchat. Snapchat—The fastest way to share a moment! [Internet]. 2022 [cited 13 September 2022]. Available from: https://www.snapchat.com/
95. Moeller K. Hybrid governance in online drug distribution. Contemp Drug Probl. 2022;49:491–504.
96. Davis A. Preventing child exploitation on our apps [Internet]. Meta. 2021 [cited 28 September 2022]. Available from: https://about.fb.com/news/2021/02/preventing-child-exploitation-on-our-apps/
97. Rideout V, Robb MB. Social media, social life: teens reveal their experiences [Internet]. San Francisco, CA: Common Sense Media; 2018. p. 32 Available from: https://www.commonsensemedia.org/sites/default/files/research/report/2018-social-media-social-life-executive-summary-web.pdf
98. Vogels EA, Gelles-Watnick R, Massarat N. Teens, social media and technology 2022 [Internet]. Washington: Pew Research Center: Internet, Science & Tech; 2022 [cited 25 September 2022]. Available from: https://www.pewresearch.org/internet/2022/08/10/teens-social-media-and-technology-2022/
99. Fleetwood J, Aldridge J, Chatwin C. Gendering research on online illegal drug markets. Addict Res Theory. 2020;28:457–66.
100. Giletta M, Choukas-Bradley S, Maes M, Linthicum KP, Card NA, Prinstein MJ. A meta-analysis of longitudinal peer influence effects in childhood and adolescence. Psychol Bull. 2021;147:719–47.
101. Meta. Family Centre | Meta [Internet]. 2022 [cited 28 September 2022]. Available from: https://familycenter.instagram.com/
102. Instagram. Can I limit sensitive content that I see on Instagram? | Instagram Help Center [Internet]. 2022 [cited 28 September 2022]. Available from: https://help.instagram.com/251027992727268
103. Statista Research Department. Views per post of global TikTok influencers [Internet]. Statista. 2023 [cited 9 February 2023]. Available from: https://www.statista.com/statistics/1251210/views-per-post-tiktok-influencers-worldwide/
104. European monitoring Centre for Drugs and Drug Addiction and Europol. EU Drug Markets Report 2019 [Internet]. Luxembourg: Publications Office of the European Union; 2019 [cited 28 September 2022]. Available from: https://www.emcdda.europa.eu/publications/eu-drug-markets_en
105. Guarita B, Belackova V, van der Gouwe D, Blankers M, Pazitny M, Griffiths P. Monitoring drug trends in the digital environment–new methods, challenges and the opportunities provided by automated approaches. Int J Drug Policy. 2021;94:103210.
106. Belackova V, Pazitny M, Drapalova E, Martinez M, van der Gouwe D, Begley E, et al. Assessing the impact of laws controlling the online availability of 25I-NBOMe, AH-7921, MDPV and MXE – outcomes of a semi-automated e-shop monitoring. Drugs Educ Prev Policy. 2018;25:109–17.
107. Winter C, Gundur RV. Challenges in gaining ethical approval for sensitive digital social science studies. Int J Soc Res Methodol. 2022;1–6.
108. Thomas DR, Pastrana S, Hutchings A, Clayton R, Beresford AR. Ethical issues in research using datasets of illicit origin. Proceedings of the 2017 internet measurement conference [Internet]. New York, NY, USA: Association for Computing Machinery; 2017. p. 445–62. (IMC '17) [cited 29 September 2022]. https://doi.org/10.1145/3131365.3131389
109. Golder S, Ahmed S, Norman G, Booth A. Attitudes toward the ethics of research using social media: a systematic review. J Med Internet Res. 2017;19:e7082.
110. Gundur RV, Berry M, Taodang D. Using digital open source and crowdsourced data in studies of deviance and crime. In: Lavorgna A, Holt TJ, editors. Researching cybercrimes: methodologies, ethics, and critical approaches [Internet]. Cham: Springer International Publishing; 2021 [cited 8 February 2023]. p. 145–67. https://doi.org/10.1007/978-3-030-74837-1_8
111. Tiidenberg K. Ethics in digital research. The SAGE Handbook of Qualitative Data Collection [Internet]. 1 Oliver's Yard, 55 City Road London EC1Y 1SP: SAGE Publications Ltd; 2018. p. 466–79 [cited 28 September 2022]. Available from: https://sk.sagepub.com/reference/the-sage-handbook-of-qualitative-data-collection/i3094.xml
112. Gold N. Using Twitter data in research guidance for researchers and ethics reviewers [Internet]. London: UCL Computer Science Ethics Committee; 2020 Available from: https://www.ucl.ac.uk/data-protection/sites/data-protection/files/using-twitter-research-v1.0.pdf

113. Ravn S, Barnwell A, Barbosa NB. What is "publicly available data"? Exploring blurred public–private boundaries and ethical practices through a case study on Instagram. J Empir Res Hum Res Ethics. 2020;15:40–5.
114. Borodovsky JT, Lee DC, Crosier BS, Gabrielli JL, Sargent JD, Budney AJ. U.S. cannabis legalization and use of vaping and edible products among youth. Drug Alcohol Depend. 2017; 177:299–306.
115. Krauss MJ, Sowles SJ, Sehi A, Spitznagel EL, Berg CJ, Bierut LJ, et al. Marijuana advertising exposure among current marijuana users in the U.S. Drug Alcohol Depend. 2017;174: 192–200.
116. Kemp S. The global state of digital in July 2022 [Internet]. DataReportal—Global Digital Insights. 2022 [cited 26 September 2022]. Available from: https://datareportal.com/reports/digital-2022-july-global-statshot
117. Romer D, Moreno M. Digital media and risks for adolescent substance abuse and problematic gambling. Pediatrics. 2017; 140(Suppl 2):S102–6.
118. Moreno MA, Whitehill JM. Influence of social media on alcohol use in adolescents and young adults. Alcohol Res. 2014;36: 91–100.
119. Sidebottom A, Tilley N. EMMIE and the what works Centre for Crime Reduction: Progress, challenges, and future directions for evidence-based policing and crime reduction in the United Kingdom. The globalization of evidence-based policing. Abingdon: Routledge; 2021.
120. College of Policing. What Works Centre for Crime Reduction [Internet]. What Works Centre for Crime Reduction. 2022 [cited 28 September 2022]. Available from: https://www.college.police.uk/research/what-works-centre-crime-reduction
121. Snapchat. Snap Inc. Transparency Report [Internet]. 2022 [cited 27 September 2022]. Available from: https://snap.com/en-GB/privacy/transparency

SUPPORTING INFORMATION

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

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APPENDIX A

TABLE A1 Key concepts for scoping review and their translation into search terms.

Key concepts	Search terms
Young people	'young*' **OR** 'young people' **OR** 'young adults' **OR** 'child*' **OR** 'teen*' **OR** 'student*' **OR** 'kid?'
	AND
Drug advertisement and sale	'drug?' **OR** 'drug? advertis*' **OR** 'drug sale' **OR** 'drug NEAR/2 dealing' **OR** 'drug NEAR/2 purchase' **OR** 'drug market*' **OR** 'illicit drugs' **OR** 'illegal drugs'
	AND
Social media	'social media' **OR** 'direct NEAR/2 messag*' **OR** 'instant NEAR/2 messag*' **OR** 'Facebook' **OR** 'Snap*' **OR** 'Twitter' **OR** 'Instagram' **OR** 'WhatsApp' **OR** 'Telegram' **OR** 'Wickr' **OR** 'TikTok'