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Introduction

Cuyahoga County, Ohio

Cuyahoga County, Ohio, the second largest county in Ohio, has a population of over 1.2 million residents (U.S. Census Bureau, 2021b). Cleveland is the County’s largest city with approximately 367,991 residents (U.S. Census, 2021a). In 2019, Cleveland had the highest poverty rate of any large city in the United States and remained in last place for childhood poverty with an overall rate of 46% (Campbell, 2020). A third (32%) of Cleveland’s residents live in poverty compared to 16% in Cuyahoga County, and 11% in the nation (U.S. Census Bureau, 2021c).

Despite being approximately a third of the County’s population, Cleveland Division of Police’s (CDP) felony submissions comprise more than half of the cases submitted to the Cuyahoga County Prosecutor’s Office. In addition, Cleveland’s violent crime rate (1,517 violent crimes per 100,000 residents) was almost four times the national rate (366.7 per 100,000) in 2019, making Cleveland the sixth most violent city in the U.S. Cleveland's 2019 homicide rate (24.1 per 100,000) was nearly five times the national average (5.0 per 100,000) and the robbery rate (496.3 per 100,000) was six times the national average (81.6 per 100,000) (Uniform Crime Report, 2019).

The CCPO’s Crime Strategies Unit

The Cuyahoga County Prosecutor’s Office (CCPO) handles only felony prosecutions in the County, working with 50+ police municipalities and other law enforcement agencies to prosecute violent offenders. The CCPO formed the Crime Strategies Unit (CSU) in 2015 to coordinate efforts across multiple law enforcement agencies to implement strategies to decrease violent crime. (*For more information on CSU’s structure and process, see a related brief from 2019-YX-BX-0018 titled “Cuyahoga County’s Crime Strategies Unit: Structure and Process”*)

Purpose of the Study

With funding provided by a 2019 Innovative Prosecution Solutions award (2019-YX-BX-0018) through the Department of Justice (DOJ)’s Bureau of Justice Assistance, the CCPO’s CSU, and researchers from the Begun Center for Violence Prevention Research and Education (Begun Center) at Case Western Reserve University (CWRU)ⁱ collaboratively developed a methodology to identify the “top violent offenders” in the County (among other tasks)ⁱⁱ.

The top offender criteria were created to address challenges in effectively and efficiently identifying the small number of people committing most of the crimes throughout the County and to use data-driven strategies for prioritizing cases for investigations and prosecutions.

CSU Data

The criteria were developed from a database developed and maintained by CSU based on incident reports for violent and/or gun crimes from the Cleveland Division of Police (CDP), the Cuyahoga Metropolitan Housing Authority Police Department (CMHAPD), Garfield Heights Police Department (GHPD), and Maple Heights Police Department (MHPD) (hereafter termed the Access database). However, CDP comprises the vast majority of the incidents in the database (94%). CSU began collecting these data as a way to summarize violent and/or gun offenses from several police departments in the County, disseminate these summaries to various departments, and analyze the incidents for common factors or crime patterns.

Data entry began in March 2016 for CDP and CMHAPD but expanded, becoming fully populated by 2017. Data continues to be entered daily into the Access database by CSU crime analysts who proactively review incidents with offenses related to assaults, burglaries, homicides, robberies, shooting offenses, and weapon violations. (They also maintain a separate database related to carjacking offenses from the same data sources as the Access database, mentioned above.)

How a crime is categorized and in what order the crime types are listed in the incident reports varies greatly from police report to police report. To help with standardizing this, prior to the start of this grant, CSU developed a coding scheme (standardized method) and codebook (instructions) for how crimes are labeled in the Access database (e.g., who or what was shot [a person, a habitation] or what was stolen [motor vehicle]). Additionally,

given the CSU crime analysts' level of access to the electronic management system for the police departments, they can only see the first three crime types in a police report. Data from the “front sheets” of the police reports (e.g., discrete fields) are also entered, including incident address, information regarding a primary suspect (if known), information regarding a primary victim (if known), the type of weapon involved, and a narrative paragraph written by the CSU crime analysts summarizing pertinent information regarding the incident.

This database on violent crime is unique in its level of detail and volume in the county.

Descriptives of the Access data

After the research teams identified and removed duplicate incidents, the data include 33,242 total incidents from 2016 through July 2021.

Since these data are derived from incident reports, the vast majority of incidents do not have named suspects. Out of 33,242 incidents, 20,152 had unnamed suspects (61%).

Of incidents with unnamed suspects (n = 20,152), the most frequent crime types in these data (in rank order) are:

- street robbery (n = 4,848),
- shooting offenses (not into habitation) (n = 4,201),
- shooting into habitation (n = 2,452),
- commercial robbery (n = 1,606),
- carjacking (n = 1,565),
- physical assault (n = 1,437),
- stolen vehicle (n = 8,45),
- homicide (n = 540), and
- acquaintance robbery (n = 513).

Types of weapons connected to these 20,152 incidents included:

- firearm (n = 13,101),
- hands, fists, and feet (n = 3,051),
- blunt object (n = 1,111),
- unknown weapon (n = 1,477),
- car (n = 295), and
- other, missing, or threat of a weapon comprised the remaining percentage

This database also includes 11,740 named suspects connected with 13,090 incidents. There are 11,517 suspects with two or fewer offenses (connected with 12,364 incidents), and 223 offenders with three or more incidents (connected with 726 incidents). Analyses of the latter are detailed in future sections.

Generating a Top Offender List

Aims and Objectives

CSU uses the information collected in the Access database along with other data sources, such as forensic intelligence data (e.g., ballistic evidence) to conduct (near) real-time queries on violent crimes in the county that are shared with other Cuyahoga County law enforcement agencies to help identify potential linkages (in conjunction with police departments) and identify which cases should be prioritized for investigations and prosecution. However, these queries are often conducted on a case-by-case basis. Prior to the research discussed here, CSU had yet to develop a data-driven set of criteria for identifying those “top violent offenders” from the Access database.

