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Understanding Police Enforcement: A Multicity 911 Analysis

Report Submitted to Arnold Ventures

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Executive Summary

S. Rebecca Neusteter, Sarah Scaffidi, Abdul Rad, and Daniel Bodah

At least 240 million calls to 911 are made each year.[1] Responding to these calls takes up a sizable amount of police officers' time, even though relatively few calls stem from crimes in progress. Despite their prevalence in police work, little research about the nature of 911 calls or how police respond is available. Basic information, such as the number of calls and reasons they are made, how call volumes vary across different call types, and what happens from the time a call is placed to when an officer arrives on the scene, is unknown. The 911 call system plays a critical role in policing practice and should be studied, not only to measure performance but also to aid in decision-making processes, inform strategic decisions, and understand opportunities to advance call processing and alternative responses.[2]

The current study was designed to define the landscape of 911 calls for police service and answer fundamental questions about how communications personnel and police respond to them. To begin, the study explores 911 call processing by examining what happens when 911 calls are answered and what training, protocols, standards, and management possibilities exist at each stage of 911 call processing. The study also examines how accurately 911 calls are categorized and handled when received by public safety personnel. Questions about the overall volume and rate of 911 calls for service, typical response time, and ordinary duration of responses to 911 calls, as well as how these vary by the call type, time, and location are also considered. To understand how characteristics of 911 calls impact police officers in the field, the study analyzes what proportion of officers' activities represent responses to 911 calls versus those proactively initiated by officers.

The study examines how 911 calls are resolved by identifying the categories of dispositions and their frequency, as well as how they vary by call volume, type, time, and location. The ultimate outcomes of police contacts initiated by 911 calls are also reviewed to understand what factors have the greatest contribution to 911 call responses. In addition, the current research examines communications systems among call-takers, dispatchers, and police officers in the field to determine whether all information relevant to outcomes is being effectively conveyed. The study further explores whether it is possible to improve outcomes for police and civilians by

[1] National Emergency Number Association (NENA), "9-1-1 Statistics," https://www.nena.org/?page=911Statistics.
[2] National 911 Program, *Review of Nationwide 911 Data Collection,* 2018, https://www.911.gov/pdf/National_911_Program_Review_of_Nationwide_Data_Collection_2017.pdf; Police Data Initiative, "About," https://www.policedatainitiative.org/about/.

identifying 911 calls that may be handled more appropriately by a response other than sending sworn officers.

The following research activities provided details about the 911 landscape to address these questions:

1) an examination of prior research on 911 calls in the policing context;

2) an analysis of 911 call and computer-aided dispatch (CAD) data to identify 911 call types, processing, and outcomes in Camden County (NJ) and Tucson (AZ) police and public safety communications departments;

3) the development of a system processing map to trace calls from receipt through closure, which was achieved using data from focus groups, interviews, audio analysis of a sample of 911 calls, and field observations in Camden County Police Department (CCPD), Camden County Communications Center (CCCC), Tucson Police Department (TPD), and Tucson Public Safety Communications Division (PSCD);

4) an examination of publicly available 911 call and CAD data from Detroit, New Orleans, and Seattle; and

5) a convening of police, emergency communications practitioners, and other stakeholders to contextualize these findings and explore alternatives to sworn police response.

The Vera Institute of Justice's (Vera's) review of the existing literature on 911 calls for service (detailed in Chapter 2) reveals a need for innovation in this space, as well as more research exploring key features of the system (such as call volumes, types, and outcomes at the national, state, and local levels). Since the birth of 911 in the late 1960s and its congressionally mandated national deployment in 1999, the emergency communications field has become professionalized and transformed by new technologies, such as Enhanced 911 (E911) and Next-Generation 911 (NG911).[3] However, much remains to be learned about how 911 calls are processed, how personnel are trained, and where opportunities for alternative responses need development or can be expanded.

As a first step toward understanding how 911 calls are processed, Vera created a system processing map. This map (given in Chapter 3) shows that, when a community member calls

[3] E911 and NG911 attempt to use advances in technology, specifically mobile phones and smartphones, to provide more complete information (i.e., more precise location coordinates) to 911 communications centers. For additional information, please visit "Enhanced 911 – Wireless Services," *Federal Communications Commission,* https://www.fcc.gov/general/enhanced-9-1-1-wireless-services; and "Next Generation 911," 911.gov, https://www.911.gov/issue_nextgeneration911.html.

911, the caller relays information to a call-taker at a public safety communications center. The call-taker gathers relevant information from the caller; determines whether the call requires a response by fire, police, medical personnel, or a combination thereof; enters information and categorizes the call using a CAD system; and may give the caller instructions about what to expect or actions to take. The information the call-taker enters into the CAD system is sent to the appropriate dispatcher for further action. The dispatcher assigns officers to respond to the call based on the priority level of the reported incident, the narrative information entered in the CAD system by the call-taker, and available police resources. The dispatcher may, during this process, reclassify the call type or priority level. The assigned patrol officers then respond to the location given in the call, where they may take a report, provide instructions, resolve conditions found there, call for other resources, or take law enforcement action. Vera's analysis of Camden and Tucson data shows that, with slight variations, this core set of actors and actions defines the landscape of 911 call processing. Within this system, call codes, training, and standards exist to guide the actions of call-takers and dispatchers; however, codes, training, and standards are not uniform across 911 call systems, and opportunities exist to improve outcomes by diverting appropriate calls to non-law enforcement responders.

Vera's detailed analysis of CAD data and 911 audio recordings from Camden and Tucson sheds further light on how the 911 system operates (presented in Chapters 4 and 5).

- As many as half of CAD records may be of limited reliability due to lack of call type specificity and other call information omitted from the narrative.
- Officers spend a substantial proportion of their time responding to calls for service, few of which are related to crimes in progress, let alone serious crime in progress.
- Most calls do not relate to serious or violent crime; instead, the most frequent calls involve nuisance complaints and low-level crimes.
- Trends across the departments differed. In 2016 and 2017, TPD officers spent most of their time responding to 911 calls for service, whereas CCPD officers engaged primarily in proactive police activity. (As explained in chapter 5, this finding may be a function of differences in departmental record keeping.)

These observations of Camden and Tucson are further supported through the findings from the open data sites—Detroit, New Orleans, and Seattle. Highlights from the five-city analysis demonstrate the following:

- The most frequent incident type was noncriminal in nature. In four of the five sites, the most frequent incident type was some variation of a complaint or request for an officer to perform a welfare check. Across all sites, the most common priority types were nonemergency.

- The five sites have a wide range of dispatcher and officer response times. The two sites (Detroit and New Orleans) that have response time available by priority level show that response times are faster in emergency incidents. Among call types, the fastest response times for dispatchers and officers were behavioral health incidents, medical emergencies, traffic stops, officer requests for help, area checks, and alarms.

- Examining CAD events generated through 911 calls for service and those that are officer-initiated reveals that, in Tucson and New Orleans, 911 calls were most prevalent in the CAD system. However, in both Camden and Seattle, officer-initiated events accounted for most CAD entries. In Detroit, the proportions of CAD entries varied across the study period, shifting from being mostly 911 responses to mostly officer-initiated events.

The findings across all sites suggest the need for future research and local conversations about whether certain types of 911 calls for service require responses by police. There are critical gaps in knowledge regarding the underlying needs, causes, and consequences for these resource-intensive calls for service that do not involve a crime.

The current research also produced initial empirical evidence of how data collected by call-takers and dispatchers relates to officer activity on the ground (discussed in Chapter 6). In both Camden and Tucson, incidents labeled as violent were more likely to result in arrest than those labeled nonviolent. However, incidents categorized as nonviolent were more likely to result in arrest when initiated by police than when originating from a 911 call, revealing a divergence that suggests the need for additional research. To a large extent, mental health and medical incidents were diverted from criminal justice enforcement, potentially indicating that the focus on mental health awareness has the potential to pay dividends. Vera's analysis also revealed the potential for gathering additional data in the 911 call context to advance broader insights, such as how to improve call-taker and dispatcher operations to support improvements in criminal justice outcomes and the integration of additional variables to permit more varied and appropriate responses to 911 calls.

The research also sought to test the viability of data science methods known as Natural Language Processing (NLP) in order to understand if data contained within CAD narrative fields (which makes up much of the CAD data) appears frequently enough to merit developing mechanisms to capture and analyze this information in a more structured manner (e.g., to develop new structured CAD codes). Several key findings emerged from applying the NLP approach, methods, and techniques to Camden and Tucson's 911 data (described in Chapter 7). The high-level results include the following:

- The narrative fields in the CAD entries are essential to making accurate policing decisions.

- Subjective bias can be injected into the narrative fields by call-takers, dispatchers, and officers.

