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Research Article

Internet Search for Illicit Drugs in Italy: Infodemiological Analysis of Six Years of Research

Giuseppe Di Martino[1,2] **Vincenza Gianfredi**[3] **Alessandro Catalini**[4] **Marco Fonzo**[5] **Tiziana Menegon**[6] **Flavia Pennisi**[7] **Gianluca Russo**[8] **Lorenzo Stacchini**[9] **Omar Enzo Santangelo**[10,11] **and Fabrizio Cedrone**[12]

[1]*Department of Medicine and Ageing Sciences, "G. d'Annunzio" University of Chieti-Pescara, Chieti 66100, Italy*
[2]*Unit of Hygiene, Epidemiology and Preventive Medicine, ASL Pescara, Pescara 65100, Italy*
[3]*Department of Biomedical Sciences for Health, University of Milan, Milan 20133, Italy*
[4]*Food Safety and Nutrition Unit, Local Health Authority of Macerata, Macerata 62100, Italy*
[5]*Hygiene and Public Health Unit, Department of Cardiac-Thoracic-Vascular Sciences and Public Health, University of Padova, Padova 35131, Italy*
[6]*Health Promotion Unit, Azienda ULSS Marca Trevigiana, Treviso 31100, Italy*
[7]*Faculty of Medicine, University Vita-Salute San Raffaele, Milan, Italy*
[8]*UOC Oncologia Medica, Ospedale Santo Spirito, Pescara 65100, Italy*
[9]*Department of Health Science, University of Florence, Florence 50134, Italy*
[10]*Regional Health Care and Social Agency of Lodi, ASST Lodi, Lodi 26900, Italy*
[11]*University of Milan, Milan 20122, Italy*
[12]*Hospital Management, Local Health Authority of Pescara, Pescara 65100, Italy*

Correspondence should be addressed to Omar Enzo Santangelo; omarenzosantangelo@hotmail.it

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This study explores the potential of Internet search data from Google Trends and Wikipedia as innovative tools for monitoring public interest and behavior related to illicit drug information. Employing a cross-sectional study design, this research investigates the correlations between search patterns on these platforms and provides insights into public health monitoring. Our analysis indicates significant correlations between searches for various illicit drugs, with correlation coefficients ranging from 0.71 to 0.83, suggesting that these searches can not only reflect but also potentially predict public interest and shifts in drug use patterns. This approach highlights specific periods and demographics showing increased interest in drugs, thereby allowing for targeted public health interventions. The study found that searches related to drugs like cannabis, cocaine, and opioids are not only frequent but also show a tendency to be conducted in tandem, possibly due to synergistic effects. Moreover, the data underscore the importance of providing timely and accurate information to the public through authoritative online sources. With the vast reach of the Internet, ensuring that institutional websites and social networks offer correct information becomes crucial to prevent the spread of misinformation. This study supports Internet-based data as a complementary tool to traditional drug monitoring systems, which can enhance public health response capabilities by providing real-time, nonintrusive insights. This research advocates for integrating big data analytics into public health strategy, emphasizing the role of Internet searches in shaping public health policies and practices. The findings suggest that properly leveraged, Internet search data could greatly assist in the precision and effectiveness of public health interventions and preparedness.

Keywords: digital epidemiology; dope; drug; epidemiology; Google; infodemiology; infoveillance; Italy; medical informatics computing; narcotic; Wikipedia

1. Introduction

The history of the interaction with potentially addictive drugs dates back over 8000 years ago [1]. However, the term "addiction" only emerged in the 19th century, coinciding with the refinement of various drug preparations that could include craving and compulsive use [2]. Several social and economic factors have influenced the global spread of drugs, significantly impacting in terms of direct and indirect costs [3]. Drug abuse is associated with numerous medical consequences, including infections, psychiatric disorders, and neurological and cardiovascular complications [2]. Drug misuse may also result in indirect health consequences due to typical addiction behaviors, such as needle sharing or unprotected sex, which can lead to serious medical conditions [4].

Over the past few decades, the epidemiology of drug consumption and abuse has evolved across industrialized countries. Although cannabis remains the most abused drug, there is an upward trend in the use of cocaine and synthetic drugs [5]. Italy, the third-largest consumer of drugs in Europe, has enhanced its monitoring capacities over the last 20 years to better understand the drug addiction situation [6].

Countries with high Internet penetration, search engines, and social networks can reflect the possible interests or behavior of people regarding illicit drugs. Consumers may search the Internet for information about substances, their effects, adverse reactions, and dependence management. Analyzing Internet traffic can serve as an alternative and complementary method to monitor the dynamics of drug consumption and consumer behaviors. This innovative research field, also known as "infodemiology," has had a significant impact on other medical conditions, as already demonstrated for both infectious and noncommunicable diseases [7–9].

The use of data derived from Internet-based systems can enhance traditional surveillance systems in evaluating the impact of drug abuse on public health or to address the emergence of new illicit substances. This application has already been applied in other countries [10, 11], detecting emerging trends in the use of new psychoactive substances. The magnitude of public health concern about opioid consumption and the opioid crisis in USA has also been investigated via Google Trends (GT), showing significant online interest across North American countries [12]. This approach has proven to be a valuable tool in monitoring the opioid overdose epidemic, complementing existing official data sources. The purpose of this study was to evaluate the trend in Internet of searches related to illicit drugs in Italy. We also examined whether there is a correlation or association between searches on Google and Wikipedia, as well as among searches for different substances.