As part of this research, we were tasked with developing and implementing a ranking/standardized data-driven set of criteria for prioritizing the investigation and prosecution of cases with the following parameters. The criteria needed to be:

- *practical*—based on data contained in or could be merged with the Access database (data on linkages from incidents data). CSU is unique because it is housed in a prosecutor's office, rather than a police department, and works closely with prosecutors and investigators. This means that CSU's access to data may not always be as immediate or comprehensive as it would be in a police department. Under these circumstances, a criteria system needed to be based on current data that would not place an undue burden on CSU staff to collect or update;
- *manageable*—to work effectively, the top offender list needed to have a manageable number of individuals by which to prioritize—in other words, a relatively small number of individuals;
- *comprehensive*—information that was readily available for all or most of the incidents;
- *statistically variable and correlated*—criteria needed sufficient statistical variation (e.g., not all individuals could be in one category) but also be interconnected with the other criteria to be meaningful and useful, and
- *sustainable*—the criteria needed to be developed in such a way that CSU could maintain a "live" scoring system and update the list in real-time

The criteria presented here meet these parameters and are empirically based, serving as a proof of concept or a framework by which CSU can readily:

- run queries on those connected to a large number of crimes,
- generate a list of top offenders via analysis of CSU databases,
- rank those individuals by threat level, and
- conduct social network and spatial analyses to help identify and visualize linkages.

Of note, several commonly used criteria in top offender lists were not used (e.g., Fox, Allen, & Toth, 2022). The criminal histories were not included in the criteria developed here because these data are not readily available to the unit in a database format (see the comprehensive parameter mentioned above). Instead, each person would have to be looked up individually. Additionally, standardized criminal justice screeners that assess an individual’s risk of recidivism are regularly administered in this jurisdiction, including the *Ohio Risk Assessment System: Community Supervision Tool* and the *Ohio Risk Assessment System: Pretrial Assessment Tool*. However, the information from these screeners was not useful for the purposes described here because these screeners either did not have sufficient statistical variation in the scoring or were not consistently administered for all or most individuals.

Developing Top Offender Criteria

In developing the criteria for the top offender list, researchers consulted with CSU, subject matter experts, and relevant literature, and conducted preliminary analyses of the data (the latter is discussed below). The analyses presented here are based on data collected from the earliest point in the database, 2016, through July 2021.

The Access database is comprised of *incidents*, but we sought to identify the higher-risk *individuals* from these data. Therefore, in contrast to many “top offender” lists, the criteria used in this study are based primarily on the characteristics of the incidents instead of the characteristics of the individuals.

We began our top offender criteria development by examining the number of incidents connected to name/known suspects in the Access database. Given the manageable parameter mentioned above, researchers focused on the criteria that would include the most prolific, violent offenders.

A total of 13,090 out of 33,242 incidents had a named suspect. Of these incidents, 82% (n = 10,670) were connected to an individual who was named in one incident in the database,

13% (n = 1,694) were connected to two incidents, and 6% (n = 726) were connected to three or more.

Given this distribution, our **first criterion** for the top offender list is being a suspect in 3+ incidents in the Access database. (Statistical analyses of these cut-off scores are discussed below.)

The **remaining criteria** pertain to ranking or assigning a threat level to incidents connected to named suspects with 3+ incidents, as not all incidents are equally violent or serious. (See Figure 1.) This threat level was indicated through a series of variables from lowest to highest threat based on:

- presence of a firearm(s) at the incident;
- when present, firearm(s) was discharged or used as a threat;
- presence of multiple suspects at the incident (a potential indication of an organized crime network or activity), and
- presence of multiple suspects and multiple firearms at the incident.

While the Access database includes the above information, the data are not entered as discrete variables in the database. To collect this, the research team read and coded the summary narratives entered in by CSU crime analysts for the incidents connected to named suspects with 3+ incidents. For example, the Access database captures discrete information for the primary suspect only. Information about subsequent suspects is captured in the summary narratives (typically mentioned as "Susp1" or "Susp2"), and information on firearms is often denoted with the inclusion of the firearm's serial number. For those incidents with more than one suspect involved, we developed a method to automate finding additional information about the other suspects and multiple firearms by creating a macro using SAS, a commonly used statistical software, to isolate the mention of multiple suspects and firearms in the narrative.

Top Offender List	Threat Level 1: Listed as a suspect in 3 or more incidents
	Threat Level 2: Presence of a firearm(s) at the incident
	Threat Level 3: Firearm fired or used as a threat during the incident
	Threat Level 4: Multiple suspects at the incident
	Highest Threat Level: Multiple suspects and multiple firearms at the incident

Figure 1. Top Offender/Threat Level Criteria

Incidents with unnamed suspects (61% of the incidents in the Access database) require additional investigative resources and time and often rely on forensic evidence (i.e., when there is no suspect, but a firearm is discharged). Therefore, for the purposes of this project, researchers focused on the incidents with named suspects and connected to top offenders to provide the most useful, efficient analysis to CSU.

Results

Top Offender List: Suspects Named with 3+ incidents

Below we present the descriptive statistics related to the top offenders (n = 223).

Crime Type & Weapon Use

From a total of 11,175 identified suspects in the Access Database, there were 223 named suspects with 3+ incidents connected to 723 violent crime incidents.

The most frequent of these 723 offenses were physical assaults (n = 119; 16%), carrying a concealed weapon (n = 110; 15%), shootings (n = 97; 13%), and acquaintance robberies (n = 97; 13%)

The majority of 223 suspects (connected to the 723 incidents) used firearms (n = 409 incidents; 56%), followed by hands, fists, or feet (n = 156; 22%). Of the offenses that included a firearm, a firearm was present but not discharged in 45% of the incidents, 22% involved suspects. Similarly, 22% of these cases pertained to a concealed carry charge or having a weapon while under disability—meaning the firearm was present on the suspect’s body or in their vehicle but was not drawn during the incident, and 33% involved a firearm being discharged at a person, object, or into the air.