- Additional research is needed to understand why this detectable difference between the narrative field and the structured data exists; how call-takers, dispatchers, and officers use the narrative field; and how much cognitive load is placed on officers when consuming the narrative data as opposed to the structured data. This inquiry would require researchers to review the data manually and identify another method to compare structured and unstructured data fields prior to employing a computational/algorithmic approach.

To further explore the empirical findings that resulted from the research activities, Vera hosted a national convening of law enforcement leaders and system stakeholders (summarized in Chapter 8). At the convening, researchers presented their findings, explored alternatives to enforcement, and collaborated to identify opportunities for reform. This convening was held in partnership with Arnold Ventures and George Mason University's Center for Evidence-Based Crime Policy (CEBCP). Both research teams (Vera and CEBCP) presented their findings to explore implications of the research and spark innovations, particularly around alternatives to enforcement. Participants from 40 organizations across the country were in attendance, including representatives from 10 police departments, five public safety communications agencies, and 10 research organizations. The room was full and engaged. The convening's energy and insights provided clear evidence that additional conversation and collaboration on the topic is both needed and wanted.

This report concludes with a number of key policy recommendations and practitioner innovations (presented in Chapter 9), ranging from developing new protocols for how and if police departments should respond to unverified burglar alarms to providing de-escalation tactics trainings to 911 call-takers and dispatchers. Clear needs have emerged for better call-taking and recording practices, as well as standardized codes and procedures, with the goal of improving procedural justice, customer service, and the safety and wellbeing of officers, community members, call-takers, and dispatchers. Many practical solutions exist, some of which are currently being implemented and tested and others that are on the cutting edge. One effort that is feasible and valuable in the immediate term is developing a national coalition to advance thinking, practice, research, and standardization. This can be achieved through the roundtable model that has successfully mobilized reform in many other areas of the justice system for the past several decades.[4] Alternatives to police response and collaborative community responses have shown great promise for integration into 911 call processing. Additional investments in this research and practice can help inform taking them to scale in local jurisdictions nationally. Many opportunities exist, and needs abound—this research makes clear that the 911 system is both massive and neglected.

Though much was accomplished through the course of this current research effort, in most places the 911 call-taking, dispatching, and police response continuum continues to operate as a 'black box,' and there is a pressing need for further investment and research. Myriad opportunities exist to further develop this work, including continued and expanded analysis of the data already in hand. Other opportunities to expand the national conversation with roundtables about national standards, best practices, and building coalitions for understanding practice and moving it forward present an immediate first step in continuing to meaningfully advance this work. The goal of this and future work is to enhance public safety, promote meaningful alternatives to 911, and eliminate unnecessary police response and enforcement.

[4] For an example of two such roundtable programs, see Columbia Justice Lab, "Square One," https://justicelab.columbia.edu/squareone; and The Urban Institute, "Reentry Roundtables," http://research.urban.org/UploadedPDF/from_prison_to_home.pdf.

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The views expressed in this report are the authors' and do not necessarily reflect the views of Arnold Ventures.

Credits

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Requests for additional information about the research described in this report should be directed to Jim Parsons, vice president, research, monitoring, evaluation & learning at the above address or to jparsons@vera.org.

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Chapter 1: Introduction

S. Rebecca Neusteter, Abdul Rad, and Sarah Scaffidi

Front line police officers spend a substantial amount of their time reactively responding to 911 calls. Though the vast majority of calls for service (CFS) are unrelated to serious emergencies or crimes in progress, police are often the de facto responders, which makes responding to emergency communications a critical aspect of the day-to-day responsibilities officers are tasked with.[5] Given that most 911 calls are unrelated to crimes in progress, officers need a wide range of resources to respond effectively to different community needs, including clearly communicated and detailed upfront information, training to respond to emergency situations involving mental health and substance use issues, and training on available alternatives to traditional enforcement approaches. Additionally, 911 calls often require the translation of information from initial 911 call-takers to law enforcement dispatch to the officers who respond to the scene. Yet, there is a notable absence of evidence-informed strategies for processing and responding to 911 calls, and this void in the field has likely contributed to overuse of police resources, officer frustration with misdirected service calls, and harm to those who unnecessarily come into contact with law enforcement.

Due to a historical lack of research or data gathering, little is known about how effective current 911 call processing protocols are. Emergency communication, including whether calls are being properly routed, plays a critical role in policing practice and should be studied not only to measure performance but also to aid in decision-making processes, inform strategic decisions, and understand opportunities to improve call processing and develop alternative responses.[6] To that end, the Vera Institute of Justice (Vera) worked with the Camden County (NJ) Police Department (CCPD), Camden County Communications Center (CCCC), Tucson (AZ) Police Department (TPD), and Tucson Public Safety Communications Department (PSCD) to conduct an exploratory study that defines the landscape of 911 calls for service, how they are processed, what outcomes they produce, and what alternatives might exist. This study comprises the following research activities:

- an examination of extant literature on 911 calls for police service to identify existing knowledge and gaps to be filled;
- a quantitative analysis of police related 911 computer-aided dispatch (CAD) data for trends in call types, processing, and outcomes, including detailed analyses of

[5] The field often uses the terms "911 calls" and "calls for service" interchangeably, as will this report. National data on the nature of 911 calls is not available, but Vera's review of several very different jurisdictions' computer-aided dispatch (CAD) data (e.g., Camden and Tucson) reveals that approximately 75 percent of calls are unrelated to crimes in progress; see also Thomas Wieczorek et al., "Police Operations and Data Analysis Report, Tucson Arizona," 2015, Center for Public Safety Management, http://www.cpsm.us/wp-content/uploads/2019/08/TucsonAZ_DataAnalysisPolice_Final_30Dec2015.pdf.
[6] National 911 Program, *Review of Nationwide 911 Data,* 2018; Police Data Initiative, "About," https://www.policedatainitiative.org/about/.

Camden and Tucson data that was provided to the research team, as well as analyses of more limited samples from Detroit, New Orleans, and Seattle police departments' publicly available CAD data;
- qualitative analyses of a sample of 911 call audio records to explore whether call-takers appear to apply standard procedures and practices to recording CAD system data to be communicated to dispatchers and responding officers;
- the development of a qualitative research-informed 911 system processing map, based on a series of focus groups, interviews, and ride-alongs at each police department; and
- a national convening of law enforcement leaders and system stakeholders to present research findings, explore alternatives to enforcement, and identify opportunities for reform.

Research questions and hypotheses

Given the large gaps in the literature, this exploratory study aimed to answer several research questions. To answer these questions, the following research activities were completed:

1. **CAD/records management system (RMS) analyses**. Vera conducted quantitative analyses of 911 CAD data for trends in call types, processing, and outcomes.
2. **Audio analyses.** Vera analyzed of a sample of 911 call audio records to explore whether call-takers appear to apply standard procedures and practices to recording data in CAD systems, to be communicated with dispatchers and responding officers.
3. **Focus groups and observations.** A qualitative research-informed 911 system-processing map was developed after a series of focus groups, interviews, and ride-alongs were conducted at each police department.

The table below provides an overview of each of this study's research questions, hypotheses, analyses used to answer those questions, and the corresponding chapter covering each:

Figure 1.1: Research questions, hypotheses, and associated chapters

	Research question	Hypothesis	Chapter
1.	How are 911 calls processed, from placement to final outcomes—including key personnel, responsibilities, means of communication and prioritization, data entry points, and decision points?	Call-takers receive the 911 calls, record a summary of the call into the CAD system, and decide what information must be communicated, and whether the call warrants police response. Dispatchers decide which officers to send to the scene and record related	System Processing Map

	Research question	Hypothesis	Chapter
		information. The officers decide which disposition/outcome is most appropriate and record this portion of CAD and RMS data.	
2.	What types of training, protocols, standardizations, management practices, and alternatives exist relative to 911 call processing at each level (e.g., call-takers, dispatchers, and responding officers)?	Limited trainings, protocols, standardizations, and management practices exist relative to 911 call processing for call-takers and dispatch. Officers have training/protocols on what dispositions/outcomes are available, but little training or management relative to non-enforcement outcomes.	System Processing Map
3.	Is 911 call data entered reliably into CAD systems (i.e., are different call-takers likely to record information similarly), and does this vary by call type?	CAD data is entered unreliably in the absence of standards, trainings, protocols, and/or management practices, and calls unrelated to serious crimes in progress are entered with the lowest reliability.	Audio Analyses
4.	What is the volume / rate (per capita) of 911 calls received, and how does this vary by incident type (e.g., nuisance complaint, crime in progress, medical emergency, domestic violence incidents, officer involved shootings), time of day, and geographic location?	911 call volume is large, consists primarily of nuisance complaints/not crimes in progress, and comprises calls that are placed most often on the weekends, at night, and in low socio-economic status [SES] geographic areas.	Descriptive Analyses
5.	How promptly are calls responded to—by a call-receiver, dispatcher, and an officer on-scene—and how does this vary by call volume, incident-type, time of day, and geographic location?	Overall, response times may be an outdated/flawed metric of success, in that promptly addressed calls for service may be correlated with an increased likelihood of repeat and/or unresolved incidents. Both call-takers and officers respond more slowly when/where call volumes are high (e.g., weekends, nights, low SES geographic areas). Officers respond to the scene	Descriptive Analyses

