Examining Journey to Overdose Using Spatial Social Network Analysis

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Introduction

Over the past 16 years, the United States has experienced a dramatic increase in deaths from opioid overdose and other Opioid Use Disorder (OUD). Pandemic has worsened the crisis, leading to an increase in the number of deaths. Overall, the crisis has affected urban and suburban areas, though its effects are more damaging among the marginalized communities in urban neighbourhoods (Farahmand et al., 2020, Forati et al., 2021).

A considerable proportion of drug overdoses occur at locations other than residences (Ghose et al. 2022). On average, in Milwaukee County, 26.72% of overdose deaths occurred away from the decedents' residential address.

Inspired by the "journey to crime" notion in criminology studies, we define the "journey to overdose" as the distance between the decedent residence and the overdose incident location, though the actual journey to overdose might be complex involving multiple stops, backtracking, or loops around areas before the overdose incident (Ackerman& Rossmo, 2015; Johnson et al., 2013).

Using an innovative adaptation of HITS algorithm, this study examines the journey to overdose in Milwaukee County (2017-2020) through spatial social network analysis to pinpoint focal points of geographically discordant overdoses incidents and original residence. Our innovative methodology is equally applicable to other places, allowing for nuanced policy interventions to take place.

Method

We obtained death certificates with the precise location of fatal opioid overdose deaths from the Milwaukee County Medical Examiner office. The dataset was joined to the administrative boundary shapefile of census tracts collected from the TIGER / Line database (www.census.gov) using ArcGIS Desktop 10.7.

Spatial Social Network

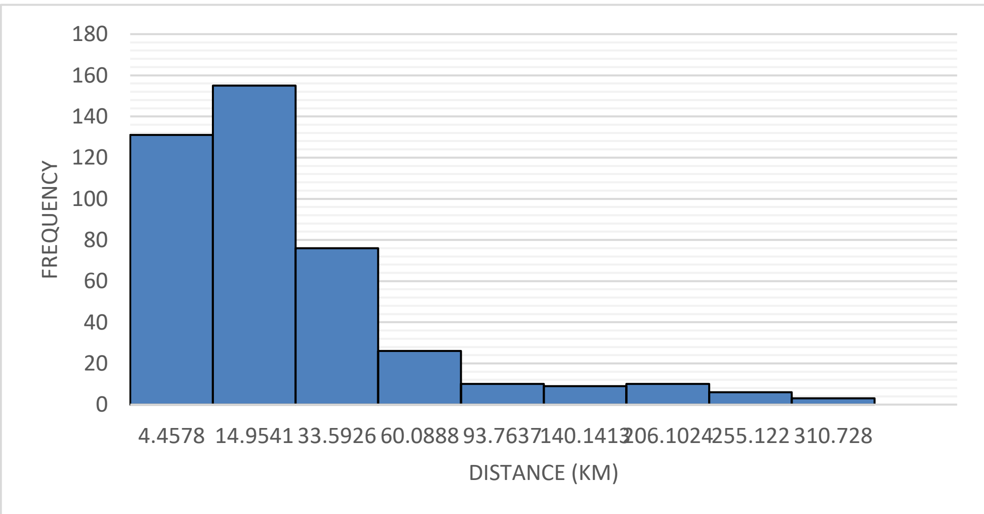
In 1999, Jon Kleinberg developed the Hyperlink-Induced Topic Search (HITS), a significant ranking algorithm. HITS is a node importance metric that calculates both an authority centrality and a hub centrality for all nodes in the network. The authority centrality of a given node is proportional to the sum of hub centralities of all the nodes to which it points to, and the hub centrality is proportional to the sum of authority centralities of all the nodes which point to the given node. The HITS algorithm has been improved and widely used across a wide range of applications, including bioinformatics (Nickerson et al., 2018; Liu et al., 2020), education (Yang & Sun, 2013), and economics (Zhang et al., 2017; Deguchi et al. 2014).