Age of Suspects

In terms of the suspects’ ages,

- 6% were under 18 years of age,
- 36% between 18 and 24,
- 50% between 25 and 40,
- 8% between 41 and 64, and
- <1% over 65.

In analyzing the number of years between the first incident and last incident associated with these suspects,

- 10% were within less than 1 year,
- 19% within 1 year,
- 25% within 2 years,
- 26% within 3 years,
- 13% within 4 years,
- 7% within 5 years, and
- <1% greater than 5 years.

Multiple Suspects

In order to assess incidents involving multiple suspects and multiple firearms (as these indicate a higher threat level), our research team isolated incidents whose narratives indicated whether more than one suspect was involved. We found:

- 15% of 723 incidents (n = 112) had multiple suspects (n = 82 suspects), and
- 14% of the 112 incidents (n = 17) with multiple suspects also mentioned multiple firearms.

The incidents with multiple suspects were disproportionately connected with younger suspects compared to the age distribution of the analytic sample (the n = 223 individuals, discussed above). Of the n = 112 incidents with multiple suspects, 48% of the suspects

were between 18 and 24 years old, and 38% were between 25 and 40. The same pattern holds when examining the $n = 17$ incidents with multiple suspects and multiple firearms—59% of the suspects were between 18 and 24 years old, 28% were between 25 and 40 years old, and 6% were under 18 years of age.

Statistical Analysis of the Top Offender Criteria

We grouped incidents by whether a suspect was named in 1 incident, 2 incidents, or 3+ incidents and conducted several statistical tests to assess the relationships between these groups (1, 2, and 3+ incidents as a named suspect) and the other top offender criteria (plus age of the suspects). This was done to determine whether the cut-off should be 2 or 3+ incidents and whether the criteria are interconnected as hypothesized.

With regard to the cut-off and *multiple firearms*, statistical tests revealed that incidents where a suspect was named in 2 incidents and 3+ incidents more frequently had multiple firearms recovered ($p = .008$). However, the 2 and 3+ incident groups were not significantly from each other in terms of the frequency of having multiple firearms. The odds of multiple firearms are significantly lower in the 1 incident group vs. the 2 or 3+ incident groups ($p = .002$). More specifically, if the incident did not have multiple firearms, it was 1.5 times more likely to be in the 1 incident group.

With regard to the cut-off and *weapons*, statistical tests revealed no significant differences between the 2 and 3+ incidents groups in the type of weapon involved ($p = .211$). However, suspects in the 1 incident group more frequently used blunt objects or car/auto and less frequently used firearms than the 2 or 3+ incidents groups.

With regard to the cut-off and *types of crimes*, statistical tests revealed no significant differences between the 2 and 3+ incidents groups in the type of crime (e.g., assault, car jacking, homicide, etc.) ($p = .070$). The 2 and 3+ incident groups were more frequently associated with carjackings, commercial/bank robberies, shootings, shootings into habitations, street/delivery robberies. The 1 incident group was more frequently associated with assaults, physical assaults, stabbings, and vehicle assaults.

With regard to the cut-off and *multiple suspects*, statistical tests revealed no significant differences between the three groups (1, 2, or 3+) and whether there were multiple suspects involved.

With regard to the cut-off and *age at the time of the first incident*, statistical tests revealed no significant differences between the 2 and 3+ incidents groups in the type of crime ($p = .314$); however, younger suspects (<18 years of age and 18-24 years of age) were more frequent in the 2 and 3+ incidents groups and older suspects (41-64 years of age) were more frequent in the 1 incident group.

The findings indicate our criteria are sufficiently interconnected per the parameters discussed above. However, we found no statistical differences between the 2 and 3+ incident groups. This suggests there is empirical evidence to support CSU expanding its top offender list to include those being connected to 2+ incidents. However, this would entail a trade-off of being less manageable in terms of prioritization. The issue of a larger top offender list could potentially be mitigated by CSU via the threat-level criteria discussed above.

Summary of the Top Offenders

In terms of identifying and differentiating between the top offenders, we began with a list of 11,175 named suspects in the entire Access database. Figure 2 breaks down the frequencies of top offenders in each threat level from lowest to highest.