2. Materials and Methods

A cross-sectional study design was used. Data on Internet searches were obtained from GT, based on Google Search—the most widely used Internet search engine [13]. We used the Italian search terms listed in Table 1. The research area of interest was limited to Italy. Data covering partly overlapping time frame, from July 2015 to December 2022 (July 2015 marks the beginning of data availability on Wikipedia), were extracted. GT produces relative search volume (RSV) scaled to the week with the highest search proportion, computed as the percentage of queries concerning a specific term for a particular location and time period, with 100 being the maximum value and 0 the minimum. Thus, RSV allows for direct comparison across search terms. Data on page views from Wikipedia [14] were extracted as monthly data corresponding to the monthly report of Google's RSV. The number of monthly views by users from July 2015 to December 2022 of the Wikipedia pages listed in Table 1 was analyzed. The drugs in Table 1 were selected because they are the most consumed substances in Italy according to the report on drug addiction by the Ministry of Health of Italy [15]. The files in "CSV" format have been downloaded. We overlapped GT and Wikipedia data to perform linear regression and correlation analysis. Cross-correlation results are obtained as product-moment correlations between the two-time series. The advantage of using cross-correlations is that they account for time dependence between two time-series variables. Statistical analyses were performed using either Pearson product-moment correlation coefficient (r) or Spearman's rank correlation coefficient (rho), with the Bonferroni correction applied to the correlations. According to a rule of thumb, a rho value greater than 0.7 indicates a strong correlation, between 0.3 and 0.7 indicates a moderate correlation, and less than 0.3 indicates a weak correlation [16]. Linear regression models considered Wikipedia searches as the dependent variable and GT RSV as independent variable; results are expressed as coefficients with 95% confidence intervals (95% CIs). Potential autocorrelation was ascertained through the Durbin–Watson (DW) statistics. The DW test, or d, is a statistic test used to detect the presence of autocorrelation in the residuals (prediction errors) from a regression analysis [17]. The DW test statistic or d always lies between 0 and 4. If the d is substantially less than 2, there is evidence of positive serial correlation, while values greater than 2 suggest no autocorrelation. Representative linear model and correlation charts of the data were calculated, including the calculation of the R^2 for the model. The statistical significance level for the analyses was set at 0.05. Data were analyzed using the STATA statistical software, Version 14 [18], and Microsoft Excel . The data download and analyses were completed on June 21, 2023.

3. Results

The raw data for GT and Wikipedia are shown in Figure 1. Figure 2 displays the linear regression models between Wikipedia searches and Google's RSV for the search terms listed in Table 1. A temporal correlation was observed between GT terms and Wikipedia pages. In this section, only strong correlations are reported to simplify the reading. For medium and weak correlations, please see Tables 2, 3, and 4.

Table 1: Google terms searched in Italian, Wikipedia pages in Italian viewed, and translation in English.

Google Trends	Wikipedia	Translation in English
Droga	Droga	Drug (dope/narcotic)
Acido gamma-idrossibutirrico	Acido γ-idrossibutirrico	Gamma-hydroxybutyric acid
Amfetamina	Amfetamina	Amphetamine
Barbiturici	Barbiturici	Barbiturates
Benzodiazepine	Benzodiazepine	Benzodiazepines
Buprenorfina	Buprenorfina	Buprenorphine
Cannabinoidi	Cannabinoidi	Cannabinoids
Cannabis	Cannabis	Cannabis
Catinone	Catinone	Cathinone
Cocaina	Cocaina	Cocaine
Eroina	Eroina	Heroin
Fentanyl	Fentanyl	Fentanyl
Hashish	Hashish	Hashish
Ketamina	Ketamina	Ketamine
LSD	LSD	LSD
Marijuana	Marijuana	Marijuana
MDMA	MDMA	MDMA
Metadone	Metadone	Methadone
Metanfetamina	Metanfetamina	Methamphetamine
Oppiacei	Oppiacei	Opiates

The Wikipedia pages that exhibit a strong, statistically significant correlation with each other include Cannabinoidi-Buprenorfina ($r = 0.73$), Cannabis-Benzodiazepine ($r = 0.72$), Cannabis-Cannabinoidi ($r = 0.71$), Cocaina-Cannabinoidi ($r = 0.77$), LSD-Cocaina ($r = 0.72$), LSD-Eroina (0.73), Marijuana-Buprenorfina ($r = 0.76$), Marijuana-Cannabinoidi ($r = 0.75$), Marijuana-Cocaina ($r = 0.74$), Marijuana-Eroina ($r = 0.72$), Marijuana-Hashish ($r = 0.77$), Marijuana-LSD ($r = 0.83$), Metanfetamine-Cocaina ($r = 0.72$), Mentanfetamine-LSD ($r = 0.81$), Metanfetamnine-Marijuana-Hashish ($r = 0.82$), Oppiacei-Cannabinoidi ($r = 0.76$), and Oppiace-Cannabis ($r = 0.72$) (see Table 2).

The GT terms that show a strong, statistically significant correlation with each other are Marijuana-Cannabis ($r = 0.81$) and Mentanfetamine-Hashish ($r = 0.73$) (see Table 3).

GT Internet search data show a strong correlation with Wikipedia pages for Eroina GT-Eroina Wiki (rho = 0.76), Fentanyl GT-Fentanyl Wiki (rho = 0.72), Marijuana Wiki-Eroina GT (rho = 0.74), Marijuana GT-Marijuana Wiki (rho = 0.73), Metadone Wiki-Eroina GT (rho = 0.71), Metanfetamine Wiki-Eroina GT (rho = 0.71), Metanfetamine GT-Marijuana Wiki (rho = 0.71), and Metanfetamine GT-Metanfetamine Wiki (rho = 0.78) (see Table 4).

As shown in Table 5, there is a statistically significant association for the same GT words and Wikipedia pages, except for Catinone, Barbiturici, Benzodiazepine, Ketamina, and Oppiacei. Among the linear regression models between Wikipedia searches and Google's RSV, the best are the ones concerning Fentanyl ($R^2 = 0.7333$) and MDMA ($R^2 = 0.7418$) (see Figure 2).

4. Discussion

This study employed a cross-sectional design to explore the relationship between Internet search behaviors and the prevalence of illegal drugs and narcotic substance use, as captured by GT and Wikipedia page views. It analyzed Internet searches made by Italian users from July 2015 to December 2022. The significant correlations found between search terms and page views suggest that online search behavior can serve as a proxy for drug interest and possibly consumption patterns within the Italian population. Strong correlations were observed between several pairs of drugs across the two platforms, such as Marijuana and LSD with R-values exceeding 0.80, indicating a high level of synchronous interest in these substances. This could reflect broader trends in drug use or public interest, which merit further investigation by public health authorities. Google and Wikipedia were both investigated because they serve different purposes. Google is a search engine commonly used to access general information, whereas Wikipedia allows users to search for specific details and delve deeper into various aspects. Therefore, the correlation between searches on Google and Wikipedia is particularly interesting. While a search on Google represents an initial approach to a topic of interest, the continuation on Wikipedia suggests a desire or need for an in-depth exploration of lesser-known or unknown aspects. This correlation can be considered an indicator of genuine interest in the searched topic, rather than a random search, as suggested by several studies [19]. Moreover, the application of linear regression models showed that Wikipedia searches could be predicted from Google's RSV data, particularly for substances like Fentanyl and MDMA where R^2 values were above 0.73. This indicates a robust relationship between search frequency on Google and the subsequent information seeking on Wikipedia. These models provide a valuable predictive tool for monitoring drug interest trends, potentially enabling rapid responses to emerging drug issues.

