Identifying Chicago's High Users of Police-Involved Emergency Services

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Abstract

Objectives. To identify individuals at risk for behavioral health (BH)–involved encounters with police in Chicago, Illinois.

Methods. We linked Chicago Police Department (CPD) arrest and Fire Department (CFD) BH-involved ambulance event data. We identified at-risk individuals who accumulated at least 1 BH-involved ambulance and at least 1 arrest event between May 2016 and April 2017. We identified a high-use subgroup displaying most intensive services use. We identified high-use locations with highest volume of ambulance events with only CFD data.

Results. Of 83 392 individuals and 116 105 events in the linked emergency events dat[a,] at-risk individuals accounted for 2.2% of individuals, 5.6% of all events, and 16% of BH-involved CFD events with police involvement. A total of 330 high-use individuals accounted for 0.4% of individuals, 2% of events, and 4.7% of CFD events with police involvement. Top-100 high-use locations accounted for 9% of CFD events, and individuals of high-use location events are largely distinct from high-use individuals.

Conclusions. Integrated police and ambulance data hold promise to identify individuals at risk for BH-involved encounters with police and to support proactive interventions to prevent or improve response at these encounters.

Emergency encounters between police and community members experiencing behavioral crises increase likelihood of violence, avoidable arrests, and jail stays, posing a significant public health and safety challenge.

Family members or others often call 911 in the event of an acute behavioral health (BH) crisis, which may arise from serious mental illness, substance use disorders,[1] or intellectual or developmental disabilities.[2,3] Such encounters bring heightened risk of injury to the individual and others, particularly when first responders lack appropriate resources and training. Paramedics are trained and equipped to respond to medical emergencies. Police officers are trained and equipped to respond to public safety threats and may be poorly equipped to deescalate confrontations with someone who does not or cannot comply with instructions or who behaves in unexpected ways. Individuals with serious mental illness, who rarely pose a public safety threat, experience 3 times more police interactions than does the general population.[4] Up to 25% have been arrested.[5] Individuals living with serious mental illness account for 4% to 5% of the adult population[6,7] and for 14% to 31% of the correctional population,[6,8,9] within which individuals with intellectual or developmental disabilities are also overrepresented.[2]

Cities face the challenge of improving their response to BH crises and of deploying proactive measures for individuals at risk.

Crisis Intervention Team (CIT) training is one prominent "event-based" approach to improve emergency responses to BH crises. This training includes a 40-hour training for police officers, including role plays to teach officers to recognize signs of mental illness and to defuse crisis situations. The CIT model also requires training 911 call dispatchers and relies on them to send CIT-trained officers to likely BH-involved calls. Deployment of CIT-trained officers has been shown to decrease arrests and increase linkages to mental health s
at such encounters.[10]

A few cities have piloted "person-based" preventive programs that seek to identify high-risk individuals[11,12] (where current and past frequency of BH-involved encounters with police serve as proxy for risk of future encounters) for proactive outreach and interventions.[13–15] Exact definitions of high users and identification strategies vary because of differences in population and data availability. Some approaches combine police administrative data with qualitative observations from officers to identify individuals who encounter police while in BH crisis. Such strategies rely heavily on manual and subjective components. These time-consuming strategies provide rich insights but render the identification process challenging to generalize or replicate.

Houston, Texas's Chronic Consumer Stabilization Initiative is one prominent person-based preventive intervention. Initiated in 2007, after 3 deadly police encounters involving individuals with histories of serious mental illness, the Chronic Consumer Stabilization Initiative partners with mental health stakeholders to provide intensive case management to individuals identified solely through Houston Police Department data as posing elevated risk. Nonexperimental pre–post evaluation found an 86% decrease in emergency contacts among 67 participants, relative to their 6 most-active months before the intervention.[15]

Other cities have implemented "place-based" interventions. Traditional hotspot mapping identifies locations with high concentrations of crime or 911 calls and facilitates focused interventions at high-use locations.[16] In the case of BH-involved emergencies, cities might deploy outreach workers to these hotspots. A Baltimore, Maryland, demonstration project sent teams of officers and mental health care providers door to door in areas with high violent crime and self-reported mental health needs. A lessons-learned summary reported improved relationship between police and residents and improved ability to reach individuals who otherwise would not have sought services.[17]

While both person-based and place-based approaches have been implemented to identify and assist individuals at risk of BH-involved police encounters, these approaches have rarely been considered together. Little is known about their interaction or overlap. Do high users of emergency services congregate at hotspot locations? Do individuals who experience behavioral crises at hotspots frequently experience such events?