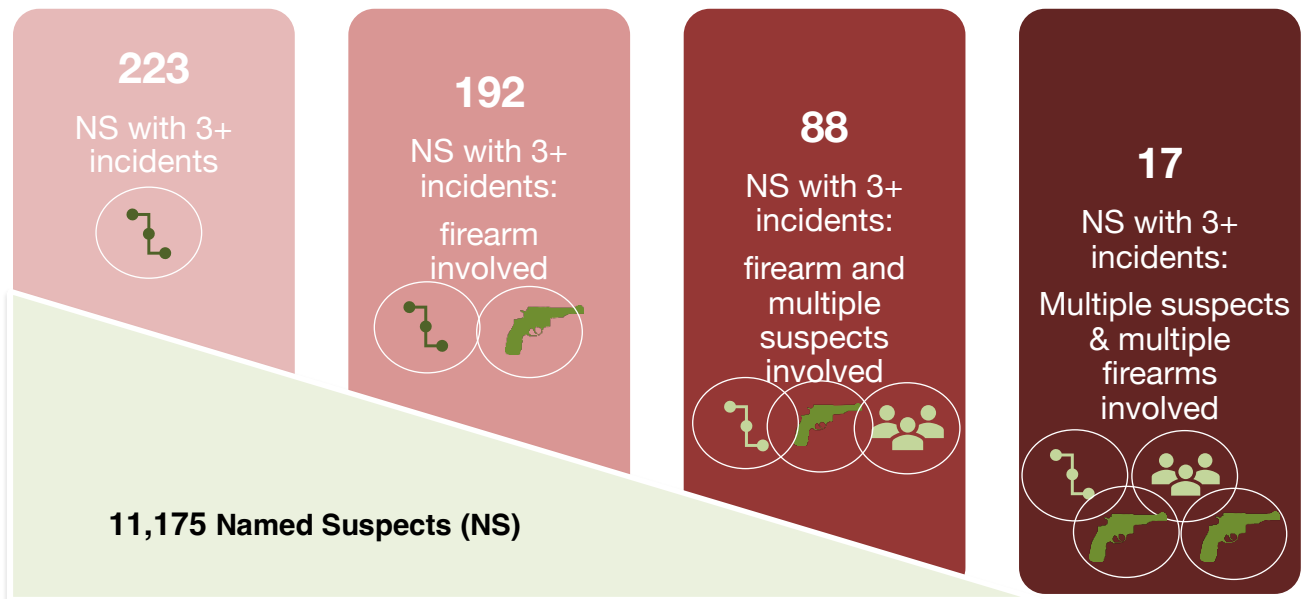


Figure 2. Frequencies of Top Offenders by Rank Ordered Threat

Mapping the Top Offenders

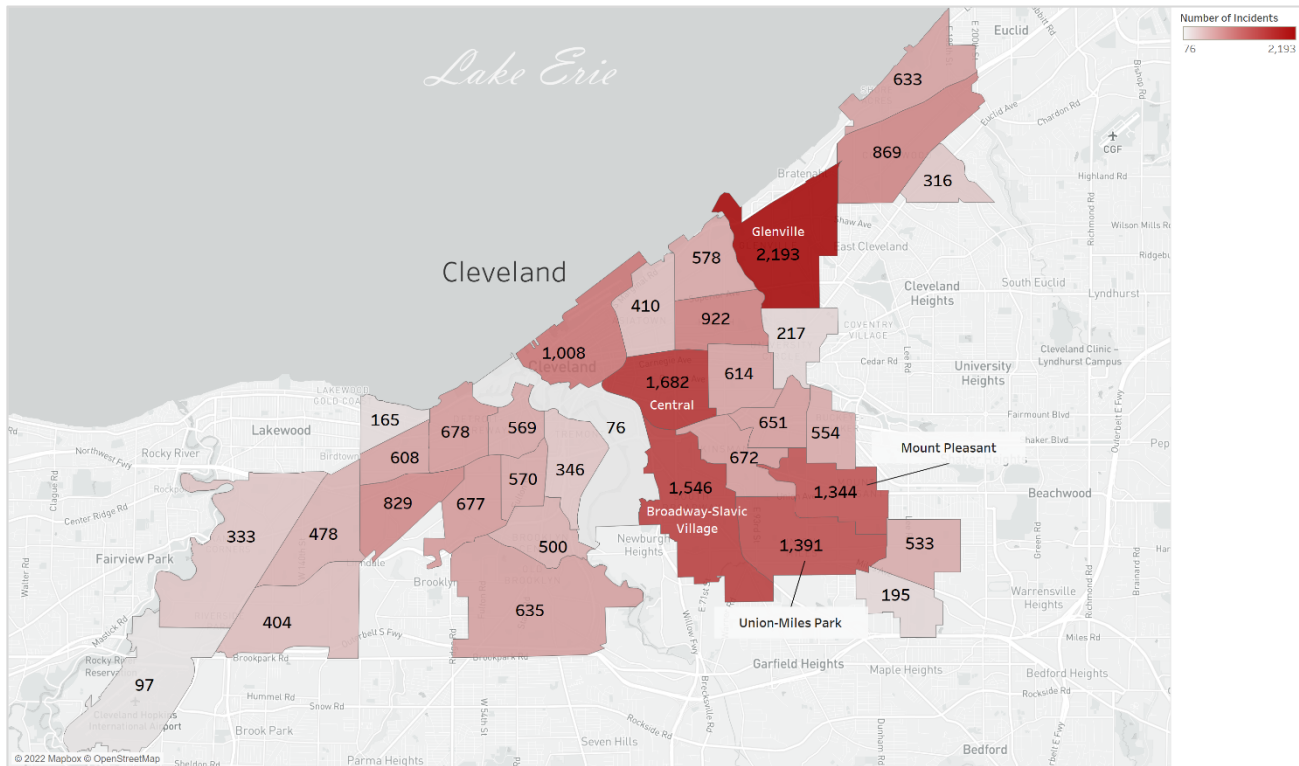
To better understand where the top offenders are most active and concentrated, our research team geocoded the incident locations and reported addresses of the primary suspect for all incidents in the Access database from 2017 to 2020. For this analysis, we chose to analyze incident data at the neighborhood level because neighborhoods are often more familiar as geographic reference points than ZIP codes or census tracts. There are 34 neighborhoods in the City of Cleveland (see Figure 3). Batch geocoding was accomplished using ArcMap®. The data were cleaned using Tableau Prep Builder® and mapped and analyzed in Tableau®.



Figure 3. Cleveland's (Ohio) 34 Neighborhoods

Mapping Results

The total number of incidents from the Access database that were geocoded and assigned to an individual neighborhood in the City of Cleveland during the analysis period (2017-2020) was 23,293. The mean and median number of incidents by neighborhood were 655 and 593, respectively. The highest number of incidents occurred in the Glenville neighborhood, which accounted for 9% (n = 2,193) of all incidents, followed by Central (n = 1,682). The lowest reported incident count by neighborhood was in Cuyahoga Valley (n = 76) (see Figure 4). As evidenced in the map below (Figure 4), there are several neighborhoods on the east side of Cleveland that account for a large proportion of overall incidents: Glenville (n = 2,193), Central (n = 1,682), Broadway-Slavic Village (n = 1,546), Union-Miles Park (n = 1,391), and Mount Pleasant (n = 1,344) neighborhoods account for 35% of all incidents (8,156 of 23,293).