The findings of this study are consistent with existing literature, which highlights a high incidence of psychoactive

Figure 1: Search trends of Wikipedia pages and Google RSV.

legal drug use initiation among young adults. Many continue using medication without ongoing supervision, underscoring a trend toward the irrational use of medicines—a significant public health concern due to both high pharmaceutical expenditures and potential health risks [20]. This pattern of unsupervised drug use may be reflected in the strong correlations observed between online searches for psychoactive substances and Wikipedia page views, as Internet searches may also be indicative of unsupervised information seeking and possibly unsupervised drug use.

The discussion about the correlation in the research of different substances represents a complex element in terms of data interpretation. Firstly, users may combine searches for substances to evaluate the possibility of interaction, either out of concern or in an attempt to enhance their effects. While a certain level of pharmacological knowledge is

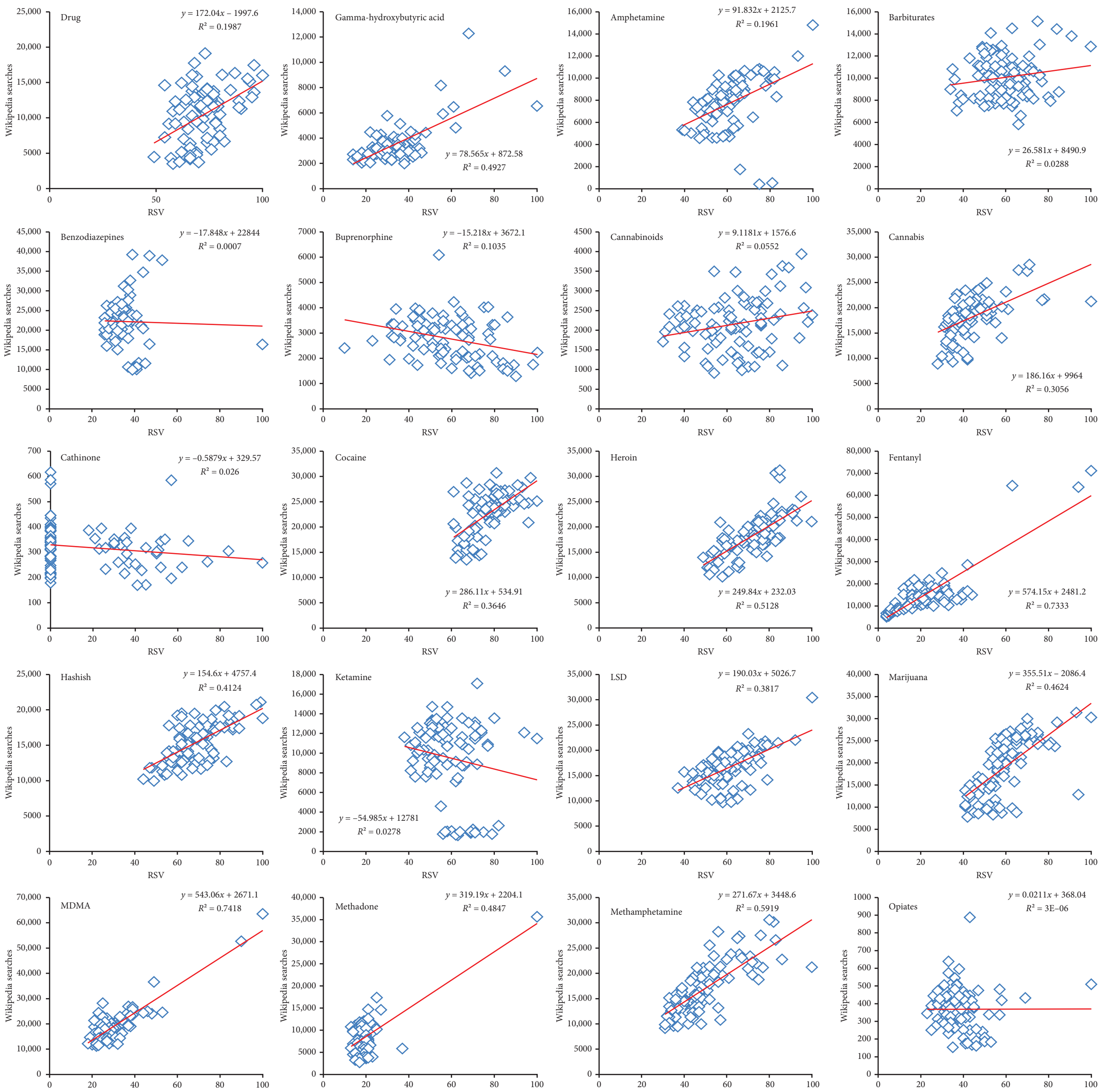

FIGURE 2: Linear regression models between Wikipedia searches and Google's RSV. The red line shows the model; the equation and the corresponding R^2 are shown in the figure.

typically required to understand these mechanisms, it is also true that the level of information and synthesis provided by platforms like Wikipedia allows users to gain a basic understanding of such interactions. Nevertheless, the correlation and regression analyses affirm the utility of Internet-based monitoring tools in the public health domain, particularly for understanding dynamics surrounding less frequently discussed substances such as Fentanyl and Methamphetamine. Internet-based data can complement traditional drug monitoring systems, offering real-time insights that are less intrusive and costly.

Some substances that showed correlations with each other in the analysis have known pharmacological interactions. For example, Buprenorphine, a partial μ-opioid agonist widely used for opioid maintenance therapy (OMT), is primarily metabolized to norbuprenorphine (one of its active metabolites) by the cytochrome P450 (CYP) 3A4 isoenzyme. Cannabis, a potential inhibitor of CYP3A4, may decrease the formation of norbuprenorphine and increase buprenorphine blood concentrations, most likely through inhibition of CYP3A4. This pharmacokinetic interaction could result in enhanced or altered opioid activity and the risk of intoxication [21]. Regarding Cannabis-Cocaine, earlier studies reported that the use of cannabis increased plasma levels of cocaine, probably due to vasodilation (nasal mucosa) induced by cannabis, which increased the absorption of cocaine when snorted. Another reason could be that cocaine is metabolized into the inactive metabolite

Table 2: Correlation between Wikipedia pages.