	Research question	Hypothesis	Chapter
		fastest when the incident involves a serious crime in progress.	
6.	What proportion of police activity—especially enforcement—is proactive (i.e., officer initiated, such as traffic stops and directed patrols) versus reactive (i.e., in response to 911 calls / reported incidents)?	Most police activity and enforcement are reactive rather than proactive.	Descriptive Analyses, CAD/RMS Analyses
7.	Are 911 calls more likely to result in arrest versus other outcomes such as citations, warrants, summonses, justice system diversion [e.g., social service, program, or community service referral, issuing verbal warnings]? Does this vary by call volume, incident-type, time of day, and geographic location?	Enforcement-related outcomes (e.g., arrests, citations, warrants, and summonses) issued on-scene are most common, especially in response to serious crimes in progress. Limited standardized data exists relative to non-enforcement outcomes; however, what is available is hypothesized to reveal that diversion strategies are more common in high SES areas, when call volumes are low (e.g., weekdays, mornings), and in response to low-level offenses, mental health and/or family crises, and/or nuisance complaints.	CAD/RMS analyses
8.	What are the predictors of 911 calls that result in arrest?	Beyond standardized protocols, call-takers' interpretations of what information to record in CAD system variables and narrative fields, along with dispatchers' decisions on when to send officers to the scene, and with what information, influences call outcomes.	CAD/RMS analyses
9.	Which, if any, new variables or data systems should be integrated into CAD datasets, to systematically capture information important to 911 call responses? (In other words, what, if any, relevant	New variables, such as known disabilities and/or support systems, repeat calls, interest in non-police response, and nearby social services should be added to CAD systems to systematically collect and transfer relevant information.	CAD/RMS analyses, Natural Language Processing

Research question		Hypothesis	Chapter
	information is routinely captured exclusively in “narrative field” portions of CAD datasets).		

Methodology

Site selection

Vera worked with the Camden County (NJ) and Tucson (AZ) Police and Communications Departments on this project. These agencies and their key personnel, including their chiefs and public safety communications executives, contributed to the work by collaborating on the design and research proposal; participating in and facilitating regular meetings, focus groups, and interviews; providing access to data, analyses, policies, procedures, and other documentation; actively participating at the national convening; and reviewing and commenting on drafts of the reports and briefs to ensure factual accuracy.

To provide context on the research sites, demographic and operational agency information for the contributing agencies are shown below:

Figure 1.2: Research site key demographic and operational features

	Camden County Police Department[7]	Tucson Police Department
Estimated population[8]	76,005	527,586
Median household income[9]	$26,214	$37,973
Median age[10]	28.9	33.2
Hispanic ethnicity[11]	48%	43%
Race[12]		
White alone (not Hispanic or Latino)	5%	46%
Black or African American alone	42%	5%
Asian alone	3%	3%
Other race/ethnicity combinations	50%	46%

[7] Camden County Police Department is the primary law enforcement agency for the City of Camden; thus, the census data here represents the city. Furthermore, census data is an imperfect estimator of jurisdictional demographics (e.g., local data suggests far more racial diversity), especially in Camden, where the reliability of available demographic data has been questioned.
[8] U.S. Department of Commerce, Census Bureau, “ACS Demographic and Housing Estimates: 2012-2016 American Community Survey 5-Year Estimates,” https://data.census.gov/cedsci/all?q=ACS%20Demographic%20and%20Housing%20Estimates&hidePreview=false&tid=ACSDP1Y2018.DP05&t=Counts,%20Estimates,%20and%20Projections%3AHousing&vintage=2018.
[9] Census Bureau, “Median Income in the Past 12 Months (In 2016 Inflation-Adjusted Dollars): 2012-2016 American Community Survey 5-Year Estimates,” https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_16_5YR_S1903&prodType=table.
[10] Census Bureau, “ACS Demographic and Housing Estimates: 2012-2016.”
[11] Ibid.
[12] Ibid.

Number of authorized sworn police officers[13]	400	850
Number of authorized professional staff[14]	62	323
Agency budget[15]	$63.4 million	$188.6 million
Violent crime rate (per 100,000 inhabitants)[16]	1,977	657
Property crime rate (per 100,000 inhabitants)[17]	3,632	6,659
Arrest rate (per 100,000 inhabitants)[18]	10,345	6,312
Part I crime clearance rate[19]	19%	13%

The departments are notably different in the communities they serve and the resources they have access to. Considered jointly, they embody much of the diversity in the United States. These departments allowed the researchers to develop an informed perspective on trends in how 911 calls are received and processed, especially when supplemented with publicly available data from other national agencies. The Tucson Police and Communications Department is reengineering its communications center both physically (e.g., building remodeling to accommodate unified emergency services agencies) and operationally (e.g., implementing a new 311 system), and Camden County Police Department and Communications Center will be responding to calls from additional jurisdictions across the county. Because both jurisdictions are modernizing various aspects of their call taking protocols, they served as appropriate laboratories for future exploration of alternatives to police enforcement.

Analysis of CAD/RMS data

Vera analyzed two years of 911 call-related computer-aided dispatch (CAD)[20] and Records

[13] City of Tucson, Arizona, "Adopted Budget Fiscal Year 2018," 2017; https://www.tucsonaz.gov/files/budget/COT_Adopted_Budget_Fiscal_Year_2018_online_book_final_updated.pdf Jason Laday, "Two Years of the Camden County Police Department: By the Numbers," NJ.com, May 02, 2015, http://www.nj.com/camden/index.ssf/2015/05/two_years_of_the_camden_county_police_department_b.html; and Jason Laday, "County Police Officially Take Over Public Safety in Camden," NJ.com, April 29, 2013, http://www.nj.com/camden/index.ssf/2013/04/county_police_officially_take.html.
[14] Ibid.
[15] Ibid.
[16] United States Department of Justice, Federal Bureau of Investigation (FBI), "Offenses Known to Law Enforcement: Arizona, 2015," https://ucr.fbi.gov/crime-in-the-u.s/2015/crime-in-the-u.s.-2015/tables/table-8/table-8-state-pieces/table_8_offenses_known_to_law_enforcement_arizona_by_city_2015.xls; FBI, "Offenses Known to Law Enforcement: New Jersey, 2015," https://ucr.fbi.gov/crime-in-the-u.s/2015/crime-in-the-u.s.-2015/tables/table-10/table-10-state-pieces/table_10_offenses_known_to_law_enforcement_new_jersey_by_metropolitan_and_nonmetropolitan_counties_2015.xls.
[17] Ibid.
[18] FBI, *Uniform Crime Reporting Program Data: Arrests by Age, Sex, and Race (ICPSR 36394)* (Ann Arbor, MI: Inter-university Consortium for Political and Social Research, 2016), http://doi.org/10.3886/ICPSR36394.v1.
[19] Ibid.
[20] Computer-aided dispatch (CAD) systems were developed starting in the 1960s to provide technological support and assist in the dispatch of patrol units. CAD systems allow public safety agencies to provide emergency responders with critical information and allocate resources and personnel effectively; see Tom McEwen, Jacqueline Ahn, Steve Pendleton, et al., *Computer Aided Dispatch in Support of Community Policing, Final Report* (Alexandria, VA: Institute for Law and Justice, 2002), 1, https://www.ncjrs.gov/pdffiles1/nij/grants/204025.pdf; Law Enforcement Information Technology Standards Council, *Standard Functional Specifications for Law Enforcement Computer Aided Dispatch (CAD) Systems* (Washington, DC: U.S. Department of Justice, 2006), 1, https://it.ojp.gov/documents/LEITSC_Law_Enforcement_CAD_Systems.pdf.

Management Systems (RMS)[21] data from Camden County Police Department (CCPD), Tucson Police Department (TPD), and their respective public safety communications departments. CAD data is collected primarily by 911 call-takers and dispatchers while they process calls for service, and RMS data is collected primarily by responding officers, recording the community outcomes of these calls. The information is quantitatively coded, though narrative fields are also featured, allowing call-takers, dispatchers, and responding officers to record relevant notes not captured by the structured data fields (e.g., fields where emergency communications personnel can enter information about the call type code, priority level, etc.). These data sources were used to examine trends and relationships among calls for service, police dispatches, and community outcomes, as well as to highlight opportunities for alternative approaches. Furthermore, to ensure that the results obtained by the two participating agencies can be generalized to other jurisdictions, Vera also analyzed data from three additional agencies—Detroit Police Department (DPD), New Orleans Police Department (NOPD), and Seattle Police Department (SPD)—through publicly available CAD datasets.