*Figure 4. Frequency of Incidents by Cleveland (Ohio) Neighborhood from 2017-2020 (n = 23,293)
Note. Top five neighborhoods are labeled by name.*

We then filtered the data to include only incidents associated with “top offenders,” and only those incidents which occurred in the City of Cleveland for the same period (2017-2020). The results when looking at the sub-group of suspects identified as “top offenders” reveals that the same aforementioned top-five high-incident neighborhoods accounted for 42% (228 of 541) of incidents associated with “top offender” suspects (see Figure 5).

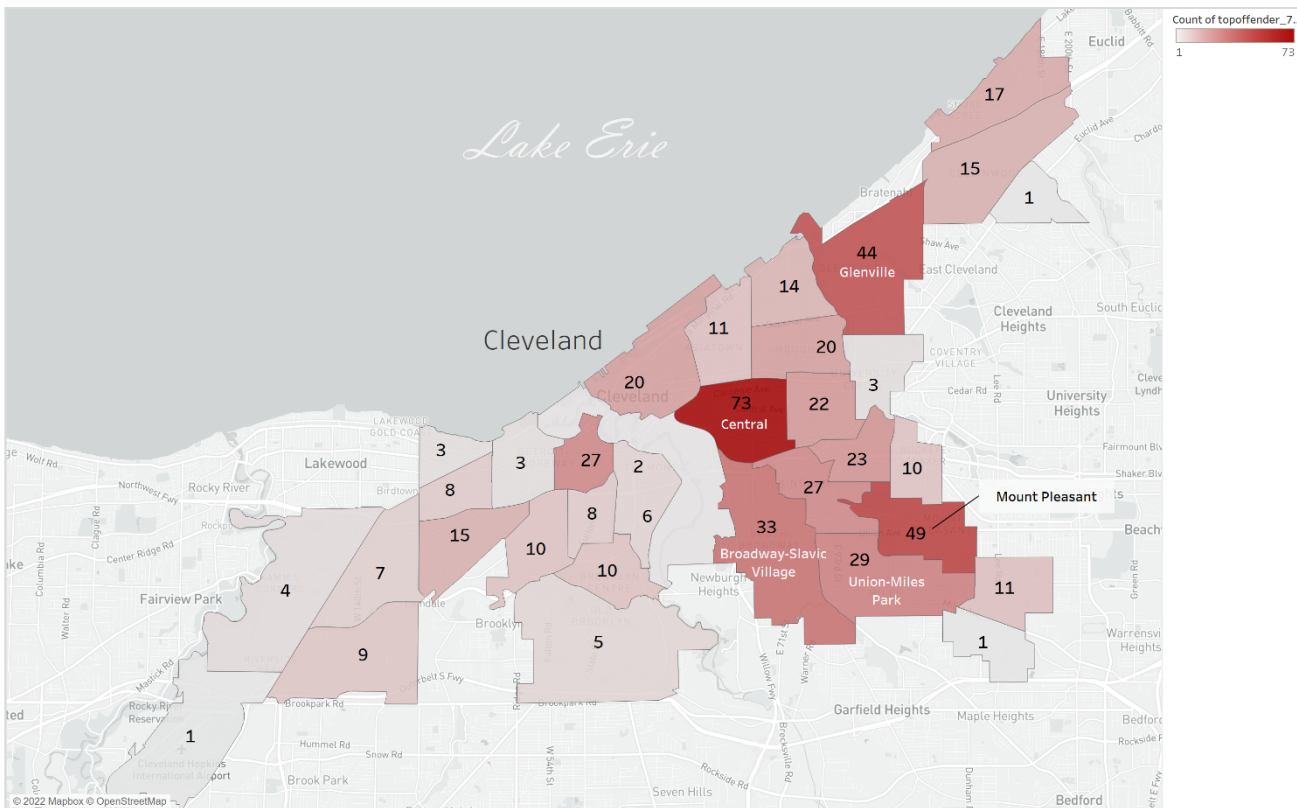


Figure 5. Frequency of Incidents Associated with “Top Offenders” by Cleveland (Ohio) Neighborhood from 2017-2020 (n = 541)
 Note. Top five neighborhoods are labeled by name.

The Access database also includes suspect addresses when reported by police officers. Incorporating where suspects live in relation to the crimes they commit can improve policing, investigative, and intelligence efforts. For the purposes of this report, we performed an analysis of two of the 34 neighborhoods. Specifically, we mapped reported addresses of suspected identified as top offenders and the associated crimes they

committed for suspects living in the top two incident neighborhoods of Glenville and Central.

The Access database contains location information for 22 individuals who were identified as suspects in 38 incidents in the City of Cleveland from 2017-2020 and reportedly living in the Glenville neighborhood.ⁱⁱⁱ The average distance from the incident to the suspect’s address was 3.06 miles for the 38 incidents that were committed in the City of Cleveland.

Table 1 shows the average distance by incident type, as coded by CSU. The most frequent crime committed by Glenville's top offenders was shootings, with an average distance to the crime of 2.49 miles.

Incident Type	Count of Incidents	Average Distance to Incident (miles)
Shooting	8	2.49
Acquaintance Robbery	7	2.22
Commercial Robbery	2	6.62
Carrying Concealed Weapon Other	6	2.39
Carrying Concealed Weapon Traffic Stop	3	5.18
Stolen Vehicle	1	7.04
Shooting into Habitation	1	6.92
Physical Assault	4	1.88
Vehicle Assault	1	4.70
Shots Fired	2	3.06
Assault Other	2	2.66
Stabbing	1	0.00
TOTAL	38	3.06

Table 1. Incident Types and Average Distance for “Top Offenders” from Glenville Neighborhood from 2017 to 2020 (n = 38)

Looking at the Central neighborhood, there were 27 top offenders who accounted for 48 crimes that were committed in Cleveland (based on incident address geocoded results). The most frequent crime was physical assault, with an average distance to the crime of 2.49 miles. Table 2 captures incidents specific to Central top offenders.