	Droga	Acido γ-idrossibutirrico	Amfetamina	Barbiturici	Benzodiazepine	Buprenorfina	Cannabinoidi	Cannabis	Catinone	Cocaina	Eroina	Fentanyl	Hashish	Ketamina	LSD	Marijuana	MDMA	Metadone	Metanfetamina	Oppiacei
Droga	1																			
Acido γ-idrossibutirrico	0.0753	1																		
Amfetamina	0.5366*	0.0673	1																	
Barbiturici	0.2802	0.0744	0.3234	1																
Benzodiazepine	0.4033*	0.1071	0.5260*	0.4574*	1															
Buprenorfina	0.3071	0.1414	0.5622*	0.0993	0.4712*	1														
Cannabinoidi	0.5522*	0.0586	0.6482*	0.2172	0.6338*	0.7252*	1													
Cannabis	0.3981*	0.1133	0.5528*	0.3549	0.7196*	0.6222*	0.7106*	1												
Catinone	0.0818	−0.0203	0.0044	0.1412	0.1232	−0.0743	0.0344	0.0527	1											
Cocaina	0.5271*	0.0081	0.6186*	0.3218	0.6727*	0.6792*	0.7737*	0.6879*	−0.0058	1										
Eroina	0.4707*	0.1361	0.3595	0.0912	0.3428	0.4969*	0.5304*	0.4778*	−0.2451	0.6748*	1									
Fentanyl	0.0078	0.0382	0.0981	0.1504	0.2298	0.1351	0.1243	0.2646	0.1352	0.1551	−0.0251	1								
Hashish	0.2979	0.0422	0.2706	0.0494	0.2184	0.6722*	0.4782*	0.4789*	−0.1470	0.5888*	0.5840*	0.0838	1							
Ketamina	−0.0713	−0.1256	−0.1395	0.2028	0.2362	−0.0714	0.1372	0.1923	0.4598*	0.0647	−0.1675	0.2118	−0.1477	1						
LSD	0.4446*	0.0793	0.4930*	0.0954	0.4039*	0.6304*	0.6499*	0.5956*	−0.3247	0.7167*	0.7267*	−0.0331	0.6068*	−0.1263	1					
Marijuana	0.3786*	0.0536	0.4574*	−0.0227	0.3715	0.7583*	0.7447*	0.6191*	−0.3015	0.7440*	0.7228*	−0.0244	0.7705*	−0.1883	0.8326*	1				
MDMA	−0.0355	−0.0527	−0.0798	−0.1232	0.0620	0.3898*	0.3415	0.3257	−0.2782	0.4191*	0.5602*	−0.0178	0.5759*	0.0626	0.5859*	0.6567*	1			
Metadone	0.1304	0.0392	0.4136*	−0.0230	0.2336	0.5282*	0.4797*	0.4129*	−0.1858	0.4593*	0.4278*	0.0291	0.3207	−0.1215	0.4929*	0.5984*	0.3504	1		
Metanfetamina	0.3909*	0.0617	0.5506*	0.1193	0.3237	0.6324*	0.6807*	0.4657*	−0.3534	0.7168*	0.6466*	−0.0333	0.5532*	−0.2583	0.8058*	0.8165*	0.4989*	0.5084*	1	
Oppiacei	0.4027*	0.0547	0.4823*	0.2890	0.5514*	0.6652*	0.7600*	0.7178*	−0.0145	0.6727*	0.4802*	0.2028	0.5047*	0.1697	0.6200*	0.6533*	0.3795*	0.4549*	0.5197*	1

Note: Used the Pearson product-moment correlation coefficient (r). Strong correlation if r or rho > 0.7. Moderate correlation if the value of r or rho is between 0.3 and 0.7.
$^*p < 0.05$.

Table 3: Correlation between Google Trends search terms.

	Droga	Acido γ-idrossibutirrico	Amfetamina	Barbiturici	Benzodiazepine	Buprenorfina	Cannabinoidi	Cannabis	Catinone	Cocaina	Eroina	Fentanyl	Hashish	Ketamina	LSD	Marijuana	MDMA	Metadone	Metanfetamina	Oppiacei
Droga	1																			
Acido γ-idrossibutirrico	0.1129	1																		
Amfetamina	0.4160*	0.0592	1																	
Barbiturici	0.3249	−0.0745	0.2922	1																
Benzodiazepine	0.0431	0.1151	−0.1009	−0.0837	1															
Buprenorfina	−0.0358	0.0323	−0.2330	−0.0680	0.3953*	1														
Cannabinoidi	0.1391	−0.0854	−0.1544	−0.1761	0.2624	0.2313	1													
Cannabis	0.1255	0.0534	0.3386	0.1376	−0.0605	−0.0482	−0.0585	1												
Catinone	−0.0039	0.0490	0.1202	0.1232	0.2264	−0.0490	−0.1785	0.0937	1											
Cocaina	0.4988*	−0.0826	0.4174*	0.4251*	−0.2687	−0.3680	−0.1254	0.1236	−0.0116	1										
Eroina	0.3072	−0.0796	0.3853*	0.2391	−0.4204*	−0.4704*	−0.2350	0.2355	0.0371	0.5439*	1									
Fentanyl	0.0036	0.0452	−0.2783	−0.0721	0.2928	0.1607	0.3173	−0.1587	0.0399	−0.1817	−0.3272	1								
Hashish	0.3341	0.1133	0.5165*	0.4760*	−0.1135	−0.1653	−0.2812	0.2426	0.1288	0.4421*	0.5122*	−0.1940	1							
Ketamina	0.1210	0.0498	0.3317	0.4248*	0.0059	−0.0580	−0.1601	0.1840	0.0995	0.4007*	0.2062	−0.0894	0.6216*	1						
LSD	0.3880*	0.1121	0.5978*	0.2652	0.0627	−0.1989	−0.1948	0.1582	0.1873	0.4342*	0.4460*	−0.2010	0.6561*	0.4548*	1					
Marijuana	0.3068	0.0862	0.5404*	0.3245	−0.1262	−0.2547	−0.2370	0.8052*	0.1883	0.3798*	0.4821*	−0.2460	0.5893*	0.3957*	0.4749*	1				
MDMA	0.1362	0.1257	0.4601*	0.2534	0.0929	−0.2823	−0.3332	0.3160	0.1087	0.4000*	0.3125	−0.1935	0.5988*	0.6216*	0.5734*	0.5470*	1			
Metadone	0.0035	0.0239	0.1628	−0.0094	0.0247	0.1689	0.0096	0.0456	0.1162	−0.0624	−0.0909	0.0346	−0.0287	0.1314	−0.0062	0.0113	0.0421	1		
Metanfetamina	0.3779*	0.0390	0.6647*	0.4046*	−0.1761	−0.4008*	−0.3441	0.2049	0.2268	0.5772*	0.5836*	−0.3189	0.7313*	0.5270*	0.6894*	0.5921*	0.6141*	0.0541	1	
Oppiacei	0.0674	0.0488	−0.0577	−0.0725	0.1563	0.1992	0.1408	−0.1175	−0.0763	0.0095	−0.0116	0.2733	−0.0099	0.0695	0.1877	0.0913	−0.0566	0.0376	−0.0438	1

Note: Used the Pearson product-moment correlation coefficient (r). Strong correlation if r or rho > 0.7. Moderate correlation if the value of r or rho is between 0.3 and 0.7. Weak correlation if r or rho < 0.3.
$^*p < 0.05$.

