Innovating opioid research with social media data: A social network analysis of Twitter conversations

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Abstract
Background: Opioid overdose deaths remain a critical public health challenge in the United States. Social media platforms have emerged as important venues for information sharing, peer support, and shaping public discourse about the opioid crisis. Twitter/X is widely used to discuss opioid use, prevention, policy, and personal experiences. However, little is known about how these conversations are structured, who the key voices are, and what topics are most shared. Few studies have used social network analysis to investigate these trends. This study aimed to uncover the structure of the opioid-related network and identify key influencers, top hashtags, and top content producers.
Methods: We used NodeXL to import, visualize, and analyze data from public Twitter/X accounts. A total of 32,745 tweets containing the keyword “opioid” were collected between December 18, 2024, and March 26, 2025.
Results: Network analysis of opioid-related conversations on Twitter/X identified 21,654 users and 32,743 interactions. The network showed low density, but clustered communities centered on the opioid crisis. Top accounts were primarily health-related, though AI-driven accounts also played a growing role in information dissemination. Key themes included fentanyl, crisis, and overdose, with hashtags such as #opioid and #fentanyl most frequent. Findings highlight both public concern and the influence of AI-driven accounts in shaping online opioid discourse.
Conclusion: Twitter/X provides key insights into the actors and narratives influencing discussions about opioids. The growing role of AI systems underscores the need for public health officials to enhance their digital presence and prioritize accurate information over misinformation.

Keywords: opioids, Twitter/X, social network analysis, social media, public health

Introduction

The opioid epidemic continues to pose a serious public health challenge in the United States.[1] Drug overdose mortality rate in the United States rose from 16.3 deaths per 100,000 population in 2015 to a peak of 32.6 in 2022, before declining to 31.3 in 2023 and further to 23.1 in 2024.[2,3] The fluctuations in U.S. life expectancy can be attributed to these drug overdose mortality trends.[4] The trajectory of the overdose epidemic has been shaped by shifting drug trends, beginning with prescription opioid misuse. It later escalated with the rising prevalence of heroin and highly potent synthetic opioids such as fentanyl.[5–7] Although there has been a recent decrease in overdose deaths, opioid-related overdoses remain the leading cause of death among adults in the United States aged 18–44 years.[8,9]

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The opioid crisis not only leads to a tragic loss of life but also imposes a significant economic burden. Data from the Centers for Disease Control and Prevention (CDC) estimated the combined financial cost of opioid use disorder and fatal opioid overdose in the U.S. at approximately $1.02 trillion in 2017, reflecting health care, lost productivity, and quality of life losses. More recent federal analysis from the White House Council of Economic Advisers indicates that illicit opioids, mainly fentanyl, may have cost the U.S. economy around $2.7 trillion in 2023, or nearly 10% of gross domestic product (GDP).[10–12]

Social media have significantly transformed how information is shared and received globally.[13] Nearly 97% of adults utilize at least one online social media platform.[14] Twitter, now known as X, is a popular social networking site globally with approximately 600 million active users per month.[15] Platforms, such as Twitter/X, have become crucial venues for disseminating public health information. Twitter/X data provides valuable real-time insights into user attitudes and behaviors related to public health monitoring. Leveraging Twitter/X data for public health surveillance offers notable advantages over traditional survey methods. It enables real-time analysis of public discourse, reduces reliance on self-reported data, and effectively captures spontaneous health conversations through automated data mining and natural language processing techniques. This approach can help us better understand public health trends and develop response strategies.[16]

In recent years, health scientists have leveraged Twitter/X data to examine public discourse, health behaviors, and the spread of information.[17,18] Research has shown that Twitter/X is a valuable platform for collecting real time data and analyzing public discourse on health-related issues such as antibiotic misuse, flu trends, cardiovascular diseases, and diabetes. The platform has been utilized across diverse public health applications, including improving influenza forecasting accuracy, revealing geographic links between health discussion and disease prevention, characterizing communication in cardiovascular disease, and identifying potential misuse or misunderstanding of antibiotics that can reach hundreds of thousands of users through information sharing networks.[18–22]