CCPD and TPD provided de-identified CAD datasets for 2016 and 2017. These raw datasets were recoded for call type categories (e.g., medical emergencies, calls related to behavioral health). For more detailed information on the recoding process, see the technical appendices in Chapters 5.3 and 6.2. The researchers conducted descriptive analyses to examine patterns in the volume of various call types, the time of day when these calls are received, and distributions across priority level and geographic sectors. Response times were also calculated and analyzed for both departments—for CCPD, this information was extracted from the CAD data, and for TPD, a separate dataset containing response time information was provided.

Exploratory analysis of audio data

Vera also analyzed a sample of 911 call audio records to explore whether call-takers appear to apply standard procedures and practices to the CAD system-recorded data communicated with dispatchers and responding officers. Fifty Camden and 50 Tucson 911 audio recordings were randomly selected for inclusion. Certain types of calls that are particularly challenging to process or commonly occurring (e.g., mental health calls and calls where alternatives to police responses seem especially relevant) were weighted in the selection process to ensure their adequate inclusion for statistical analyses. Vera researchers coded the audio recordings using the same standardized fields present within CAD data (including the narrative fields) and conducted exploratory content analyses on the 911 call audio recordings.

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[21] Records Management Systems (RMS) are agency-wide systems that allow police departments to store, retrieve, retain, manipulate, archive, and view information, records, documents, and/or files related to law enforcement operations. Vera used RMS data primarily to capture outcome data (e.g., arrests and other dispositions); see United States Department of Justice, Bureau of Justice Assistance, *Standard Functional Specifications for Law Enforcement Records Management Systems (RMS)* (Washington, DC: Bureau of Justice Assistance, 2002), https://it.ojp.gov/documents/leitsc_law_enforcement_rms_systems.pdf.

Analysis of qualitative data

To support the qualitative research activities, Vera conducted three site visits each to Camden and Tucson. On these visits, Vera observed police response, dispatch, and public safety call-taking. Vera also conducted focus groups and interviews with municipal public safety employees and community members in the locations. The purpose of these research activities was to explore emerging themes among what happens between the time a call is placed and when/if an officer responds to a scene, how information is transferred across key personnel, and community resources that could potentially be of assistance. This qualitative data helped to contextualize the information captured in the CAD data and 911 audio recordings. Interviews were coded for:

- Key personnel involved during the 911 process;
- How information is conveyed across personnel;
- Common issues that surface during 911 call processing;
- Critical information that is key to successful job performance;
- Common and/or standardized protocols; and
- Training required for call-taking and dispatching positions.

National convening

In addition to conducting the empirical research tasks outlined above, Vera hosted a national convening of law enforcement leaders and system stakeholders to present research findings, explore alternatives to enforcement, and identify opportunities for reform. This convening, held in partnership with Arnold Ventures and George Mason University's Center for Evidence-Based Crime Policy (CEBCP), welcomed participants from 40 organizations across the country, including representatives from 10 different police departments, five public safety communications agencies, and 10 research organizations. Both CEBCP's and Vera's research teams presented findings related to 911 call trends, processes, system maps, and outcomes to field experts. The convening served as a venue to seek feedback on the research findings to date and spark innovation regarding next steps, with an emphasis on alternatives to enforcement.

Recommendations and next steps

The current study sought to complete an ambitious research agenda and project plan over a short period of time to fill an important gap in the field. Prior to this research, little was known or comprehensively organized around 911 call-taking and dispatching as it relates to police response. This research was carried out with the explicit goal of decreasing unnecessary police response and enforcement. One key factor to be explained, which has been substantiated through this work, is that most 911 calls for police service do not involve a crime. This is important knowledge that can help make meaningful advancements in the field.

Though much remains to be understood about 911 call-taking, these efforts have identified key stakeholders and a systemized path forward. There exists both a clear need and immeasurable opportunity—in the immediate term—to begin charting a new course for 911 response. Expanding the current research to include additional inquiries and sites, as well as additional disciplines—namely behavioral economics—can advance the current research agenda in short and impactful order. It will also be important to include the perspectives of those who are most directly impacted by policing practices, members of the general public that are contacting police for service, and those who are affected by the outcomes of these calls.

Significant progress has been made throughout the course of the current research. Yet, vast opportunities remain to advance understanding and practice in the 911 system with the goals of improving public safety, promoting alternatives, and eliminating unnecessary enforcement.

Chapter 2: The 911 Call Processing System:

A Review of the Literature as it Relates to Policing

S. Rebecca Neusteter, Maris Mapolski, Mawia Khogali, and Megan O'Toole

When people think of 911, they may think first of emergency medical services. But a significant portion of the 911 calls made every year in the United States are routed to police departments. There's only one problem: nobody knows how many.

The 911 system is complex and involves many actors. First there is the caller. He or she places a call for help that is connected to a call-taker. The call-taker gathers information about the emergency and inputs it into a system designed to identify the caller's location and categorize the call. Next, a dispatcher (who may also be the call-taker, depending on the jurisdiction) uses this information to assign emergency responders to the location of the emergency. Once they arrive, the responders provide assistance. Even after that, the system is still gathering data: responders are filling out their own reports, comparing their assessment of the emergency to the call-taker's, and logging the amount of time spent arriving at and then responding to the emergency.

With 911 systems capturing all of this information, it might seem like 911 would be easy to study, and there would exist a broad body of literature analyzing patterns among calls and helping police do their jobs. But 911 call centers (called public service answering points, or PSAPs) operate independently and locally. They cannot transfer calls to each other and, if your call is routed to the wrong PSAP—for example, if you are traveling near a state line and calling from a cell phone—they may not be able to send responders to your emergency. The development of PSAPs allowed 911 to spread rapidly through the United States, but today it is one of the greatest hindrances to actually understanding the system we use and its effects.

For this report, the Vera Institute of Justice (Vera) examined the body of literature that has developed as researchers have attempted to collect and study 911 data in the context of policing. Researchers have taken two main approaches to the study of the 911 system. First, there are studies using simplified, but more readily available, metrics such as call volume, call type, and response time. These studies allow researchers to draw broad generalizations about several jurisdictions at the same time but are limited in their ability to inform about trends with any specificity—they simply collapse too many variables into too few categories. Then there are complex studies modeling caller behavior, call type patterns over time, and factors affecting the ability to respond in a timely fashion. These latter studies demonstrate the richness of 911 data available from individual jurisdictions but are limited in scope because researchers can't compare this data across jurisdictions. The report concludes with a call for research to fill gaps in the current 911 literature in order to chart a path forward using 911 data to improve police efficiency and provide the most effective and appropriate responses to true emergencies.

The history of 911

In 1957, the International Association of Fire Chiefs began to lobby for a single telephone number for fire reporting.[22] A decade later, the Commission on Law Enforcement and Administration issued a report recommending the same system for contacting police departments.[23] In 1968, AT&T—then the provider for most U.S. telephone service—designated 911 as that emergency number.[24] The first U.S.-based 911 call was made in 1968 in Haleyville, Alabama.[25] Although it was originally envisioned as a fire reporting system, 911 quickly became an all-purpose emergency response system and—by connecting callers with police—one of the fastest-expanding components of the U.S. criminal justice system.[26] By the end of the 20th century, 93 percent of the country's population—and 96 percent of its geographic area—was covered by 911 service.[27] But despite the ubiquitous nature of 911, Congress did not officially adopt it as the nation's emergency calling number until the Public Safety Act of 1999.[28] This may have something to do with its piecemeal growth: each jurisdiction independently developed its own 911 system—and only later did national-level guidelines begin to emerge.[29]

Today's 911 systems bear little resemblance to the rudimentary, ad hoc dispatching of the early 1970s. Technological advances have made it possible for call-takers to communicate more clearly and reliably with both callers and dispatchers. Enhanced 911 (E911, the system most people are familiar with today) was developed in the mid-1970s.[30] It added critical features to call-takers' repertoires, like selective routing (responsible for making sure that 911 calls reach emergency services covering the address the call is made from), automatic caller location information, automatic telephone number identification, and call recording.[31] And public safety Computer Aided Dispatch (CAD) systems—a parallel policing dispatch system that enables dispatchers to assess available resources, send messages, and store data—which developed in the 1960s to provide support for and assist in the dispatch of patrol units, also quickly became integrated into the 911 system.[32]

Early 911 call-takers did not necessarily have specialized dispatch training and created their own descriptions for fire, medical, or police services to explain the emergency. As the system aged, the business of call-taking began to professionalize, and call-takers in many locations received training not only in generalized dispatch, but also in specialized medical, police, or fire dispatch. One of the services that modern callers are most familiar with through media depictions, the "pre-arrival instruction," was not used until almost a decade after 911 came into service. In 1976, a woman whose baby wasn't breathing called 911 and, rather than making her wait until responders could reach her, the call-taker gave her instructions that were