Answering such questions may help cities improve the allocation of scarce emergency response resources. Place-based interventions may be most efficient if most BH-involved emergencies occur at high-use locations, particularly if high-use individuals often enc first responders at these locations. Conversely, person-based interventions may be r efficient if most risky events involve high-users, and high-users are not easily targete intervention at high-use locations.

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In this analysis, we used integrated administrative data from Chicago's 2 primary first-response agencies to identify high-use individuals. This automated, explicit, and replicable approach was designed to generalize to other contexts, with appropriate modification to accommodate local data resources. We describe characteristics of these individuals and present evidence suggesting that the same intervention targets could not be identified with either data source alone. We identified high-use locations from CFD data alone and explored overlap in identification between person- and place-based strategies.

METHODS

For this analysis, we had access to a subset of CPD and CFD administrative data covering the period May 2016 to April 2017. Data from the CPD consisted of every encounter between police and a community member that resulted in arrest. Data from the CFD consisted of every ambulance run encounter between emergency medical technicians or paramedics and a community member in which the encounter was flagged as a BH crisis, as described in the next paragraph.

In partnership with CFD operational and data experts, we implemented term-search text analysis of the "complaint" and "impression" fields to identify ambulance run events that involved a community member experiencing BH crisis. In particular, our data query included patient complaints of agitated, anxiety, crying, tearful, depression, distressed, fear, hallucination, hostile, irritable, nervous, panic, stress, suicidal, and violent, and CFD responder impressions of agitated, combative, anxiety, behavioral or psychiatric, depression, suicidal, and Taser injury.

These encounter events will hereafter be referred to as arrest events and BH-involved CFD or just CFD events, respectively, and collectively as emergency events or just events.

Individuals and Utilization Per Person

Chicago Police Department.

Each arrest event record includes information about the event (e.g., time, location, charge) and about the community member involved in the event, including demographic data (e.g., name, age, address). Importantly, CPD arrest data include a fingerprint-verified unique individual identifier, known as an individual record number. Individual record numbers can be used to (1) count unique individuals in arrest event data and (2) attribute events t individuals over time. Demographic data recorded at each event may vary for the sa individual because of transcription or other errors (e.g., "Jonathon Kaufman" and "Jonathon Koffman" in separate events). For each individual, we retained demographic data as recorded in the first observed arrest event.

Chicago Fire Department.

Each CFD event record includes information about the event and about the community member involved in the event, including demographic data (e.g., name, age, address). Unlike CPD arrest data, CFD data provide no unique individual identifier. We used name and age data to construct and assign a unique identifier that identifies unique individuals across CFD events.

As noted, demographic data recording can be error-prone. Reliance on exact matching overstates the number of unique individuals and understates events per person. We therefore implemented probabilistic (fuzzy) matching on name. Specifically, we used the Levenshtein distance metric to calculate the probability that the name collected at one event is the same as a name collected at another event, for all events in the data. We employed a probability threshold of 0.96 to call a true match.

We assigned a unique individual identifier ("CFD Unique ID") to each individual, and attributed each event to a single CFD Unique ID. We used this ID to (1) count unique individuals in CFD event data and (2) attribute events to unique individuals over time. For each individual, we retained demographic data as recorded in the first observed CFD event.

Across both event data sources.

As there is no unique individual identifier that allows identification of the same individual who may appear in both CPD arrest and CFD event data sets, we used demographic data (name, age, address) to construct and assign a unique individual identifier across CPD and CFD event data.