Table 4: Correlation between Google Trends search terms and Wikipedia pages.

	Droga_Wiki	Droga_GT	Acido γ-idrossibutirrico_Wiki	Acido gamma-idrossibutirrico_GT	Amfetamina_Wiki	Amfetamina_GT	Barbiturici_Wiki	Barbiturici_GT	Benzodiazepine_Wiki	Benzodiazepine_GT	Buprenorfina_Wiki	Buprenorfina_GT	Cannabinoidi_Wiki	Cannabinoidi_GT	Cannabis_Wiki	Cannabis_GT	Catinone_Wiki	Catinone_GT	Cocaina_Wiki	Cocaina_GT	Eroina_Wiki	Eroina_GT	Fentanyl_Wiki	Fentanyl_GT	Hashish_Wiki	Hashish_GT	Ketamina_Wiki	Ketamina_GT	LSD_Wiki	LSD_GT	Marijuana_Wiki	Marijuana_GT	MDMA_Wiki	MDMA_GT	Metadone_Wiki	Metadone_GT	Metanfetamina_Wiki	Metanfetamina_GT	Oppiacei_Wiki	Oppiacei_GT
Droga_Wiki	1																																							
Droga_GT	0.4268*	1																																						
Acido γ-idrossibutirrico_Wiki	0.2913	0.1585	1																																					
Acido gamma-idrossibutirrico_GT	0.0866	0.2240	0.4717*	1																																				
Amfetamina_Wiki	0.5870*	0.3659	0.4106*	−0.0243	1																																			
Amfetamina_GT	0.2639	0.4695*	0.2335	0.2574	0.5514*	1																																		
Barbiturici_Wiki	0.3019	−0.0376	0.0979	−0.2798	0.2917	−0.1213	1																																	
Barbiturici_GT	0.0838	0.3440	−0.0970	0.0368	−0.0024	0.3175	0.0783	1																																
Benzodiazepine_Wiki	0.4481*	0.1128	0.2355	−0.2999	0.5594*	−0.0248	0.6210*	−0.0584	1																															
Benzodiazepine_GT	−0.0846	0.0247	−0.1284	0.1905	−0.2282	−0.1804	0.1657	−0.0604	0.0218	1																														
Buprenorfina_Wiki	0.3528	0.4050	0.3846	−0.1125	0.7086*	0.4594*	0.1077	0.1819	0.4662*	−0.5082*	1																													
Buprenorfina_GT	−0.1334	−0.0548	−0.1595	0.0542	−0.3195	−0.1977	−0.0420	−0.0386	−0.1799	0.4649*	−0.3330	1																												
Cannabinoidi_Wiki	0.5675*	0.4471*	0.3166	−0.2199	0.7611*	0.3537	0.2593	0.1033	0.6037*	−0.3732	0.7986*	−0.4217*	1																											
Cannabinoidi_GT	0.1243	0.1226	−0.0369	−0.1081	0.0693	−0.2059	0.2447	−0.1574	0.3484	0.3342	0.0159	0.2330	0.2115	1																										
Cannabis_Wiki	0.3604	0.2069	0.1624	−0.2922	0.5274*	0.2459	0.3694	−0.0431	0.6838*	−0.2273	0.6048*	−0.2352	0.6548*	0.2219	1																									
Cannabis_GT	0.1340	0.1835	0.1889	−0.0487	0.2525	0.4408*	0.0416	0.2089	0.1693	−0.1668	0.4327*	−0.0426	0.3693	−0.0039	0.6181*	1																								
Catinone_Wiki	0.1000	−0.1056	−0.1104	−0.1850	−0.1157	−0.3770	0.2944	−0.2282	0.2818	0.2231	−0.1607	0.1696	0.0234	0.5380*	0.1042	−0.0990	1																							
Catinone_GT	−0.0848	0.0004	−0.0464	0.0538	−0.0775	0.0464	−0.0500	0.1415	−0.0883	−0.0390	−0.0902	0.0013	−0.1373	−0.1859	−0.0161	0.0583	−0.1735	1																						
Cocaina_Wiki	0.5323*	0.3572	0.2941	−0.1465	0.7013*	0.2915	0.3457	0.0540	0.6622*	−0.3309	0.6482*	−0.4608*	0.7437*	0.0572	0.5528*	0.1498	0.0221	−0.0195	1																					
Cocaina_GT	0.2240	0.5068*	0.2274	−0.0270	0.4289*	0.4530*	0.1034	0.3829	0.3214	−0.3342	0.6458*	−0.3444	0.4859*	−0.1589	0.3693	0.2174	−0.2682	−0.0061	0.5988*	1																				
Eroina_Wiki	0.5478*	0.3306	0.4290*	0.0286	0.5858*	0.4790*	0.1159	0.1598	0.3474	−0.4703*	0.6180*	−0.4320*	0.6139*	−0.2450	0.4624*	0.3095	−0.3296	0.0315	0.6945*	0.5659*	1																			
Eroina_GT	0.2953	0.3194	0.2694	−0.0437	0.4896*	0.4144*	0.0209	0.2291	0.2246	−0.5062*	0.6519*	−0.4331*	0.5704*	−0.2407	0.4193*	0.3536	−0.3797	0.0377	0.5259*	0.5414*	0.7631*	1																		
Fentanyl_Wiki	0.0321	−0.0378	−0.0229	−0.1961	−0.0794	−0.4239*	0.2787	−0.2029	0.3157	0.1203	−0.0134	0.2180	0.0814	0.5105*	0.3038	0.0011	0.5313*	−0.1095	−0.0099	−0.2601	−0.2325	−0.2201	1																	
Fentanyl_GT	−0.2215	−0.1200	−0.3203	−0.0302	−0.4128*	−0.4903*	0.1535	−0.1350	−0.0328	0.4925*	−0.4618*	0.3844	−0.4282*	0.4258*	−0.1222	−0.2620	0.4548*	0.0240	−0.3736	−0.4817*	−0.6285*	−0.5519*	0.7119*	1																
Hashish_Wiki	0.3481	0.3986	0.2128	0.0336	0.3705	0.4271*	0.0207	0.3148	0.2320	−0.4814*	0.6724*	−0.4080	0.5297*	−0.0914	0.4866*	0.4286*	−0.1804	0.0277	0.5238*	0.6029*	0.6351*	0.6604*	−0.0629	−0.3670	1															