[22] Industry Council for Emergency Response Technologies (iCERT), *History of 911 and What It Means for the Future of Emergency Communications* (Washington, DC: iCERT, 2015), 3, https://perma.cc/YL97-9J9C.
[23] Ibid.
[24] Ibid.
[25] Ibid.
[26] Ibid.
[27] NENA,"9-1-1 Origin & History," https://perma.cc/X3NB-SL8R.
[28] iCERT, *History of 911*, 2015, 3.
[29] Ibid., 4.
[30] Ibid.
[31] Ibid.
[32] Tom McEwen, Jacqueline Ahn, Steve Pendleton, et al., *Computer Aided Dispatch in Support of Community Policing, Final Report* (Alexandria, VA: Institute for Law and Justice, 2002), 1, https://perma.cc/4UAY-ZTML.

instrumental in saving the baby's life.[33] By 1997, emergency medical dispatchers had access to a protocol database—called the Advanced Medical Protocol Dispatch System (AMPDS)—with 88 million question-and-answer combinations developed by the International Academy of Emergency Medical Dispatch available to guide them through analysis and care instructions.[34]

911 is still evolving, largely in response to the advent of wireless communications. One of E911's greatest limitations is that it did not anticipate the widespread use of cell phones, which results in complications for call-takers and dispatchers.[35] Cell phone calls are typically associated with the address of the cell phone tower closest to the call's point of origin, rather than the exact location from which the emergency call has been made. This means that automated location databases—which inform the call-taker where the call is coming from based on the telephone billing address—do not typically display the location from which the wireless call is being made.[36] This can be particularly problematic for 911 hang-ups: most police agencies dispatch officers to investigate abandoned 911 calls—even if sometimes that means merely searching the vicinity of the cell tower in question—which cannot be easily done if no address is available.[37]

A digital system referred to as Next Generation 911 (NG911), which allows callers to provide information through a variety of media including voice, photo, interactive video, and text message, addresses many of the limitations of E911, including location and accessibility concerns for such populations as people who are Deaf or hard of hearing or for whom English is not their first language, as well as individuals who are in need of police assistance but a call to 911 and communication with a call-taker itself may put the caller at risk of harm.[38] As of 2017, 16 states, regions within or among states, or U.S. territories had adopted plans to implement NG911; eight had sought proposals from vendors for statewide components for a NG911 system; 11 had awarded a contract for at least one NG911 system component (such as an IP network); and 13 had a fully functional NG911 system and were processing NG911 emergency calls for service.[39]

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[33] Isabel Gardett, Jeff Clawson, Greg Scott, et al., "Past, Present, and Future of Emergency Dispatch Research: A Systematic Literature Review," *Annals of Emergency Dispatch & Response*, 2016, 29-42, 29, https://perma.cc/SQ3N-DEQW.
[34] Jeff. J. Clawson, "The DNA of Dispatch: The Reasons for a Unified Medical Dispatch Protocol," *Journal of Emergency Medical Services*, 1997, https://perma.cc/5X87-4QQ9.
[35] Alexis Sobel Fitts, "When 911 Operators Can't Find Their Callers," *Atlantic*, November 19, 2015, https://perma.cc/BBZ6-JWCZ.
[36] United States Federal Communications Commission (FCC), "911 and E911 Services," https://perma.cc/XWQ2-XF3M.
[37] NENA, *NENA Silent or Hang-Up 9-1-1 Calls for Service: An Operations-Focused Study* (Alexandria, VA: NENA, 2002), 10, 16-17, https://perma.cc/25CC-DUFG.
[38] National 911 Program, "Next Generation 911," https://perma.cc/YQ5W-BSAU. In jurisdictions where silent communication is not available, at-risk callers are given advice to "tip off" call-takers with verbal cues, and call-takers may ask them to press a button if they cannot safely speak. These solutions involve a significant amount of guesswork on the part of the call-taker and may not allow the caller to provide an accurate address where responders can reach them. Ni'Kesia Pannell, "How to Get Help in a Dangerous Situation If You Can't Talk Out Loud," *Insider*, December 4, 2018, https://perma.cc/7TC3-H4MN.
[39] National 911 Program, "NG911 Progress Snapshot Across the U.S. Now Available," https://perma.cc/5GWG-AQDB. In addition to the 50 states, the National 911 Program progress report collects data from U.S. territories and substates (geographic regions within or among states): American Samoa, Delaware, Guam, New Hampshire, Rhode Island, and the U.S. Minor Outlying Islands did not provide data.

But for all 911's advantages, the system is still far from perfect. Its decentralized nature means that each of the thousands of PSAPs across the nation operates independently.[40] Some locations still do not have the full range of E911 services, let alone NG911.[41] And, although CAD systems and AMPDS are widely used and valued tools, they are not necessarily standardized across the country—or even among cooperating local jurisdictions.[42] For example, some jurisdictions are using versions of the AMPDS database that may be out of date. And, although CAD as a system is in wide use, each locality is likely to have its own set of CAD codes to convey information between dispatcher and responder.

The technology of emergencies

To someone experiencing an emergency, 911 is designed to be simple: press three numbers, get help. But dialing these three digits sets in motion a complicated process involving several layers of technology and multiple personnel—and data on each decision is logged every step of the way.

The call

When a caller dials 911, she is connected to a PSAP, the call center responsible for responding to emergencies.[43] There are more than 6,000 PSAPs in the United States, each operating independently—some by state and local governments, others by law enforcement agencies, fire departments, and emergency management agencies.[44] Practices vary by jurisdiction in terms of whether call-takers can double as dispatchers; whether they exclusively or collectively respond to fire, medical, or police emergencies; and whether they are required to be certified in specific or general dispatch techniques.[45] (For more information about call-takers, see "911 call-takers: Their training, role, and well-being" on page 28.)

Locating the emergency

To route an emergency call to the correct PSAP, the phone company must be able to associate a phone number with a location. If a call is made from a landline, it is automatically directed to the nearest PSAP based on the address associated with the landline, and the address the phone number is registered to appears on the call-taker's screen.[46] Calls from wireless phones, however, are more complicated. If a call is made from a cell phone, the phone's signal is transmitted to the nearest cell phone tower, and that signal is then transmitted to the "nearest" PSAP.[47] This can cause problems when a call is made near a jurisdictional border, because the nearest cell tower may route to a PSAP that does not serve the caller's location.[48] Because PSAPs

[40] NENA, Next Generation 9-1-1 – The Future for Emergency Communications (Alexandria, VA: NENA, 2007), https://perma.cc/2JEE-TGLU. For the operation of public safety answering points (PSAPs), see David Jones, "Next-Generation 911 is a Game-Changer," Government Technology, November 19, 2014, https://perma.cc/Z2RW-J6V8.
[41] iCERT, *History of 911*, 2015, 5. In addition to the problem of aging infrastructure that cannot support enhanced call services, 2.1 percent of households in the United States do not have a telephone. Census Bureau, "Historical Census of Housing Tables: Telephones," https://perma.cc/FV64-JNR4.
[42] Kate Snyder, "Officials Look at Consolidating 911 into One Agency in Lucas County," *Blade*, April 5, 2019, https://perma.cc/5DWB-Y6W5.
[43] FCC, "911 and E911 Services," 2019.
[44] NENA, *The Future for Emergency Communications*, 2007.
[45] Association of Public-Safety Communications Officials (APCO) International, "Training Disciplines," https://perma.cc/VLY8-6G59.
[46] Superior Ambulance Center, "How 911 Dispatch Works," https://perma.cc/9QWS-RXV4.
[47] Ibid.
[48] Brendan Carr, commissioner of the FCC, "Location-Based Routing for 911 Calls" (statement in support of inquiry before Public Safety and Homeland Security Bureau), 33 FCC Rcd 3238 (4), 2018, 1, https://perma.cc/64WX-Z958.

are not necessarily networked, this can mean significant delays in—or even failure to provide—service.[49] This is a rapidly growing and significant problem. In 2016, approximately 80 percent of 911 calls came from cell phones.[50]