We again used probabilistic matching on name. For all CFD Unique IDs and CPD individual record numbers, we used the Levenshtein distance metric to calculate the probability that the name associated with a CFD Unique ID is the same as the name associated with a CPD individual record number. We again used a probability threshold of 0.96 to call a true match. We further required minimum agreement on address or zip code data collected on the individual from each data source and that each ID in a matched pair had no other match.

The final product after matching was a lookup table with corresponding CFD and CPD identifiers for each individual captured by both data sources. Using this lookup table merged CFD and CPD event data to form a complete picture of individuals' usage of emergency services across both agencies during the 12-month study period.

Identification of At-Risk and High-Use Individuals

Within our data, we identified 2 groups of individuals at elevated risk for future BH-involved encounter with police.

We considered individuals to be at risk if they had accumulated at least 1 BH-involved CFD event and at least 1 arrest in the 12-month observation period. We identified a subset of at-risk individuals as high use if, in addition•

- they accumulated at least 4 events during the 12-month observation period, and
- they accumulated at least 1 event in at least 4 months of the 12-month observation period, and
- their first event occurred within the first 5 months of the 12-month observation period, providing 7 months of observation following the first event.

We hypothesized that these use patterns represented an intensity and chronicity that may identify a small subset of the at-risk group who are (1) particularly vulnerable, (2) unlikely to self-resolve, and (3) may warrant intensive, proactive interventions.

Identification of High-Use Places

Using BH-involved CFD event data only, we counted number of events per unique location. We created lists of the top 1000, 100, and 10 of the most frequently occurring locations, and defined locations on any these lists as high-use places. We accessed publicly available zoning and public facility location data (e.g., shelter, clinic, park) maintained by the city of Chicago and by the state of Illinois to classify locations as residential versus nonresidential and to identify public facilities whenever possible. We manually entered nonresidential top-100 high-use place addresses into Google Maps to categorize location type (e.g., senior living facility, public transportation stop, homeless shelter).

RESULTS

We identified 61 977 unique individuals in our CPD arrest data and 24 094 unique na combinations represented within 30 651 event records in BH-involved CFD event data. Employing our matching algorithms, we identified 23 257 unique individuals in the CFD data set, a total of 83 392 unique individuals across the 2 data sets, and 1842 at-risk individuals who appeared in both data sets. We further identified 330 high-use individuals within this group.

At least 7% of at-risk and 25% of high-use individuals were indicated as homeless in CFD data. At-risk individuals accumulated 3.5 emergency events on average, more than twice the average of 1.4 in the full population. At-risk individuals accumulated 0.6 CFD events with police involvement on average, 6 times the average of 0.1 in the full population and twice the average of 0.3 in the population that only accumulates CFD events. Police presence was inferred from text analysis of CFD data narrative fields (query for "police" or "CPD"). An arrest may or may not have resulted. Police presence is noteworthy as evidence of concurrent BH crisis and police encounter. Seven percent of the full population and 24% of the population that only accumulated CFD events had at least 1 CFD event with police involvement. Fifty percent of at-risk and 57% of high-use individuals had at least 1 of these events (Table 1).

TABLE 1—
Characteristics of Emergency Service Utilizers: Chicago, IL, May 2016 to April 2017

At-risk individuals averaged more arrest events than did the population with only arrest events (1.8 vs 1.4 arrests). This reflects a higher average of misdemeanor arrests; felony arrest averages were equal in the 2 groups. High users accumulated an average of 7.4 emergency events and 1.0 CFD events with police involvement over the study period, approximately twice the averages in the at-risk group.

The at-risk group accounted for 2.2% of all individuals, 5.6% of all emergency events, and 16% of all CFD events with police involvement. High users accounted for 0.4% of all individuals, 2% of all events, and almost 5% of all CFD events with police involvement. Relative to the at-risk group, high users accounted for 18% of individuals, 37% of emergency events, and almost 30% of CFD events with police involvement.