Hashish_GT	0.1118	0.3925	0.0324	0.2256	0.1251	0.5308*	−0.1816	0.4752*	−0.2050	−0.1614	0.3359	−0.1032	0.1859	−0.2269	0.1021	0.3748	−0.4189*	0.1287	0.2040	0.3916	0.3835	0.4872*	−0.3085	−0.3086	0.5946*	1														
Ketamina_Wiki	0.0245	−0.0499	−0.0565	−0.4186*	0.0243	−0.1670	0.3386	−0.0812	0.4030	−0.1328	0.1767	−0.1834	0.3428	0.4444*	0.3969	0.0845	0.4502*	−0.0413	0.2793	0.1025	−0.0141	−0.0364	0.4502*	0.2044	0.1407	−0.2079	1													
Ketamina_GT	−0.0873	0.2251	−0.0450	0.2075	−0.0683	0.3102	−0.0833	0.4405*	−0.2102	0.0396	0.1131	0.0286	−0.1056	−0.0978	−0.0734	0.1778	−0.3695	0.0572	−0.0125	0.3503	0.0841	0.1592	−0.2851	−0.0869	0.3562	0.5493*	−0.0870	1												
LSD_Wiki	0.5071*	0.3912	0.3394	0.0146	0.6722*	0.6574*	0.0898	0.1192	0.3502	−0.4200*	0.6923*	−0.5224*	0.6956*	−0.1508	0.5652*	0.4130*	−0.3624	0.0285	0.6637*	0.6227*	0.7874*	0.6936*	−0.2735	−0.5952*	0.6537*	0.4323*	0.1133	0.1708	1											
LSD_GT	0.1430	0.3935	0.0093	0.2355	0.2001	0.6469*	−0.1620	0.3101	−0.1299	−0.0667	0.3220	−0.1508	0.1906	−0.1597	0.1762	0.3615	−0.3696	0.0989	0.0736	0.4030	0.2810	0.4278*	−0.3775	−0.2952	0.5146*	0.6406*	−0.1035	0.4169*	0.5800*	1										
Marijuana_Wiki	0.4215*	0.4371*	0.3361	−0.0107	0.6230*	0.6190*	−0.0435	0.2609	0.2851	−0.5315*	0.8093*	−0.4877*	0.7397*	−0.2048	0.5583*	0.5083*	−0.3955	0.0674	0.6655*	0.6531*	0.7891*	0.7431*	−0.2901	−0.6739*	0.7632*	0.5414*	0.0718	0.2685	0.8742*	0.4844*	1									
Marijuana_GT	0.1182	0.3810	0.2395	0.1280	0.3699	0.6225*	−0.1340	0.3268	0.0708	−0.2529	0.5666*	−0.2290	0.4751*	−0.1759	0.4860*	0.8044*	−0.3898	0.1704	0.2634	0.4150*	0.4600*	0.5443*	−0.1954	−0.4474*	0.5791*	0.6454*	−0.0206	0.3174	0.5997*	0.5619*	0.7301*	1								
MDMA_Wiki	0.1885	0.3614	0.2865	0.0323	0.4739*	0.6056*	0.0043	0.2902	0.2101	−0.4185*	0.7070*	−0.4395*	0.5889*	−0.1007	0.4604*	0.4577*	−0.3172	0.0744	0.5298*	0.6376*	0.6247*	0.6229*	−0.1253	−0.4561*	0.7292*	0.5175*	0.2504	0.3731	0.7716*	0.5340*	0.8038*	0.6766*	1							
MDMA_GT	−0.0671	0.2378	−0.0394	0.2708	0.0011	0.4921*	−0.2336	0.3584	−0.2582	−0.0704	0.2249	−0.1197	−0.0075	−0.2669	0.0265	0.3023	−0.3536	0.1109	−0.0221	0.3547	0.1488	0.2781	−0.3193	−0.1735	0.5128*	0.5504*	−0.0579	0.5270*	0.3182	0.7165*	0.3439	0.4598*	0.5675*	1						
Metadone_Wiki	0.3532	0.3729	0.3726	−0.0116	0.6874*	0.5563*	−0.0081	0.1564	0.3233	−0.5176*	0.8021*	−0.3928	0.7196*	−0.1486	0.5186*	0.4285*	−0.3554	0.0335	0.6399*	0.5763*	0.7125*	0.7111*	−0.2181	−0.6064*	0.6007*	0.3981	0.0185	0.1321	0.7724*	0.3612	0.8780*	0.6369*	0.7020*	0.2131	1					
Metadone_GT	0.0652	0.1437	−0.0624	0.0394	−0.0155	0.1167	−0.0891	0.0921	−0.0988	0.0921	0.0177	0.1628	−0.0023	−0.0662	0.0767	0.1587	−0.0534	0.1373	0.1040	0.0261	0.1904	0.2042	0.0059	−0.0137	0.0474	0.2214	−0.0588	0.1779	0.1225	0.1282	0.1544	0.2066	0.0704	0.0405	0.2901	1				
Metanfetamina_Wiki	0.4469*	0.3930	0.2995	0.0120	0.7335*	0.6157*	0.0817	0.1881	0.3497	−0.4344*	0.7442*	−0.4764*	0.7399*	−0.2060	0.4852*	0.3154	−0.3900	0.0704	0.7449*	0.6094*	0.7902*	0.7019*	−0.2704	−0.6080*	0.6135*	0.4741*	0.0280	0.1485	0.8655*	0.4120*	0.8743*	0.5986*	0.7413*	0.2465	0.8147*	0.1696	1			
Metanfetamina_GT	0.2031	0.4542*	0.0940	0.1478	0.4583*	0.7114*	−0.1171	0.3747	0.0179	−0.2352	0.5065*	−0.3458	0.4208*	−0.2869	0.2407	0.2894	−0.4946*	0.1731	0.4658*	0.6070*	0.5533*	0.5650*	−0.4341*	−0.4724*	0.5407*	0.6889*	−0.1020	0.4530*	0.6941*	0.6454*	0.7030V	0.6291*	0.6937*	0.5700*	0.6179*	0.1865	0.7848*	1		
Oppiacei_Wiki	0.4238*	0.2108	0.2658	−0.2843	0.5590*	0.2909	0.3377	0.1379	0.5660*	−0.3543	0.6928*	−0.3472	0.7416*	0.1048	0.6764*	0.5071*	−0.0293	−0.0165	0.6286*	0.5038*	0.5448*	0.5140*	0.1904	−0.2925	0.5804*	0.2665	0.4265*	0.1024	0.6630*	0.2899	0.6641*	0.5189*	0.6212*	0.1535	0.6459*	0.1352	0.6044*	0.3895	1	
Oppiacei_GT	−0.0090	0.1381	−0.2530	0.0316	−0.2076	−0.1136	0.0896	−0.0076	−0.0227	0.3912	−0.2122	0.3271	−0.2455	0.2605	−0.1806	−0.2006	0.2340	−0.0830	−0.3048	−0.0955	−0.4191*	−0.2861	0.1873	0.4093*	−0.2492	−0.0647	0.0814	0.1214	−0.2944	0.0928	−0.4138*	−0.2478	−0.2602	0.0106	−0.3366	−0.0003	−0.3678	−0.1507	−0.0889	1