In this study, we adopted the HITS algorithm to study the journey to the overdose network; hub and authority centralities were used to pinpoint the focal point of geographically discordant overdoses and original residences in the directed and weighted journey to the overdose network. Here, all census tracts are regarded as nodes with hub scores and authority scores, respectively. A census tract may point to one or more than one census tract through the overdoses link. To illustrate, suppose a census tract has widely imported (nonlocal) overdose incidents from census tracts that are home to many victims with higher hub scores. In that case, it can be regarded as the focal point of geographically discordant overdoses and ranked with a higher authority score. Conversely, suppose a census tract has been home to many victims and linking them to the focal point of geographically discordant overdoses with higher authority scores. In that case, it can be regarded as the focal point of residence of geographically discordant overdoses and ranked with a higher hub score. An edge weight indicates the degree of involvement or the number of times the journey to overdose happened between two specific census tracts.

To the best of our knowledge, HITS has never been applied in this domain of application. Adopting the HITS algorithm is a unique and promising methodology to study the journey to overdose, which makes the analysis of geographically discordant overdoses of census tracts more reasonable and the recommendation of policymaking for it more reliable since hub and authority values are constantly mutually reinforcing in the calculation process.

Results

In criminology studies, scholars have argued that when it comes to the journey to crime, offenders travel relatively short distances to commit a crime, or in other words, the distribution of journey distances follows a distance decay distribution (Block & Bernasco, 2009; Townsley & Sidebottom, 2010; Johnson et al., 2013; Levine & Lee, 2013). We used Open Source Routing Machine (OSRM) to calculate the



distance and travel time between decedent residences and overdose incident locations. The algorithm finds the optimal route by car, bicycle, or foot on the OpenStreetMap road network (Huber & Rust, 2016). In Milwaukee County, we found that 26.72% of all overdose cases are geographically discordant, and among those, on average, opioid crisis victims travelled 24.93 Km (22 mins) to their overdose incident location. On a median, 8.91 Km (11 Mins). Only 10.56% travelled greater than 50 miles, and the farthest anyone travelled was 310 miles. Figure 1 shows the distribution of distance travelled using Jenks natural breaks optimization (Jenks,1963). The histogram of distance distributions indicates that the number of victims only decreases as distance increases. Therefore, the distance decay function appears to hold true for the journey to overdose.

Figure 1: distribution of distance travelled in journey to overdoses.

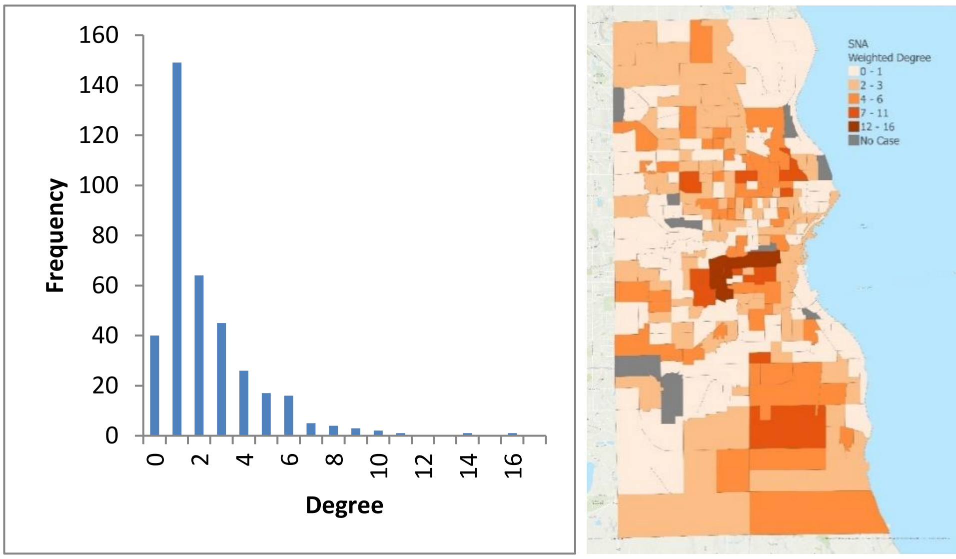


Figure 2: distribution of degree centrality of journey to overdoses.