Table 2 provides detailed utilization for the 10 highest users of these emergency services. All but 1 had at least 1 CFD event with police involvement. Felony arrests were rare, and 2 of the top 10 had more than 10 misdemeanor arrests. Among these highest users, we saw several individuals who might not have been considered highest users from the vantage poi either CPD or CFD data alone. Individuals 4 and 5 exhibited only a single arrest each. Individuals 3 and 6 displayed 12 and 9 CFD events, respectively (placing them in the t and 130, respectively, of users in CFD data alone), but reached top-10 status overall because they accumulated 14 and 13 arrest events, respectively. If we take the top 330 users in the CFD event or arrest data alone, we capture just 69 and 38, respectively, of the 330 high users identified from the linked data.

TABLE 2—

Counts of Emergency Events by Event Type for 10 Highest Utilizers of Emergency Services: Chicago, IL, May 2016–April 2017

Place-Based Analysis

The CFD event data yielded more than 19 000 unique locations. We identified the top 1000, 100, and 10 locations by number of events at each location and assessed the extent of location-based concentration of BH-involved CFD events. We also investigated whether the population of individuals who would be served by interventions targeting high-use locations overlaps with the population who would be served by interventions targeting high users.

Overlap Between Populations

Out of 19 122 unique locations, the top 1000 accounted for 26% of all CFD events and for 37% of all CFD events accumulated by high users. Twenty-four percent of all people in the CFD data and 54% of high users accumulated a CFD event at these locations. The top-100 locations accounted for 9% of total CFD events and for 14% of all CFD events accumulated by high users. Nine percent of all people in the CFD data set and 26% of high users accumulated a CFD event at these locations (Table 3). However, only 4% of unique individuals who experienced BH-involved CFD events at a top-100 location were high users, and only 6% of CFD events at these locations involved a high user; the vast majority of events at these locations did not involve high users.

TABLE 3—

Percentage of People and Events, and Utilization Patterns at High-Use Locations: Chicago, Illinois, May 2016–April 2017

On average, the population of individuals accumulating events at top-100 locations accumulated 2.3 CFD events, and 0.5 CFD events with police involvement, substantially higher than the full CFD population but lower than high users (1.3 and 3.8 events, respectiv and 1.0 events with police involvement, respectively; Tables 1 and 3; both difference significant at α ≤ .001). Of people at top-100 locations, 37% accumulated at least 1 CFD event with police involvement, compared with 26% within the full CFD population and 57% among high users (Tables 1 and 3; both differences significant at α ≤ .001). Events at these locations were slightly more likely to have police involvement than were events at any location (25% vs 23%; nonsignificant difference).

We performed manual location searches for the top-100 nonresidential locations. Transportation centers (airports, bus and train stations), homeless shelters, mental health facilities, and police stations were all highly represented. The top-10 nonresidential locations are noted in Table 4. Seven of these top 10 locations are transportation hubs—the city's 2 major airports, the bus station, and the ends of the city's major north–south elevated train line. A homeless shelter and a mental health facility were also included.

TABLE 4—

Top-10 Nonresidential High-Use Locations of Behavioral Health–Involved Chicago Fire Department Emergency Events: Chicago, IL, May 2016–April 2017

DISCUSSION

Municipalities spend millions of dollars developing administrative data systems, which contain uniquely rich data that are frequently unused or underused for operational purposes. Improved use of such data holds promises to improve the safety, quality, and cost-effectiveness of emergency response while providing a potential platform for proactive interventions.

To our knowledge, this article reports the first public health and safety analysis of cross-agency linked administrative data from Chicago agencies that provide first response for BH crises. The currency of our 2016–2017 data is noteworthy; we can identify specific individuals and places virtually in real time.

In this work, we identified basic demographic and characteristic use patterns for community members who accumulated BH-involved encounters with police. We then focused on person-based and place-based identification strategies to inform interventions. Both strategies have been used in other cities to address the public health challenge of BH-involved encounters with police. We advance the literature by (1) developing an explicit, automated, and replicable process and (2) assessing the comparative and tandem utility of person- and place-based identification strategies.