Note: Spearman's rank correlation coefficient (rho). Strong correlation if r or rho > 0.7. Moderate correlation if the value of r or rho is between 0.3 and 0.7. Weak correlation if r or rho < 0.3. Wiki: Wikipedia.
Abbreviation: GT: Google Trends.
$^{*}p < 0.05$.

Table 5: Linear regression models, based on 90 observations.

Independent variable	Coefficient	95% CI	p value	Durbin–Watson
		Dependent variable: Droga Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Droga	172.04	98.84/245.24	< 0.001	0.87
		Dependent variable: Acido gammaidrossibutirrico Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Acido gammaidrossibutirrico	78.57	61.68/95.45	< 0.001	1.08
		Dependent variable: Amfetamina Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Amfetamina	91.83	52.45/131.22	< 0.001	0.37
		Dependent variable: Barbiturici Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Barbiturici	26.58	−6.14/59.30	0.110	1.03
		Dependent variable: Benzodiazepine Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Benzodiazepine	−17.85	−156.98/121.29	0.799	0.74
		Dependent variable: Buprenorfina Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Buprenorfina	−15.22	−24.71/-5.73	0.002	0.95
		Dependent variable: Cannabinoidi Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Cannabinoidi	9.12	1.12/17.11	0.026	0.27
		Dependent variable: Cannabis Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Cannabis	186.16	126.71/245.61	< 0.001	0.45
		Dependent variable: Catinone Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Catinone	−0.58	−1.35/017	0.129	1.08
		Dependent variable: Cocaina Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Cocaina	286.11	206.09/366.12	< 0.001	0.84
		Dependent variable: Eroina Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Eroina	249.84	198.25/301.42	< 0.001	1.27
		Dependent variable: Fentanyl Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Fentanyl	574.15	500.81/647.50	< 0.001	0.72
		Dependent variable: Hashish Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Hashish	154.60	115.50/193.69	< 0.001	0.63
		Dependent variable: Ketamina Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Ketamina	−54.99	−123.90/13.93	0.116	0.29
		Dependent variable: Droga Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV LSD	190.03	138.79/241.27	< 0.001	0.49
		Dependent variable: MDMA Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV MDMA	543.06	475.18/610.94	< 0.001	0.74
		Dependent variable: Metadone Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Metadone	319.19	249.47/388.91	< 0.001	0.24
		Dependent variable: Metanfetamina Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Metanfetamina	271.67	223.89/319.45	< 0.001	0.71
		Dependent variable: Oppiacei Wikipedia		
Independent variable	**Coefficient**	**95% CI**	**p value**	**Durbin–Watson**
GT RSV Oppiacei	0.02	−2.42/2.46	0.986	0.41

Abbreviations: GT, Google Trends; RSV, relative search volume.

benzoylecgonine by the 3A isoenzyme of cytochrome P450, and the use of cannabis, an inhibitor of this metabolic pathway, could increase plasma levels of cocaine [22]. However, more recent studies suggest that the concomitant use of cannabis does not significantly influence plasma levels of cocaine. It is more likely that the combined use of these due to cannabis attenuates the negative effects of cocaine, such as loss of appetite and agitation [23].

Regarding Cannabis-Benzodiazepines, the use of cannabis derivatives and benzodiazepines is a very common combination. Both substances have sedative effects on the central nervous system, though they act on different receptors (CB1 receptors and GABA-A receptors, respectively); the effect of one can synergistically enhance the effect of the other. Furthermore, as previously mentioned, the use of cannabis can alter the metabolism of some benzodiazepines through the inhibition of some isoforms of cytochrome P450 (Cyp3A4), prolonging their effect [23]. In the case of Heroin-cannabis, the concomitant use of these substances is not particularly significant from a metabolic pathway perspective, although heroin is partly metabolized by the cytochrome P450 isoenzyme 3A4 and 2C8. More likely, web searches for these two substances might be explained by a new variety of cannabis called "Amnesia" recently marketed. Amné or Amnèsia, a very potent variant of cannabis derivatives (hashish and marijuana), is produced by spraying it with methadone, heroin, and chemical substances to enhance its psychotropic effect [24]. As for LSD-cocaine, the psychotropic effects of LSD are primarily due to the activation of the 5-HT2A and 2C receptors. Cocaine acts mainly as an inhibitor of monoamine reuptake (primarily dopamine, but also serotonin and norepinephrine), increasing their concentration in the brain, and causes its psychoactive effects [25]. The simultaneous use of the two drugs likely potentiates the psychedelic effect of LSD mediated by serotonin receptors.

Beyond these pharmacological interactions, which partly explain the research findings, it is crucial to consider the phenomenon of polydrug users as reported in the 2023 European Drug Report [26]. Polydrug consumption may play a significant role in drug overdoses, particularly among injective drug users. Polydrug use patterns have become common among opioid users, and drug interactions appear to increase the risk of harm. Additionally, novel synthetic opioids are increasingly associated with both drug-related morbidity and mortality. While overall trends in opioid-related deaths are stable [4], the proportion of deaths in older age groups is increasing. It is important to highlight that where heroin is implicated, it is often in combination with other drugs. Therefore, public health efforts must also focus on polydrug users to develop preventive strategies and reduce drug-related mortality.

4.1. Implications for Public Health Policy and Practice and Ethical Consideration. This study represents an innovative project that requires further exploration, and as such, only preliminary conclusions can be drawn at this time. Consequently, new research questions and applications of this method can be developed in the future. However, the data presented in our study are relevant because they provide insights into the general public's behavior when seeking information about illicit drugs. Internet searches can be an important source for generating hypotheses about knowledge, attitudes, and practices in public health topics [27].