In the context of opioids, prior research demonstrates that Twitter/X conversations often use stigmatizing language and rely heavily on generic terms like "pain" and "addiction", indicating limited use of scientific terminology. Keyword analysis showed that there are many misconceptions among the public regarding access to prescription drugs and their misuse.[23–25] The platform not only facilitates the identification of trends in opioid use but also reveals complex patterns of polysubstance use and the dynamic evolution of individual behaviors over time.[26] Twitter/X also acts as a venue for the platform users to voice their concerns about the addictive nature and risks associated with opioids, particularly highlighting synthetic types such as fentanyl.[27] Healthcare professionals on Twitter/X achieve higher engagement even though they tweet less frequently and discuss a variety of topics.[23] Social media exposes adolescents and young adults to drug-related content that normalizes opioid and substance use. This exposure increases the likelihood of experimentation and misuse. Posts from peers, influencers, and targeted ads indicate risky behavior as appealing.[28,29]

Although research on opioid-related discourse on Twitter/X has grown substantially, most studies have relied on sentiment analysis, content analysis, machine learning, and text mining approaches that overlook the relational structures captured by social network analysis (SNA).[23,30–33] While such methods yield valuable insights into content and sentiment, relatively few studies have applied SNA to investigate the structure and influence dynamics of opioid discussions. For instance, prior studies employed SNA to examine Coronavirus Disease of 2019 (COVID-19)–related conversations that mentioned opioids and cannabis. However, these investigations did not directly target opioid discourse as a standalone phenomenon.[34,35] This emphasizes the need for further SNA-driven research explicitly focused on opioid-related conversations, particularly given of their public health significance and the evolving digital information landscape.

Background on social network analysis

The core of social media is user engagement, which is expressed through features such as replies, follows, shares, and friend requests. User interactions on platforms such as Twitter/X result in connections that form complex network structures. SNA examines the structural and functional dynamics of communities, individuals, and groups. It offers critical insights into patterns of information dissemination, the identification of influential actors, and the mechanisms through which networks form and evolve within online conversations.[36,37] Among various public health issues, SNA has been applied to the study of COVID-19, obesity, melanoma, asthma, and other conditions.[38–41]

Monitoring the opioid crises on social media, particularly Twitter/X, has gained significant attention from academics and public health officials in recent years. Twitter/X has proven to be a valuable tool for the real-time surveillance and uncovering of major themes and conversational trends related to opioids, including overdose trends and public sentiment. This serves as a timely data source for these issues.[23,26,33,42] However, systematic reviews indicate that while social media platforms show promise, more rigorous methods are needed to fully realize their effectiveness.[42] To the best of our knowledge, only two studies have employed SNA to explore opioid-related discourse on Twitter/X.[34,35] These studies did not thoroughly capture the network's structural characteristics or provide a comprehensive view of the opioid information ecosystem, including identifying top content producers, influential accounts controlling information dissemination, and the thematic landscape of opioid-related discussions. Filling this gap is critical, especially with the rapid growth of social media, where new narratives, actors, and forms of influence emerge. To address this limitation, the present study aims to map the current network structure of opioid-related conversations on Twitter/X, identify key influencers and content producers, and uncover the most significant themes shaping public discourse.

The research questions (RQ) guiding this study are:

1. What are the structural characteristics of the opioid-related network on Twitter/X?
2. Who are the key influencers and top content producers, and what topics dominate their posts?
3. What major themes emerge from opioid-related tweets, and how do users interact around them?

Materials and Methods

We used NodeXL Pro to import and analyze data from public Twitter/X accounts. The dataset included English-language tweets containing the keyword "opioid" from December 18, 2024, to March 26, 2025 (Social Media Research Foundation, California, CA, USA).[43] In SNA, *edges* represent connections between *nodes*, (e.g., individuals or groups), and signify interactions that reveal communication, influence, and information exchange patterns. Analyzing these connections helps researchers understand network structure and

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function.[44] In this study, network *edges* reflect user-to-user interactions like retweets, replies, mentions, and quote tweets, regardless of hashtag use. In contrast, hashtag counts indicate how often specific hashtags appear in tweets, often resulting in lower frequencies compared to total interactions. Therefore, hashtag counts show key discussion topics rather than network connectivity or engagement patterns.