Incident Type ("Title")	Count of Incidents	Average Distance to Incident (miles)
Physical Assault	12	1.55
Acquaintance Robbery	6	2.62
Carrying Concealed Weapon Traffic Stop	5	1.77
Shooting into Habitation	3	3.47
Assault Other	5	0.30
Street Robbery	3	1.93
CCW Other	4	0.90
Homicide	2	2.27
Shooting	3	0.66
Stabbing	2	0.84
Commercial Robbery	1	0.69
Vehicle Assault	1	0.31
Dead Body	1	0.00
Grand Total	48	1.54

Table 2. Incident Types and Average Distance for “Top Offenders” from Central Neighborhood from 2017 to 2020 (n = 38)

Comparing these two neighborhoods based on only “top offender” incidents shows some differences (Figure 6). In terms of distance traveled from the residential address to the incident, top offenders in the Central neighborhood traveled less than half as far (mean = 1.54 miles) as those in Glenville (mean = 3.06 miles). At first glance, it appears that Glenville's top offenders commit far more shootings than Central based on the count of “shooting” incidents. However, combining the incident variables “shots fired,” “shooting into a habitation,” and “shootings” reveals that Glenville's top offenders were reported in 11 shooting incidents, while Central top offenders accounted for 8.

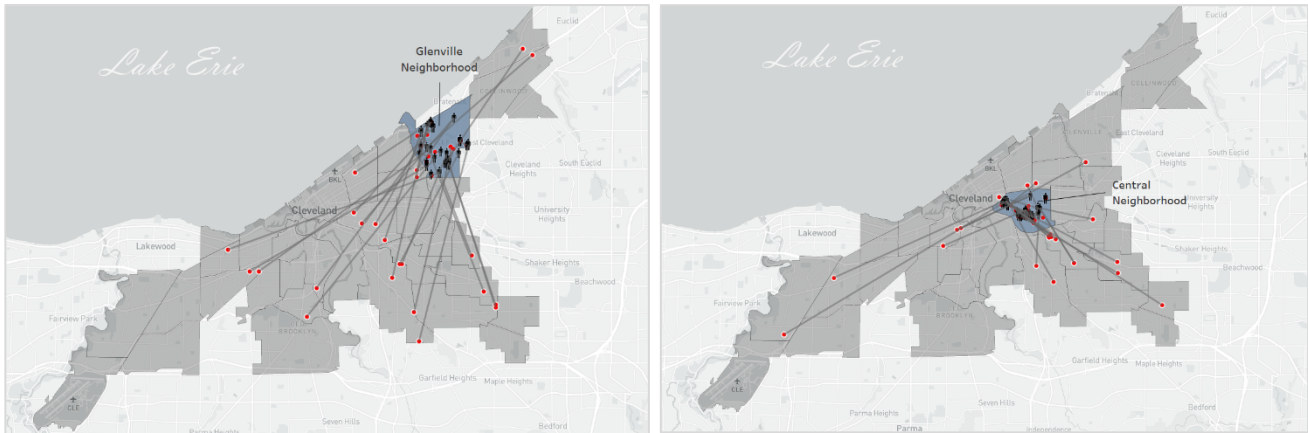


Figure 6. Suspect Reported Address (person icon) Tied to the Associated Incident (red circle) by Cleveland Neighborhood, “Top Offender” Incidents 2017 to 2020

Note. Glenville (left) includes 22 top offenders and 38 associated incidents. Central (right) includes 27 top offenders and 48 associated incidents.

A comparison of these two top incident neighborhoods reveals that Glenville neighborhood did, in fact, experience much higher numbers of violent crimes from 2017 to 2020. Table 3 provides the total count of incidents by incident type. “Shootings,” “shooting into a habitation,” and “shots fired” in Glenville totaled $n = 759$, while Central reported $n = 461$ — almost 40% lower shooting incidents.

Incident Type	Central Incident Count	Glenville Incident Count
Shooting	291	433
Physical Assault	259	247
Street Robbery	214	256
Carrying Concealed Weapon	153	121
Other		
Shooting into Habitation	137	270
Acquaintance Robbery	104	126
CCW Traffic Stop	101	83
Stabbing	79	74
Commercial Robbery	61	107
Carjacking	60	113
Assault Other	53	74
Vehicle Assault	43	72
Shots Fired	33	56
Homicide	27	57
Other Weapons	26	32
Stolen Vehicle	22	41
Delivery Robbery	9	9
Home Invasion	4	14
Weapon at School	2	1
Sexual Assault	2	3
Dead Body	2	3
Grand Total	1682	2192

Table 3. Incident Counts for Access Database Incidents in the Top Two Cleveland Neighborhoods from 2017 to 2020

Social Network Example

In order to assess the validity of the top offender criteria, we further examined the connections and relationships among the 17 individuals connected to the 17 highest-threat incidents. Even with this small number, several social connections (or networks) between the incidents were evident. In the following section, we illustrate these networks via social network analysis. Social network analysis is a method used to establish relationships, patterns, and/or connections between crime parties or incidents and present the findings in visual, easily understandable ways (Crocker, 2017). All identifying information in the example below has been altered to prevent identification.

Below is a social network analysis example of one of 17 individuals with the highest incident threat level. *Suspect Allen* is the primary suspect in *Shooting Incident 1* where multiple people and multiple firearms were involved. Officers from the Gang Impact Unit arrived at the scene and interviewed *Witness Allison*, who said that *Suspect Allen* and their accomplice *Suspect Beth* fled the scene but were on Instagram Live in a recognized location. Detectives went to this location and found *Suspects Allen and Beth*. Both were detained, and two firearms were confiscated (see Figure 7).