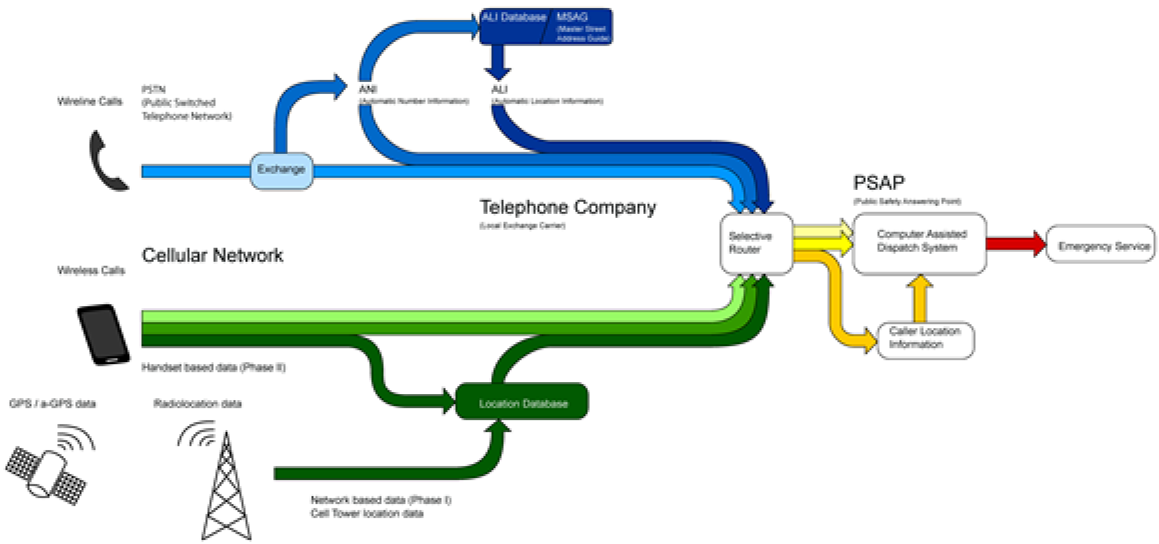
Moreover, cell phones do not remain in a fixed location and providers do not necessarily release location data for these phones.[51] In PSAPs with E911 service, the cellular provider is required to transmit the phone number and at least the location of the cell tower to which the call connected, as well as location data that includes the latitude and longitude from which the call was made (accurate to within 50 to 300 meters), depending on which E911 features have been implemented in that region.[52] This enables PSAPs to follow-up on abandoned cell phone calls and ensure that there is no emergency, where before they would have been unable to dispatch services.

As noted above, in 2016, 80 percent of 911 calls came from cell phones.[53] But voice over Internet protocol (VOIP) calls are accounting for an increasing share of 911 calls.[54] VOIP calls, because they come through an Internet service provider, also may not be associated with an address. One reason for the number of VOIP calls is that businesses and homeowners have begun bundling phone and Internet services together. Another is that a cell phone will make a VOIP call if it is connected via Wi-Fi to a network, rather than using cellular network data.[55] VOIP calls pose a unique challenge to PSAPs that may not be resolved until NG911 is fully implemented.

As an additional failsafe, 911 call-takers in many jurisdictions have begun asking "where is your emergency?" as their first question, rather than "what is your emergency?"[56] (For an overview of the 911 process, see Figure 1.3, below.)

[49] Ibid.
[50] National 911 Program, *2017 National 911 Progress Report* (Washington, DC: National 911 Program, 2017), 22, https://perma.cc/842R-J2FE.
[51] FCC, *911 Wireless Services* (Washington, DC: FCC, 2018), 1, https://www.fcc.gov/sites/default/files/911_wireless_services.pdf.
[52] Ibid.
[53] National 911 Program, *2017 National 911 Progress Report,* 2017, 22.
[54] In 2017, there were 5,086,983 VOIP calls made to 911 in the 21 states reporting data, an increase of approximately 800,000 calls over 2016 with the same number of states reporting. Twenty-three of the 45 reporting states did not segregate VOIP calls by category and reported "unknown" (Alaska reported "0"). Ibid., 23.
[55] See generally GSM Association, *IMS Profile for Voice, Video and SMS over Untrusted Wi-Fi Access, Version 6.0* (London: GSM Association, 2018), https://perma.cc/EZN3-HJ23.
[56] Karina Yandell, "911, Where's Your Emergency," *Telecom Reseller*, October 21, 2010, https://telecomreseller.com/2010/10/21/911-wheres-your-emergency/.

Figure 1.3: How the 911 system works: From call to response



Source: Adapted from Evan Mason, "9-1-1 System," via Wikimedia Commons. Licensed under the Creative Commons Attribution-Share Alike 3.0 Unported license.

Intake and processing

Assuming the caller has not abandoned the call, the call-taker will ask a series of questions dictated by the PSAP's protocols, which—like most processes related to 911—vary from jurisdiction to jurisdiction.[57] These questions are designed to triage the emergency, identify appropriate services, and give the emergency service providers—whether medical, fire, or police—the information they need to respond. At this point, the call itself is often being recorded and both the information provided by the caller and the call-taker's responses can be reviewed later by supervisors or researchers.[58]

The National Emergency Number Association (NENA), a professional organization for 911 providers, recommends that, at minimum, the following information should be gathered by call-takers:

- the address or exact location of the incident;
- a callback number;
- the type of emergency;
- the time of occurrence;
- any known hazards; and

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[57] FCC, "911 and E911 Services"; Gardett, Clawson, Scott, et al., "Past, Present, and Future," 2016, 29-42, 33; and Rhonda Harper, "Police Dispatching Tips & Tools," PSC Online, July 14, 2011, https://perma.cc/PW4N-JZQL.
[58] Although there is no national standard for PSAPs, the U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA) has promulgated guidelines for legislators planning to implement and codify NG-911 in their state, which include recordkeeping and recording requirements. NHTSA, *Guidelines for State NG-911 Legislative Language* (Washington, DC: NHTSA, 2012), 28, https://perma.cc/T32D-8RN9.

- the identities of those involved and their location.[59]

As call-takers process calls, they will either transfer them to a specialized dispatcher or perform dispatch services. This requires decision making on the part of call-takers. Do they send only medical services to an accident? Medical and police? How many responders are required? Dispatchers convey these decisions to responders not only verbally but also by entering a series of priority and descriptive codes into their CAD system that tell responders how quickly to respond and what response is desirable. For example, Houston, Texas, has 10 priority codes for police calls, ranging from “E” (an emergency response with sirens and lights) through priorities “One” down to “Nine” (a delayed call-back).[60] Often, one piece of information can change the priority level of a call: the presence of a knife might make the difference between a Priority Two and a Priority Three call.[61]

The response

Because there is no standardized protocol for police call-taking, the information gleaned during the call may not align with the categories provided for in dispatchers’ CAD systems. And it may not be optimized to give responders the information they need before arriving at the emergency. A handful of codes is likely insufficient to cover all eventualities—and, in some departments, the “other” code is the most-used description of the emergency.[62] (The “other” code, designed as a catchall for situations not already designated in a CAD system, enables call-takers to fill in their own descriptions.) And the nature of emergencies is to evolve: by the time responders arrive, a burglary may no longer be in process, a drug deal may be over or, if the delay between call and response is long enough, the caller may have left the location.[63]

Because of these circumstances, the 911 data collected by local jurisdictions does not terminate at the time of dispatch. In fact, one of the most common metrics used to assess police performance is response time.[64] Police departments also collect data on the responding officers’ assessment of the emergency and may compare that to the call-taker’s initial assessment.[65]

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[59] NENA, *Call Answering Standard*, 2017, 8.
[60] Jae-Seung Lee, Jonathan Lee, and Larry T. Hoover, “What Conditions Affect Police Response Time? Examining Situational and Neighborhood Factors,” *Police Quarterly* 20, no. 1 (2017), 61-80, 66.
[61] Ibid.
[62] In some jurisdictions, it has become common for call-takers to simply check “other” and fill in a description even if the emergency might be already covered in a menu in the CAD system. This creates significant problems for researchers who need to review CAD data to see how many burglary calls, for example, have been made in a given jurisdiction. Instead of simply accessing presorted data, the researchers must instead physically read each entry in the “other” category to determine if it belongs in a predetermined category. McEwen, Ahn, Pendleton, et al., *Computer Aided Dispatch in Support of Community Policing*, 2002.
[63] Alan Judd, “Analysis Finds Lag in Atlanta’s Response to Emergencies,” *Atlanta Journal-Constitution*, November 23, 2009, https://perma.cc/7ZNR-AG7C.
[64] John M. Stevens, Thomas C. Webster, and Brian Stipak, “Response Time: Role in Assessing Police Performance,” *Public Productivity Review* 4, no. 3 (1980), 210-230, 211-212.
[65] McEwen, Ahn, Pendleton, et al., *Computer Aided Dispatch in Support of Community Policing, 2002*, 1.

911 call-takers: Their training, role, and well-being

911 call-takers perform a critical function in emergency response. In some PSAPs, the call-taker serves both the interrogatory and dispatch functions, liaising directly with police, medical, or fire resources. In others, the call-taker routes the caller's information to a separate dispatcher through the CAD system, and that dispatcher then sends appropriate personnel to the location. During this transfer of information, the call-taker either terminates the call—by instructing the caller to await field response—or, depending on the circumstances related to the event, remains on the call with the caller. Whether the call-taker is also the dispatcher or not, their role in assessing the emergency and ensuring that the right resources are directed to it shapes the entire interaction.