To address RQ1 and RQ2, we computed centrality measures, density scores, and performed cluster analysis to identify the sub-communities within the network.[45–47] Density measures the proportion of actual connections relative to all connections in the network (0 to 1). Lower density reflects sparse and fragmented networks. Higher density signifies more interconnected networks, enhancing the potential for widespread information dissemination.[48] Betweenness centrality quantifies how often a user appears on the shortest communication paths between other users. Users with high betweenness centrality serve as essential connectors, linking different communities and facilitating the flow of information throughout the network.[49] In-degree centrality measures the number of incoming connections a user receives, such as mentions, replies, or retweets from others, indicating their popularity in the network. In contrast, out-degree centrality counts the outgoing interactions a user initiates (mentions, replies, and retweets they send), indicating how actively they engage with and amplify others' content. It shows how influential and visible they are and indicates their content-sharing activity.[50] Key terms and definitions are provided in Appendix A. To address RQ3, we calculated the frequencies of hashtags and word pairs in the dataset. The most commonly occurring hashtags and word pairs served as indicators of prominent themes and topics in opioid-related discourse.[51]

The network was visualized using NodeXL, with vertices organized into clusters, using the Clauset–Newman–Moore community detection algorithm.[52] The layout was created using the Harel–Koren fast multiscale algorithm, enabling more precise visualization of large-scale networks.

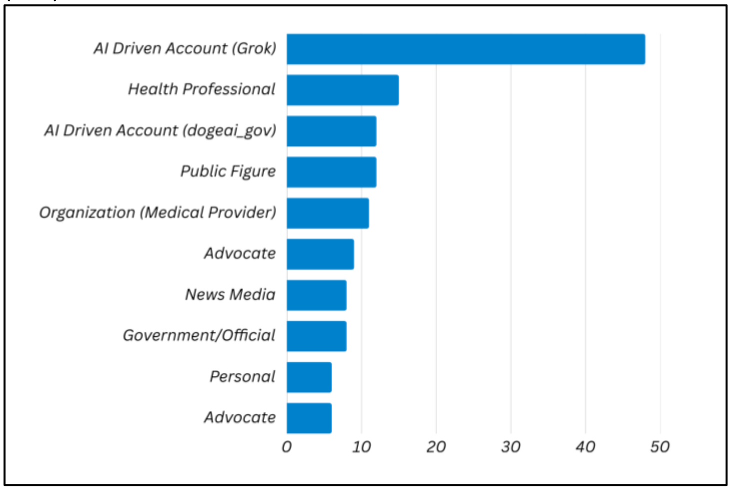
Results

Network analysis produced a directed network of 21,654 unique users, with 32,745 directed edges (tweet-based interactions). However, the network had a low-density score (D = 0.000045). The network contains thousands of small clusters and over 5,000 connected components, many of which consist of isolated single-user nodes with no links to others.

Figure 1 reveals several prominent clusters, with the largest comprising ~2,800 users, followed by clusters of 900–1,300 users, while the remainder were substantially smaller. Group 1, the largest, focused on the opioid crisis, particularly fentanyl and overdose. Group 2 was centered on pain management and chronic opioid use, especially prescription medications. Other clusters underlined overdose prevention, notably through Narcan and naloxone. The network showed strong intra-cluster engagement, with frequent replies and retweets among members of the same subgroup but limited inter-cluster connections, indicating that conversations were largely insular rather than interconnected across the broader network. Increases in tweet activity aligned with key public health announcements from U.S. Department of Health and Human Services (HHS) and Substance Abuse and Mental Health Services Administration (SAMHSA). One of the retweeted opioid-related posts in the dataset was SAMHSA amplifying an HHS post demonstrating widespread sharing of federal policy updates on the extension of a public health emergency addressing opioid and substance-use response efforts.