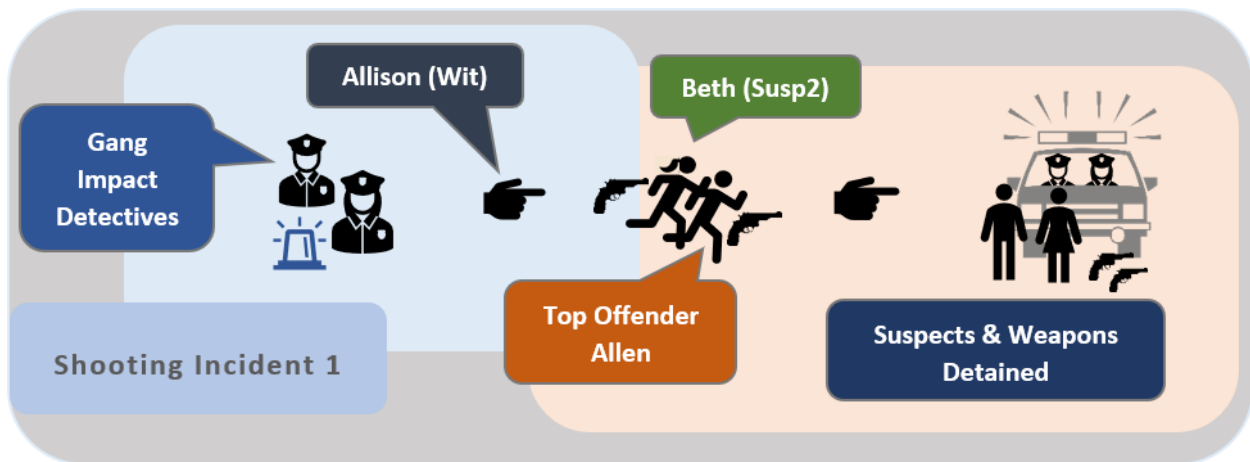


Figure 7. Visual of the Social Network for Shooting Incident 1
 Note. “Wit” refers to witness. “Susp” means suspect.

To assess this incident’s possible links to other incidents, a search of the Access database identified multiple other incidents involving *Witness Allison* and *Suspects Beth and Allen*. Results indicated that *Witness Allison* was connected in a number of ways to many

different incidents and firearms. Below (Figure 8) is a network of *Witness Allison’s* incident involvement in these data.

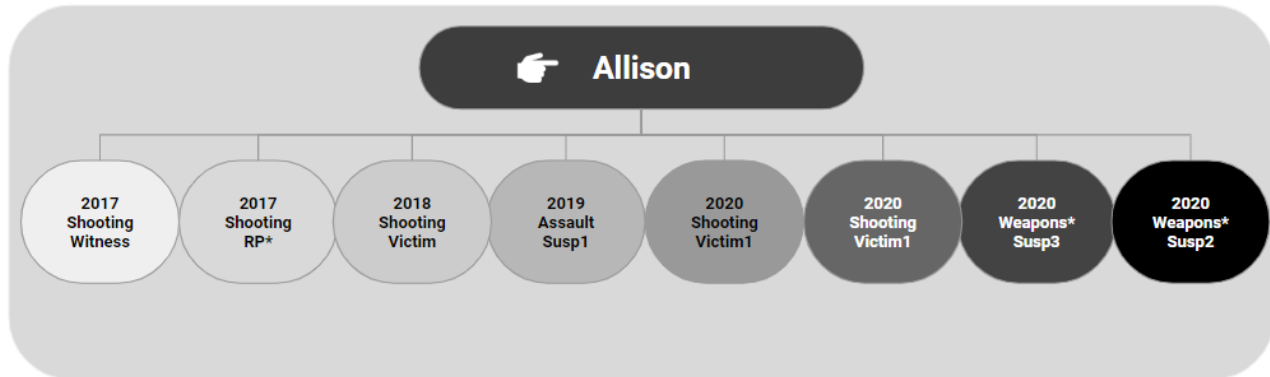


Figure 8. Visual of Allison’s Social Network

Note. RP* refers to Reporting Person, Weapons* refers to a firearm discovered during a search

The summary narratives connected to these crimes revealed important insights into the social network. Out of *Allison’s* eight incidents, *Allen* appears in six of them, and *Beth* appears in two.

According to the information contained in the summary narratives, *Allen* is *Allison’s* son. *Allison’s* other son, *Antoine*, is involved in two of the incidents in *Allison’s* network and is also on the Top Offender list. Additionally, the person listed as the Suspect (*Suspect Bill*) in *Allison’s* 2017 Shooting RP incident joins *Allison* and *Allen* as a suspect in the final incident listed (2020 Weapons Susp2). In other words, the network is complicated and dense. The image below (Figure 9) visualizes how this network pieces together from the data.