In particular, these searches can reveal the periods of the year when people are particularly interested in certain topics and are more receptive to receiving information. Furthermore, these data inform us about which topics the general population considers relevant [28]. Notably, in this study, we also observed that the search for different illicit drugs is correlated, possibly because one enhances the effect of the other. From a public health perspective, this represents a valuable opportunity to disseminate up-to-date and accurate information on prevention. This information could enhance the effectiveness of public health communications campaigns by facilitating the timely delivery of engaging content. Mass media and social networks can increase people's curiosity and encourage them to seek specific health information. Therefore, it is crucial that authoritative and institutional sites always provide updated and correct information [29].

Based on the evidence accumulated to date, the dynamic nature of our society, and the ease of Internet access, infodemic assessments represent a new approach that can provide virtually real-time data useful for informing public health initiatives [30]. Establishing systems to continuously monitor Internet search trends related to illicit drugs using tools like GT and Wikipedia page views represents a valuable solution. These systems can provide real-time data on public interest and potential drug use patterns, allowing for timely public health responses. In light of our findings, institutional communication should be implemented using all available tools, including institutional websites, institutional social networks, portals, educational tutorials/videos, forums, and smartphone applications [27]. The vast reach of the Internet allows for rapid dissemination of information to large audiences. Therefore, institutions that fail or neglect to provide scientifically valid and comprehensible information contribute to the dissemination of incomplete or deliberately misleading information [27]. Public health personnel must be proficient in digital communication using lay terms to address and respond to the public health challenges of the new millennium [31].

With respect to public health and preventative strategies, this study suggests that big data is a largely underutilized resource in healthcare, yet it can significantly inform public health policies and practices. The results demonstrated that Google and Wikipedia are relevant sources of information, widely used by the general public to find various kinds of information. These data can provide insights into public behavior and emerging drug trends, guiding the allocation of resources and the formulation of effective interventions. Specifically, focusing on the topic of this research, the use of big data may help recognize that searches for different illicit drugs often correlate. Design interventions that address the use of multiple substances, particularly those that are frequently searched together, such as cannabis and cocaine, are crucial to effectively reduce polydrug use. It is important to note that Internet searches are also strongly influenced by sociocultural and environmental factors. Among the sociocultural factors, the impact of the media plays a significant role. Indeed, there is an association between news/mass media and Internet user searches [32], while environmental factors such as the spread of Internet infrastructure in the country affect the overall Internet use. From the policy maker's point of view, this is essential as it allows for the evaluation of the effectiveness of interventions and informs how to allocate investments in a financially constrained system, such as the Italian national health system. In this perspective, customizing messages and strategies to resonate with different demographic groups and address specific local conditions is another important public health implication. By developing targeted public health interventions and enhancing public health communication, these insights can lead to more timely and effective responses to emerging drug issues. Furthermore, the results of studies like this could increase the accuracy of the public health sector's preparedness on the topic, fostering international and interdisciplinary collaboration and embracing technological advancements to maximize public health benefits. Sharing data and collaborating with international public health organizations to address global drug use trends can enhance understanding of cross-border drug issues and improve coordinated responses. Currently, there are several methodological difficulties encountered in reporting on the use of illicit drugs, as also reported by the European Monitoring Centre for Drugs and Drug Addiction [33].

First of all, the data needed for estimates of illicit drug use can vary in completeness across different substances, creating many problems for the quality of the estimates themselves.

From this arises the need to impute missing data when analyzing different countries through the calculation of correction factors [34, 35] or other methodologies [36].

Another source of data is given by surveys with the problems of selection bias that can exclude some users of some substances for example. Furthermore, the risk of underreporting in surveys can be due to recall bias but also, in the case of stigmatized behaviors, to social desirability bias.

In light of the gaps and limitations of different monitoring systems, the analysis of Internet search trends can play a complementary role to the methodologies currently used and its usefulness can be interesting in the context of monitoring the phenomenon of co-abuse of different substances, which represents an important emerging public health problem.

Utilizing Internet search data for public health surveillance brings many promising opportunities, yet it also necessitates careful attention to ethical considerations. By establishing and following comprehensive guidelines, we can responsibly harness the power of these data. Firstly, ensuring privacy is crucial, and this can be achieved by anonymizing and aggregating data to protect individual identities. Additionally, whenever possible, obtaining informed consent is important, as it keeps users aware of how their data are being used to benefit public health. Implementing strong data security measures is essential to safeguard against breaches and unauthorized access, maintaining the integrity of the data. Lastly, focusing on equity and fairness ensures that data benefit all populations and avoid bias. By adopting these guidelines, we can effectively use Internet search data to improve public health surveillance while upholding ethical standards and protecting individual rights.

4.2. Limitations and Future Research. Despite these promising findings, there are several limitations to consider, most of which are similar to other infodemiological studies. Although Google and Wikipedia require some level of informatics skills, or at least access to a computer with an Internet connection, the widespread use of smartphones today allows for a larger sample of research data to be evaluated. However, evaluating research trends cannot account for each user's priori knowledge of these topics and related factors. Moreover, the correlation does not imply causation; thus, these results should be interpreted with caution. Internet search behaviors may not directly correspond to actual drug use but rather to interest or concern about these substances. For instance, students or researchers could conduct online searches for information on illicit drugs for their assignments or for their work. Additionally, the scope of data is limited to publicly available information from Google and Wikipedia, which may not fully capture all demographic segments, especially those with limited Internet access or different Internet usage patterns. In this study, we did not consider other search engines such as Yahoo! or Bing, nor did we include data from social media platforms such as X (the previous name was Twitter). However, existing research indicates that over 80% of Internet users worldwide use Google [36]. Although GT does not have information on user characteristics, making it difficult to profile individuals who search for specific topics, these innovative data sources still offer scientists and policy makers several opportunities [37]. Wikipedia, on the other hand, is the most widely used encyclopedia or general in-depth website in the world [38]. Social networks or social media are not adequate for the type of analysis performed by the authors but are more suitable if one wants to perform a sentiment analysis (e.g., through the study and use of "#," the so-called "hashtags") [39, 40].

Future research should aim to integrate these Internet-based insights with epidemiological and clinical data to provide a more comprehensive understanding of drug use patterns. Longitudinal studies could also assess how changes in Internet search behaviors relate to drug use trends over time.

5. Conclusions

Overall, our findings underscore the potential of using Internet search data as a supplementary tool for drug surveillance and public health research. By leveraging the vast and readily available data from Internet searches, public health officials and researchers can deepen their understanding of drug-related issues, ultimately enabling more informed and timely interventions. This study highlights the importance of adapting to technological advancements and incorporating diverse data sources in public health strategies.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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