Betweenness centrality scores (BCS) were computed to identify the top 10 influencers ranked in descending order. As illustrated in Figure 2, the artificial intelligence (AI)-driven account (Grok) has the highest BCS, indicating it serves as a critical bridge in the network, followed by a health professional account, with another AI-driven account (dogeai_gov) also showing notable influence. These accounts function as key intermediaries connecting different segments of the opioid discourse network.

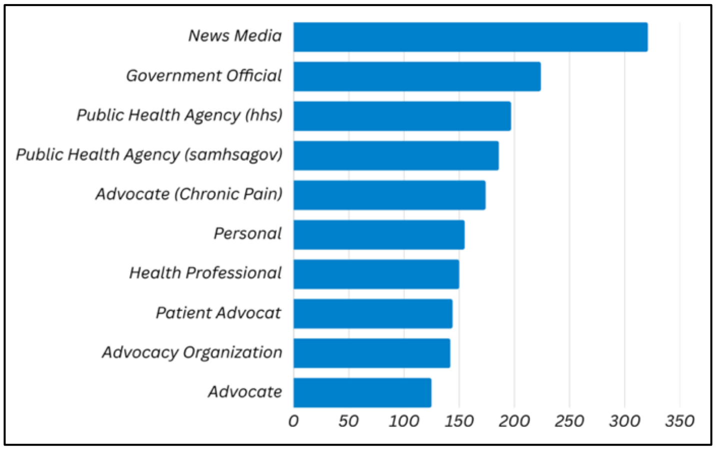
Figure 2. Top Influencers by Betweenness Centrality Scores (BCS)



Abbreviations: AI, artificial intelligence

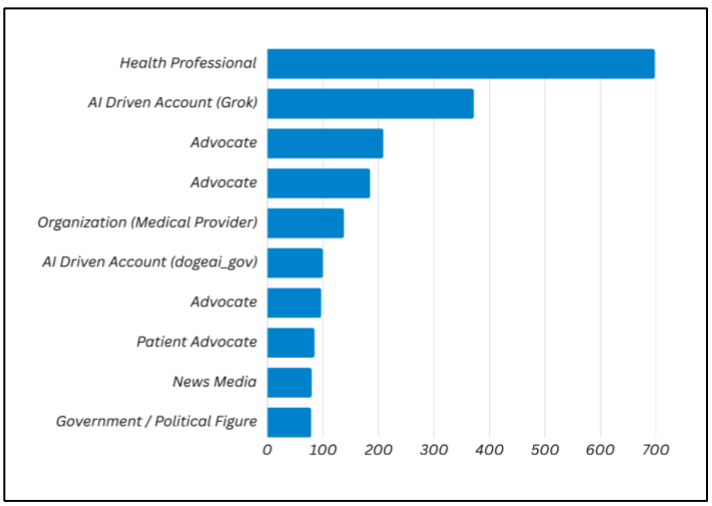
In Figure 3, accounts with high in-degree centrality serve as primary information sources, holding authority and being widely referenced within the network. News media accounts have the highest in-degree centrality, followed by government officials and public health agencies (HHS and SAMHSA). These accounts serve as trusted sources frequently cited and engaged with by other network participants in opioid-related discourse.

Figure 3. Top Content Producers by In-Degree Centrality Scores



As shown in Figure 4, accounts with the highest out-degree centrality serve as key disseminators of information within the network. Through frequent retweets, mentions, and replies, these accounts actively amplify opioid-related discourse across the network. For example, the health professional account exhibits the highest activity, followed by the AI-driven account and the advocate account.

Figure 4. Top Content Disseminators by Out-Degree Centrality Scores



Abbreviations: AI, artificial intelligence

Table 1 presents the most frequently used hashtags in opioid-related discourse. The top hashtags were #opioid (n = 127), #opioidcrisis (n = 80), and #fentanyl (n = 47), reflecting heightened concern over the opioid crisis and synthetic opioids. These frequencies serve as explicit thematic labels rather than indicators of overall engagement. Many tweets, especially replies and retweets, lack hashtags, which explains why the hashtag counts are significantly lower than the total network interactions (32,745 edges). Harm reduction content was limited to Narcan and naloxone (n = 28 and 23, respectively), representing emergency overdose reversal, while broader harm reduction strategies were largely absent from the discourse.