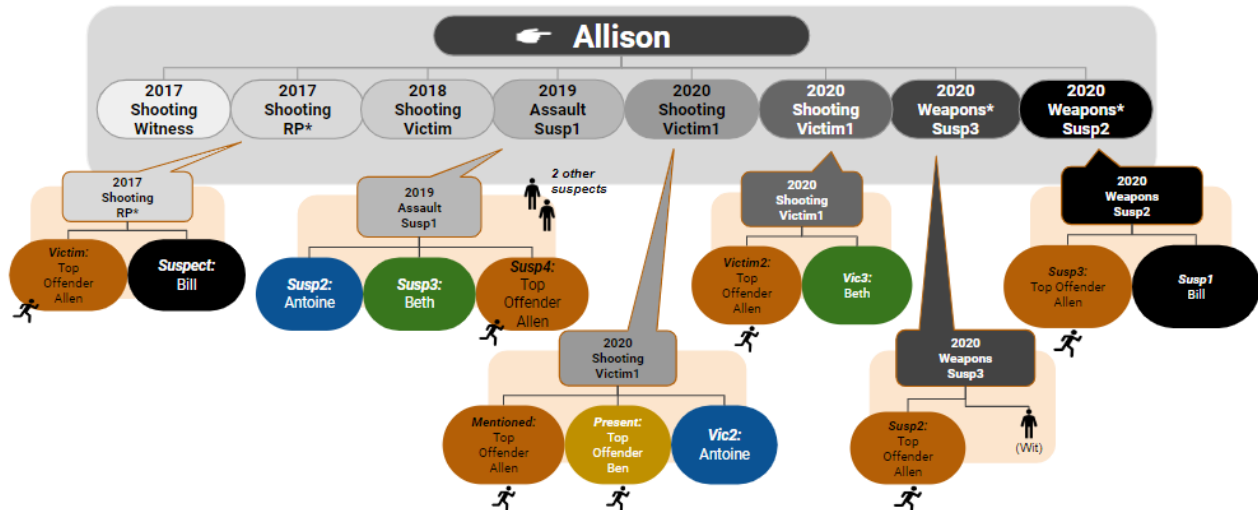


Figure 9. Visual of Allison's More Expansive Social Network

The social network findings reveal that as a top offender under the highest threat level incident, *Allen* was using firearms and strongly networked with *Allison* and *Beth*. With further investigation, not only are *Allen* and *Allison* related, but they have been involved in multiple incidents with *Antoine* (also family), *Bill*, *Ben*, and *Beth*. Data from the incident reports provide important potential linkages of individuals to each other across different crime scenes, providing qualitative details of who is connected and how they are connected to crimes.

This small illustrative SNA sample reveals the rich details contained in the Access database and the investigative potential for this data, particularly when used in combination with other intel sources. One such source is ballistics data from the National Integrated Ballistic Information Network (NIBIN), described further in this next section.

Incident Data + NIBIN Data

NIBIN is a national database of ballistic evidence from firearm test fires and shell casings to aid in linking and preventing firearm-related violent crimes, maintained by the Bureau of Alcohol Tobacco Firearms and Explosives (ATF). In addition to collecting data from police report incidents, CSU reviews NIBIN leads weekly. If NIBIN intel proves valuable for a particular case or suspect, CSU makes a note of this by placing a virtual NIBIN stamp

within the CCPO’s case management system for tracking how NIBIN leads are connected to ongoing cases. The NIBIN adds an additional layer to how crimes are linked by providing information on how firearms are potentially linked to each other at crime scenes, which is important information because the incidents mentioned above nearly all involve firearms.

Limitations

There are two major limitations to the described analyses. First, the top offender criteria are based on identified suspects from the incident reports. This is a limitation to the generalizability of all incidents. Only 39% of the incidents included named suspects at the time of the incident, as the identification of a suspect(s), if occurring at all, often comes later in the investigative process. This implies our criteria disproportionately pertain to those incidents with identified suspects at the time of the incident report and/or incidents where suspects and victims are known to each other. Yet, this is also a limitation by which the CSU functions as well (see discussion of parameters above).

A second limitation is the functioning of the Access platform. The database has some discrete fields that can be searched (e.g., first suspect’s name, DOB, description of the crimes, etc.), but most of the details of the incident are contained in the summary narratives (e.g., description of the incident, other suspects’ information) which are not as easily searchable as data contained in the discrete fields. Because of search function limitations, the CSU analysts are not able to search within the database when in the Access application. To search the database, they must first export the data into excel and perform searches for suspect names or other information there, which adds an extra step into their workflow. Since this database is updated daily, each time they want to search for something, they must export the data first to be using the most current version. CSU is well aware of this limitation and is actively working on technological improvements within its department. In the near future, they expect to be able to more easily connect multiple data sources and have a searchable database.

Additionally, extracting information from narrative text rather than discrete fields can be cumbersome and time-consuming. By developing the methodology and analytical approach described here to identify which individuals and crimes to prioritize, CSU has a blueprint for restructuring and analyzing its data to more easily “flag” the higher-threat incidents.

Finally, the Access database is currently not formatted in a way that makes social network analyses readily available to CSU. Conversations between the research team and CSU are

already underway regarding potential reformulations of the data for social network purposes.

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References

Campbell, E. Sept 21, 2020. “Cleveland is now the poorest big city in the country” *The Center for Community Solutions* <https://www.communitysolutions.com/Cleveland-now-poorest-big-city-country/>

Crocker, T. 2017. “The power of social network analysis” *Police Chief Magazine* <https://www.policechiefmagazine.org/power-social-network-analysis/>

Fox, B., Allen, S. F., & Toth, A. (2022). Evaluating the impact of Project Safe Neighborhoods (PSN) initiative on violence and gun crime in Tampa: does it work and does it last?. *Journal of experimental criminology*, 18(3), 543-567.

U.S. Census Bureau (2021a). Quickfacts: Cleveland city, Ohio population estimates. Retrieved from <https://www.census.gov/quickfacts/clevelandcityohio>

U.S. Census Bureau (2021b). Quickfacts: Cuyahoga County, Ohio population estimates. Retrieved from <https://www.census.gov/quickfacts/cuyahogacountyohio>

U.S. Census Bureau (2021c). Quickfacts: Cleveland city, Ohio poverty rate. Retrieved from <https://www.census.gov/quickfacts/clevelandcityohio>.

U.S. Department of Justice, Federal Bureau of Investigation. (2019). Uniform crime reporting handbook: UCR. Retrieved from https://ucr.fbi.gov/additional-ucr-publications/ucr_handbook.pdf

ⁱ Dr. Rachel Lovell has since taken a position as an Assistant Professor of Criminology and Director of the Criminology Research Center at Cleveland State University but is still involved with this grant.

ⁱⁱ As part of this grant, researchers were also tasked with assisting the CSU in merging and analyzing several of their databases and evaluating the process and organizational structure to inform operational changes and foster sustainability.

ⁱⁱⁱ Note that the frequencies for neighborhoods based on the suspects who lived there will differ from the previous total frequencies of all incidents associated with top offenders as some incidents occurred in the neighborhoods that were associated with suspects who did not live there. Frequencies in Figure 5 will not be the same as frequencies by neighborhood in these instances.