Because they are the first point of contact for callers, call-takers have a unique opportunity not only to provide the resources callers ask for, but the ones they actually need. For example, they may be important team members of diversion programs that help keep people out of the justice system.[a] They may assist in building a record that can supplement law enforcement's ability to identify and document escalating intimate partner violence.[b] And, with appropriate training, they can even help to interrogate caller motives and determine the best response to emergency and nonemergency calls.[c]

But call-takers are vulnerable to the same perils of decentralization as the PSAPs they work in: the fragmented, jurisdictional nature of their work means that standardization, support, and even training vary by locality.[d] The International Academies of Emergency Dispatch (IAED) is a nonprofit organization that provides certifications for a variety of dispatch roles.[e] The Association of Public-Safety Communications Officials (APCO) also provides professional development, technical assistance, and best practices for members of the emergency dispatch community.[f] Their "Minimum Training Standards for Public Safety Telecommunicators" guidelines outline the optimal standards that all telecommunicators should meet, including knowledge of receiving, processing, transmitting, and conveying public safety information to key personnel.[g] But these are opt-in standards, not a central mandate, and it is unclear how many—if any—jurisdictions mandate this type of training for their call-takers.

In recent years, call-takers have come under scrutiny as the first point of contact in a disturbing pattern of calls: callers who misuse police resources to pursue personal—often racially motivated—agendas. Social media—and news media—have made it impossible to ignore the fact that people are calling 911 to report people of color doing innocuous things like having a barbecue, waiting for a friend in Starbucks, taking a college tour, or even napping.[h] Sometimes very little happens; but other times—as in the cases of Tamir Rice or Gregory Hill—the results of the call are tragic, with far-reaching consequences for communities.[i] Caller expectations, PSAP trainings and protocols that overly emphasize customer service, and risk aversion may encourage call-takers to request and dispatchers to send police for most calls, however innocuous the situation may seem.[j] But improved call-taker training and clearer protocols for handling potentially problematic calls—by, for example, encouraging callers to articulate their underlying suspicions—as well as public awareness campaigns to redefine expectations between callers and call-takers could help preserve both scarce police resources and community well-being.

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Being a 911 call-taker has a significant impact on a person's wellness. One 1997 study found that they are emergency workers—no less than responders who are physically at the scene—for purposes of assessing the impact of disaster on their lives.[k] Their proximity to trauma can lead them to experience secondary trauma: a 2017 study found that 31 percent of call-takers experience post-traumatic stress disorder (PTSD) as compared to 8.3 percent of police and 3.5 percent of the general population.[l] The job can be physically taxing as well. One 2015 study found that 911 call-takers are at increased risk of voice stress disorders, with nearly a third of call-takers reporting at least some symptoms of disorder.[m]

[a] Melissa Reuland, A Guide to Implementing Police-based Diversion Programs for People with Mental Illness (Rockville, MD: U.S. Department of Health and Human Services, Substance Abuse and Mental Health Service Administration GAINS Center, Technical Assistance and Policy Analysis Center for Jail Diversion, 2004), https://perma.cc/LGM2-9S6G.

[b] Amy Reckdenwald, Chelsea Nordham, Adam Pritchard, and Brielle Francis, "Identification of Nonfatal Strangulation by 911 Dispatchers: Suggestions for Advances toward Evidence-Based Prosecution," Violence and Victims 32, no. 3 (2017).

[c] Isabel Gardett, Jeff Clawson, Greg Scott et al., "Past, Present, and Future of Emergency Dispatch Research: A Systematic Literature Review," Annals of Emergency Dispatch & Response (2016).

[d] Jessica W. Gillooly, "911 Operators Need Better Training, Too," San Francisco Chronicle, May 26, 2018, https://perma.cc/E5U5-SZL5.

[e] International Academies of Emergency Dispatch, "Certification," https://perma.cc/S24W-RV99.

[f] APCO International, "About APCO," https://perma.cc/V9JW-ZFQB.

[g] APCO International, Minimum Training Standards for Public Safety Telecommunicators (Daytona Beach, FL: APCO International, 2015), https://perma.cc/752L-2HFJ.

[h] See Haaziq Madyun, "Family Wants to Create Awareness After BBQ Confrontation at Lake Merritt," KRON, May 10, 2018, https://perma.cc/FDF7-LWJZ (barbecue); Melissa DePino (@missydepino), Twitter post, April 12, 2018, 2:12 pm, https://perma.cc/M9HJ-4B88 (Starbucks); Dakin Andone and Hollie Silverman, "A Mom on a College Tour Called the Cops on Two Native American Teens Because They Made Her 'Nervous'," CNN, May 4, 2018, https://perma.cc/M9HJ-4B88 https://perma.cc/M9HJ-4B88(college tour); and Brandon Griggs, "A Black Yale Graduate Student Took a Nap in Her Dorm's Common Room. So a White Student Called Police," CNN, May 9, 2018, https://perma.cc/AZR3-PXN3.

i Tamir Rice was shot and killed by police officers after a 911 caller reported that a child was waving a "probably fake" gun. German Lopez, "Cleveland Just Fired the Cop Who Shot and Killed 12-Year-Old Tamir Rice More Than 2 Years Ago," Vox, May 30, 2017, https://perma.cc/MED6-UHKQ. Gregory Hill Jr. was shot and killed by police officers after neighbors called 911 with a noise complaint. Ryan Farrick, "Family of Gregory Vaughn Hill Jr. Seeks Justice after Sheriff's Deputies Penalized $4 in Controversial Killing," Legal Reader, May 31, 2018, https://perma.cc/A6KE-YP4S. For an analysis of the community cost of deaths from police use of force, see Anthony Bui, Matthew Coates, and Ellicott Matthay, "Years Of Life Lost Due To Encounters With Law Enforcement in the USA, 2015–2016," Journal of Epidemiology and Community Health 72 (2018), 715-718, https://perma.cc/FR3D-9S3K.

[j] Gillooly, "911 Operators Need Training," 2018.

[k] Sharon Rae Jenkins, "Coping and Social Support Among Emergency Dispatchers: Hurricane Andrew," Journal of Social Behavior and Personality 12, no. 1 (1997).

[l] Sandra L. Ramey, Yelena Perkhounkova, Maria Hein et al., "Evaluation of Stress Experienced by Emergency Telecommunications Personnel Employed in a Large Metropolitan Police Department," Workplace Health & Safety 65, no. 7 (2017). For more studies of call-taker stress and trauma, see Heather Pierce and Michelle M. Lilly, "Duty-related Trauma Exposure in 911 Telecommunicators: Considering the Risk for Posttraumatic Stress," Journal of Traumatic Stress 25, no. 2 (2012) (dispatchers are likely to experience symptoms of PTSD); Benjamin Trachik, Madeline Marks, Clint Bowers et al., "Is Dispatching to a Traffic Accident as Stressful as Being in One? Acute Stress

Disorder, Secondary Traumatic Stress, and Occupational Burnout in 911 Emergency Dispatchers," Annals of Emergency Dispatch & Response 3, no. 1 (2015) (in a sample of 205 primarily female call-takers, PTSD and Acute Stress Disorder rates were high; rates did not correspond to duration of career); Kimberly D. Turner, "Effects of Stress on 9-1-1 Call-Takers and Police Dispatchers: A Study at the San Jose Police Department" (Master's thesis, San Jose State University, 2015) (911 call-taking is significantly stressful but some of the stress can be mitigated with work-life balance principles); and Elizabeth A. Hayes, "Commonly Identified Symptoms of Stress among Dispatchers: A Descriptive Assessment of Emotional, Mental, and Physical Health Consequences" (Master's thesis, St. Cloud State University, 2017) (survey of self-reported stress and health consequences of PSAP work).

[m] Heidi Johns-Fiedler and Miriam van Mersbergen, "The Prevalence of Voice Disorders in 911 Emergency Telecommunicators," Journal of Voice 29, no. 3 (2015), https://perma.cc/7TPS-BYRA.

Challenges for researchers

A review of the existing literature on 911 and policing requires first a discussion of the challenges associated with and limitations of the data needed to conduct such research. In order to analyze 911, researchers need data from the nation's many 911 systems. But, because 911 systems and PSAPs are locally operated and monitored, it is not always easy to compare "apples to apples" when talking about data. Different PSAPs use different protocols, codes, and formats for recording and storing data, which presents challenges to researchers who want to look beyond the limits of a single jurisdictional boundary.[66]

Both CAD systems and modern phone systems (especially NG911 systems) by their very nature collect and log tremendous amounts of data.[67] This data—from call time and duration to call type codes entered into dispatch logs—is available, and police departments across the nation are using it to develop police officer performance metrics, agency policies, and emergency response practices. But, except in a few instances, this data is not aggregated so that it can be compared in a meaningful way across jurisdictions to allow for broader policy development and national standardization.[68]

Part of the problem is likely technical: different CAD systems may have different categories for call logging or may store information in different formats. No nationwide analysis has examined the categories under which calls are logged, nor has there been any national-level attempt to standardize the categories, so individual departments are likely to be using lists developed locally. Greater uniformity in category identifiers would allow for more accurate cross-jurisdictional comparisons as well as national-level analyses.