Table 1. Top 10 Hashtags Used

Top Hashtags	n
opioid	127
opioid crisis	80
fentanyl	47
opioids	40
chronic pain	28
naloxone	28
addiction	26
public health	24
Narcan	23

Table 2 shows that the most frequent word pairs in opioid-related discussions on Twitter/X were “opioid, crisis” (n = 3,033), “opioid, epidemic” (n = 1,366), and “opioid, use” (n = 822), indicating a widespread focus on these themes.

Table 2. Top 10-word Pairs

Top Word Pairs in Tweet	n
opioid, crisis	3033
opioid, epidemic	1366
opioid, use	822
opioid, addiction	797
purdue, pharma	549
opioid, overdose	547
public, health	507
use, disorder	450
synthetic, opioid	433

As shown in Table 3, the most retweeted users were health professionals (n=469), news media (n=346), patient advocates (n=286), and public health agencies (e.g., hhs.gov) (n=205).

Table 3. Top Retweeted Users

Top Retweeted Users	n
Health Professional	469
News Media	346
Patient Advocate	286
U.S. HHS Secretary	235
Public Health Agency (hhs.gov)	205
Public Health Agency (samhsa.gov)	193
Public Figure	187
Personal	181
Health Advocate	157
Clinical Pharmacists	154

Abbreviations: U.S. HHS, United States Department of Health and Human Services

Discussion

The current study is among the first to employ SNA to examine opioid-related conversations on Twitter/X. Our work extends this emerging line of research by mapping the ecosystem of opioid-related content to identify key sources, top influencers, and the main topics shaping online discourse. Our analysis identified several bridging influencers with BCS. In network terms, these users occupy critical positions on the shortest

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paths between otherwise disconnected groups, allowing them to link communities and channel information across the broader network. Such actors play a disproportionate role in shaping the dissemination of opioid-related content, as their strategic positions enable them to either amplify, filter, or redirect conversations.[53] Our findings revealed that both AI-driven accounts and health professionals equally play leading roles as top influencers in opioid conversations on Twitter/X. This mirrors the broader trend of healthcare professionals being considered reliable sources for health discussions on social media, thereby improving public health literacy.[23,54–56] The credibility fostered increased online engagement, as illustrated by the American Heart Month campaigns, during which tweets from health professionals experienced higher retweets and likes.[57] Similarly, in this study, health professionals played a crucial role in shaping opioid-related discourse, exhibiting the highest levels of both out-degree centrality (indicating active engagement and content dissemination) and retweet counts (displaying content that others amplify). This dual influence indicates they serve as both active disseminators who engage with others and trusted sources whose messages are widely shared, often generating more amplification than government agencies. This multifaceted influence illustrates healthcare professionals' value as both active contributors and trusted information sources, supporting the literature's calls for greater engagement in social media health discussions to improve information quality and counter misperceptions. At the same time, our exploratory analysis found that healthcare professionals and news media are among the most retweeted users. However, important questions remain about the dynamics of these patterns. Future research should explore the content strategies of various actors, the flow of information (e.g., whether news media amplify healthcare professionals' messages or distribute original content that healthcare professionals then share), and the characteristics of content that drive high retweet rates. Understanding these mechanisms could enhance public health communication strategies on social media.

At the same time, the growing influence of AI-driven accounts reflects a significant shift in the digital health communication landscape, unlike earlier studies, such as Soni et al. (2019), which found that health professionals dominated opioid-related Twitter/X discussions and lay users focused on Tylenol and Percocet medication side effects and pregnancy-related risks. In contrast, our study reveals a shift toward broader crisis-oriented narratives.[34] We identified the growing influence of AI-driven accounts, alongside healthcare professionals, as key contributors to the discourse. The conversation is now framed mainly around the “opioid crisis,” “opioid epidemic,” and “opioid overdose,” with hashtags such as #opioid, #opioidcrisis, #fentanyl, and #addiction underscoring its portrayal as a public health emergency. This evolution from fragmented, medication-specific concerns to centralized, crisis-driven themes stress the need to monitor AI-generated content. This finding demonstrates the urgent need for healthcare professionals and public health officials to enhance their engagement on Twitter/X and other social media platforms to ensure that authoritative, evidence-based voices remain central to online health discourse. The growing presence of AI-driven accounts on social media emphasizes the need to prioritize human expertise at the forefront of public health communication, which becomes even more critical.