Our person-based strategy identified 330 high users who appeared to be chronic use[illegible] emergency services. Many would not have been identified had we used only CFD or CPD data in isolation. At least 26% of high users are indicated to be street homeless. Many other high users display geographically dispersed emergency calls, indicating high mobility and perhaps precarious housing. High users comprise just 0.4% of the Chicagoans who experience any arrest or BH-involved CFD event. While high users accounted for more than 10 times the expected number of BH-involved encounters with police given their proportion of the population, they collectively accounted for just under 5% of the total number of this type of emergency event. Nevertheless, they comprise a valuable subgroup for focused, intensive intervention. Interventions for these individuals are the subject of current research.

In a complementary approach, we also examined place-based strategies, identifying locations that account for a disproportionate share of BH-involved emergency events. Transportation hubs, homeless shelters, and mental health facilities are represented among the highest use locations. Such facilities are candidates for focused interventions with facility staff and management. Within residential settings, innovations such as Smart911 allow individuals at risk and their loved ones to provide critical information in advance that may be difficult to communicate in a crisis.[18]

Finally, our data suggest that most high users experience BH crises outside of recognized high-use locations. Conversely, individuals experiencing behavioral crises at high-use locations are generally not high users, based on our defined thresholds. Person- and place-based strategies to identify targets for focused interventions are likely complementary. Exploration of coordinate use of these approaches to target intervention resources is warranted.

Study Limitations

Our findings must be evaluated in light of several limitations. First, our analysis was based upon police and fire department administrative data. We did not have the physical or mental health diagnostic data that were collected during a structured clinical encounter or from medical records. We also relied upon the data infrastructure available in the nation's third largest city. Other localities may lack the scale or data-analytic resources to fully replicate the analyses performed here.

Second, we were only able to analyze BH-involved CFD event and CPD arrest data, not all CFD or CPD encounters. We could not examine the population of people who only encountered CPD without a resultant arrest and those who encountered CFD in an emergency not involving BH concerns. In addition, we only used BH-involved CFD event data in the identification of high-use locations.

We chose to explore 2 illustrative populations, which we hypothesized are at increased risk for future BH-involved encounters with police. To identify these populations, we used a prescriptive algorithm based on criteria that highly weight simple metrics of past utilization to predict future use. Other analysis choices would have yielded slightly different, overlapping populations.

We are now pursuing predictive–analytic strategies, using machine-learning to optimize and automate identification of a population at high risk of future BH-involved encounters with police. This approach will allow incorporation of detailed event- and person-specific information into the identification process. We hypothesized that such approaches may improve our ability to proactively identify persons at risk for BH-involved encounters with police before they make intensive use of emergency services.

Because our current approach relies heavily on high utilization, our definition of high users excludes some of the most criminally active or behaviorally dysregulated individuals who may be incarcerated or hospitalized following a single serious event.

Public Health Implications

Integrated cross-agency emergency response data can be leveraged to identify high users more effectively than can be accomplished by using police or ambulance data alone. Integrated data promise to improve understanding of the people and places linked to behavioral crisis events and may facilitate novel interventions.

Our analysis of high-use locations underscores the need for improved infrastructure and service planning. Transportation hubs, group homes, and shelters have staff equipped to work proactively with mental health providers. Staff can be trained to identify behavioral crises and to follow protocols such as requesting that 911 dispatchers assign CIT-trained officers or ambulance-only responses. The CPD is now conducting CIT community trainings and related outreach, which may be may be specifically targeted to these locations.

Identified high users may benefit from intensive case-management interventions such as Assertive Community Treatment. Emergency response administrative data may provide the foundation for proactive outreach to and engagement of these individuals in such interventions. Practical concerns, including (1) confidentiality around data sharing with service provider organizations operationalizing outreach, (2) feasibility of locating high users by using only demographic and address information available in administrative data and (3) engaging individuals in services, must be addressed. We are currently using t approach to support a pilot implementation of outreach and the offer of Assertive Community Treatment to high users, preliminary to a proposed randomized trial of this model.

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Note. Points of view or opinions in this document are those of the authors and do not necessarily represent the official position or policies of the Chicago Police Department or the Chicago Fire Department. Any errors are our own.

CONFLICTS OF INTEREST

The authors report that they have no conflicts of interest.

HUMAN PARTICIPANT PROTECTION

This study was approved by the University of Chicago institutional review board.

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