Next, we constructed a U.S. Census tract centered aggregate social network based on the dyadic (pairwise) relationship of the journey to overdose between victims' residences and overdose incident locations. The aggregate social network derived from the opioid overdose death database included 375 nodes; connected by 426 weighted, directed edges. Census tracts' degree ranges from 1 to 16, with the average weighted degree of 1.139 (figure 2)

Next, we implemented The HITS algorithm on the journey to overdose aggregate social network. The HITS algorithm's certain assumption is that an important authority (geographically discordant overdose focal point) is pointed by significant hubs (residence of geographically discordant overdose victims) and that an important hub points to many important authorities. Therefore, the importance of both an authority census tract and a hub census tract can be computed iteratively till results converge. Each census tract's authority value and hub value represent the rated geographically discordant overdose importance value and the rating importance value of each peer, respectively. Adopting the HITS algorithm, we use the hub and authority centralities to pinpoint hubs and focal points of geographically discordant overdoses (figure 3).

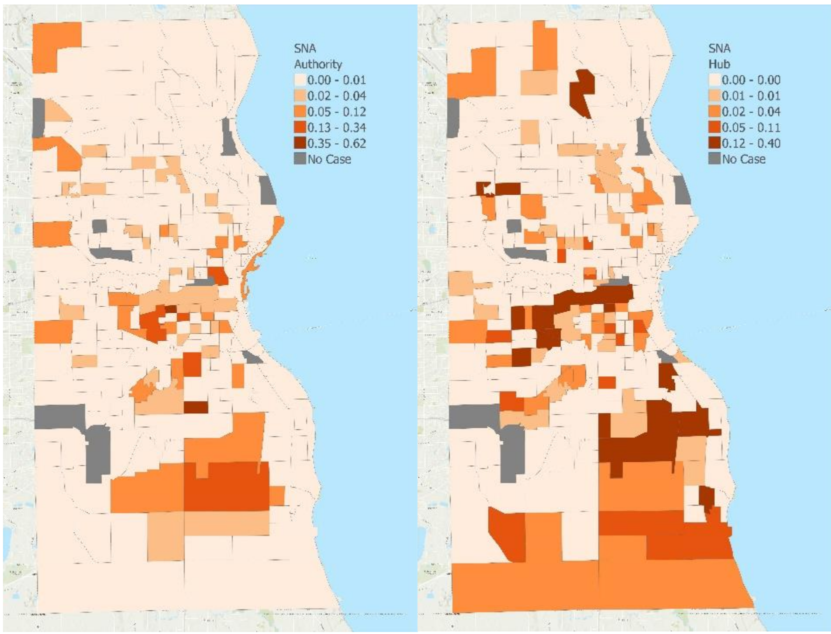


Figure 3: HITS algorithm results

As shown in figure 3, the focal points of geographically discordant overdoses (authorities) are concentrated around the central region of Milwaukee County, and original residences (hubs) of the journey to overdoses are mostly in the southern region of Milwaukee County. Demographically, the census tracts that act as authorities are dominantly Hispanic (33%) or White (50%), primarily single households with lower educational attainment, while the hub census tracts have dominantly white population (71%), higher educational attainment, and higher median household income (Table 1).

	Renter-occupied	White	Black	Hispanic	Median age	Single households	Educational attainment	Below Poverty Level	Median Household Income
Authorities	61.46%	50.68%	11.55%	33.02%	32.45	48.41%	11.60%	25.99%	39636.8
Hubs	46.66%	71.18%	12.13%	13.11%	40.09	39.01%	16.01%	17.72%	48802.3

Table 1: socioeconomic characteristics of focal points and hubs of the journey to overdoses

Discussion and Conclusion

Geographically discordant overdoses make up significant percentages of drug overdoses. Our results indicate that ‘inner-city’ census tracts are attracting individuals from other areas to procure and use drugs. On the other hand, the number of deaths is higher in inner-city tracts, where the opioid crisis has been prevalent for many years. The worst-affected areas are primarily Black/Hispanic communities shaped by decades of racial and economic segregation, with concentrated poverty and health inequalities. With little access to health care, these vulnerable neighbourhoods have limited resources to address opioid abuse, leading to a rise in OODs.

Such a journey to overdose study provides answers to several questions: where non-local decedents originate, what are their drug types, what are their demographic and socioeconomic characteristics. In turn, these answers derived from non-local decedents can be compared to those of the local decedents to gain a better understanding of contributing factors to the opioid crisis, leading to better guidance for interventions at the local, regional, and national scales. Identifying locales, potential drivers, and drug characteristics of geographically discordant overdoses can provide incredible insight into the opioid crisis in communities and help stakeholders improve substance abuse treatment accessibility and disparities.

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