Despite these strengths, the overall connectivity of the network was minimal and uneven. This suggests that most users do not have direct connections, which makes it difficult for information to circulate between different groups. As a result, critical messages concerning opioid use, treatment alternatives, and harm reduction may not be accessible to all communities. Our analysis indicated a content disparity in opioid-related Twitter discussions, with crisis and addiction narratives dominating while prevention and harm reduction messages were less visible. Although Narcan and naloxone were mentioned in conversations (representing emergency overdose reversal), many other proven harm reduction strategies were missing from key themes and hashtags. Comprehensive harm reduction includes various interventions, such as syringe service programs, supervised consumption sites, medication-assisted treatment (e.g., methadone, buprenorphine), and safe supply programs.[58,59] This suggests that opioid-related discourse on Twitter/X focuses more on crisis response than prevention, revealing a gap that health authorities need to address for better communication. Conversely, accounts with the highest in-degree centrality (individual user profiles that may represent people, organizations, or AI-driven accounts) function as primary information sources, thereby representing authority and credibility within the network. These accounts, which typically include news organizations, government agencies, medical experts, and advocacy groups, are frequently cited, underscoring their role in shaping information dissemination. Research has repeatedly shown that nodes with high in-degree centrality are critical for quickly spreading complex information through networks and serve as key hubs for knowledge dissemination.[60]

Strengths and limitations

This study is among the first to apply SNA to opioid-related discourse on Twitter/X, and one of its key contributions is the discovery of emerging dynamics that set it apart from earlier research. Contrary to the previous studies, our results indicate that AI accounts are increasingly becoming active contributors to opioid discussions. By documenting this transformation and spotlighting the rise of AI-driven accounts, the analysis underscores the dynamic evolution of social media content. This finding enhances our understanding of communication patterns and shows new opportunities for integrating AI with healthcare professionals. The dominance of AI in opioid discussions is significant, leading to two key implications. First,

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public health officials must improve their digital presence to ensure that accurate, evidence-based information prevails over misleading AI-generated content. Second, critically evaluating sources is essential for educating social media users, as AI-generated responses may lack the empathy and accuracy needed for sensitive health topics such as the opioid crisis. This can improve digital public health strategies, facilitate the dissemination of accurate information, and strengthen harm reduction initiatives.

This study had some limitations. First, our exploratory approach focused on identifying network structure, key influencers, and thematic trends rather than conducting detailed content analysis. Consequently, while we identified AI-driven accounts among top influencers, we did not assess the accuracy, quality, or appropriateness of the content they produced. Future research should utilize thorough content analysis to evaluate the reliability and public health implications of AI-generated health information. The scope of this study is confined to a single platform, Twitter/X, which limits the applicability of its findings to other digital environments or long-term communication patterns. Furthermore, examining opioid-related discussions across various social media platforms such as Reddit, YouTube, TikTok, and Instagram could offer more thorough insight into the online discourse surrounding opioids. Another limitation of this study was its exclusive focus on the Twitter/X network from December 2024 to March 2025. This temporal restriction may constrain the generalizability of our findings to other time periods. Future research could explore the evolution of Twitter/X discourse on this topic over extended time periods.

Conclusions

The ongoing opioid epidemic represents a significant public health challenge facing the United States. This study examined opioid-related discourse on Twitter/X, emphasizing key influencers, hashtags, and word pairs that shaped the flow of information. While healthcare professionals and governmental organizations offered credibility, AI-driven accounts also emerged among the most influential voices. Crisis-driven content dominated the discourse, while prevention and harm reduction strategies beyond emergency response were notably absent. This highlights the importance of increased participation from public health officials and healthcare professionals in discussions about digital health to ensure reliable information is communicated to various audiences and to address gaps in prevention messaging.

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Figure 1. Visualization of Opioids Network on Twitter/X