Other problems are more likely political: no central authority or database exists where this data can be analyzed on a national level. NENA simply aggregates 911 call volume as a whole, without disaggregating it into police, EMS, and fire calls for service, or even separating out nonemergency calls.

In the absence of centralized data collection, individual departments are using the data they have, but they may be using it in inefficient ways, such as focusing on overall response times rather than disaggregating emergency and nonemergency response times. Several studies

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[66] For a discussion of the difficulties of cross-comparison, see Daniel S. Bennett, "Police Response Times to Calls for Service: Fragmentation, Community Characteristics, and Efficiency" (paper prepared for Bradley Graduate and Postgraduate Fellowship, Stanford University, Stanford, CA, November 2018), https://perma.cc/T7W6-7BMM.
[67] See for example City of New Orleans, "Calls for Service 2017" (database) (New Orleans, LA: City of New Orleans, 2018), https://data.nola.gov/Public-Safety-and-Preparedness/Calls-for-Service-2017/bqmt-f3jk.
[68] For example, researchers have compared Houston and Dallas police departments in studying neighborhood characteristics that affect response time. Abdullah Cihan, "Social Disorganization and Police Performance to Burglary Calls: A Tale of Two Cities," *Policing* 37, no. 2 (2014), 340-354.

have shown how this data can be used more efficiently to develop predictive policing models that increase efficiency and safety.[69]

Finding a unifying metric for assessing police emergency performance is also a significant challenge. Historically, researchers have turned to broad and oversimplified metrics like total call volume and overall response time to study police emergency performance. As computing capacity has improved, better data gathering and processing abilities have given researchers new advantages in comparing and manipulating information, but in other, perhaps critical, ways, they are still stymied by the lack of uniformity among jurisdictions.

The most commonly collected data about 911 calls tends to be broad—like the number of calls for service as an aggregate for fire, medical, *and* police—and produced voluntarily by PSAPs and local jurisdictions. It is also incomplete. For example, according to NENA, about 240 million calls for service are made annually.[70] However, the data sources and research used to inform this estimate are not publicly available, and this number may well be conservative.[71] And, because NENA does not distinguish its national data by call type, it is difficult to know how many of the nation's 911 calls each year reach police departments, as opposed to emergency medical services or fire departments.[72] It's also impossible to tell how many calls go unanswered.

The U.S. Department of Justice (DOJ) launched the Law Enforcement Information Sharing Program (LEISP), which aims to allow information to be shared routinely across jurisdictional boundaries—but again, participation is voluntary.[73] Still, this program has the potential to improve access to and manipulation of data to allow researchers to develop studies with broader application. The Police Data Initiative, a policing "community of practice" that includes police agencies, researchers, and technologists, provides a platform for police agencies to upload a variety of datasets—including calls for service—to promote research and transparency.[74] The initiative has made it possible for users to view some level of 911 call data from 31 police agencies.[75] Although these datasets provide previously unavailable information, they can be unwieldy for people who are not familiar with manipulating or downloading large datasets or analyzing statistical tables. And, with only 31 of 18,000 U.S. policing agencies

[69] See for example Dan Cramer, Albert Arthur Brown, and Gongzhu Hu, "Predicting 911 Calls Using Spatial Analysis" (paper presented at the 9th International Conference on Software Engineering Research, Management and Applications, SERA 2011, Baltimore, MD, August 10-12, 2011), https://perma.cc/EKM7-J24J; Hector Jasso, Tony Fountain, Chaitan Baru, et al., "Prediction of 9-1-1 Call Volumes for Emergency Event Detection" (paper presented at the 8th Annual International Digital Government Research Conference, May 20-23, 2007), https://perma.cc/WC2D-HC55; and Alex Chohlas-Wood, Aliya Merali, Warren Reed, and Theodoros Damoulas, "Mining 911 Calls in New York City: Temporal Patterns, Detection, and Forecasting" (New York: Centers for Urban Science and Progress, 2015), https://perma.cc/7T9C-VPHQ.
[70] NENA, "9-1-1 Statistics."
[71] Vera Institute of Justice unpublished analyses.
[72] One analysis of San Francisco's 911 calls between May 2011 and February 2015 found that 56 percent to 63 percent of calls generated a computer-aided dispatch response, and 83 percent of those required police response rather than fire or medical. Diara Dankert, James Driscoll, and Nancy Torres, *San Francisco's 911 Call Volume Increase* (Mountainview, CA: Google, 2015), 9, https://perma.cc/QHU3-C4AH.
[73] U.S. Department of Justice (DOJ), *LEISP Exchange Specifications 3.0* (Washington, DC: DOJ, 2007), 6, https://perma.cc/UJ44-9QKK.
[74] Police Data Initiative, "About."
[75] Ibid.

reporting data, the ultimate statistical validity of assumptions drawn from that data may be of concern.[76]

But information-sharing on this level is still relatively new, and many 911 systems—especially those with only limited E911 functionality—do not support it. In the absence of shareable, uniformly identified data, researchers have fallen back on the broad categories of call volume, response time, and—at a local level—call location. Although useful information can be gleaned from this data, it is not always—or even often—focused on effective police response.

Findings from the literature

Vera researchers reviewed studies of the 911 system and selected 35 of them for inclusion in this report. Researchers began by sorting the body of literature into broad categories depending on whether studies were focused on dispatch, medical, police, or fire response. Studies primarily focused on medical and fire response were excluded from analysis. Of the studies focused on dispatch, Vera researchers retained those that studied the mechanics of and training surrounding call-taking and dispatch. An additional body of literature focused on call-taker stress and well-being is discussed in "911 call-takers: Their training, role, and well-being" on page 28.

The remaining studies fell roughly into two types:

- studies using simplified, easily comparable metrics like call volume, call type, and response time; and
- studies incorporating more granular data like call subtypes, locations within a city, and neighborhood characteristics. Of this second category, a smaller subcategory of studies analyzed 911 data theoretically to determine what data is gathered and what can be done with that information to improve police response and efficiency more generally.

Studies analyzing broad 911 metrics

<u>Call volume</u>

According to the National 911 Program, an organization that produces annual reports on the progress of NG911 implementation, 38 states and U.S. territories reported their overall call volume data for 2017, which can be seen in Figure 2.1 below.[77] Since it was first published in 2012, the number of states reporting their data has almost doubled, potentially signifying a growing recognition of the value of national-level aggregation of calls for service data, reporting, and standardization.[78]

[76] For the number of law enforcement agencies, see Duren Banks, Joshua Hendrix, Matthew Hickman, and Tracey Kyckelhahn, "National Sources of Law Enforcement Employment Data," (Washington, DC: DOJ, 2016), 3, https://perma.cc/33JX-GHAZ.
[77] National 911 Program, *2017 National 911 Progress Report*, 2017, 6, 19.
[78] Ibid., 6.

Figure 2.1: 2017 911 call volume by jurisdiction

Jurisdiction	Call volume	Population	Call rate[1]	Jurisdiction	Call volume	Population	Call rate[1]
AK	447,451	739,795	60	MP[2]	4,215	55,144	8
AZ	4,299,711	7,016,270	61	NC	757,065	10,273,419	7
CA	25,727,909	39,536,653	65	ND	245,561	755,393	33
CO	6,152,554	5,607,154	110	NE	1,152,512	1,920,076	60
CT	2,198,755	3,588,184	61	NJ	8,100,000	9,005,644	90
DC	1,407,012	693,972	203	NM	1,315,194	2,088,070	63
FL	22,208,165	20,984,400	106	NY	23,048,141	19,849,399	116
HI	1,402,800	1,427,538	98	OH	7,798,078	11,658,609	67
IA	1,119,306	3,145,711	36	OR	1,813,503	4,142,776	44
IL	10,346,413	12,802,023	81	PA	9,536,270	12,805,537	74
IN	5,037,955	6,666,818	76	PR[3]	2,320,804	3,663,131	63
KS	2,095,193	2,913,123	72	SD	307,866	869,666	35
KY	3,468,994	4,454,189	78	TX	27,247,770	28,304,596	96
LA	4,176,460	4,684,333	89	UT	1,022,955	3,101,833	33
MA	3,691,748	6,859,819	54	VA	4,470,764	8,470,020	53
MD	5,005,403	6,052,177	83	VI[4]	331,692	104,901	316
ME	559,632	1,335,907	42	VT	203,142	623,657	33
MI	6,357,656	9,962,311	64	WA	6,706,648	7,405,743	91
MN	2,883,120	5,576,606	52	WY	248,222	579,315	43
Total	204,880,732	240,341,478	85				

[1] Call rates are per 100 people
[2] Northern Mariana Islands
[3] Puerto Rico
[4] United States Virgin Islands

Source: State call volume data comes from National 911 Program, *2017 Progress Report*, 2017, 19. Population data for each state comes from U.S. Census Bureau, "Quick Facts," https://perma.cc/6HL9-CYEC.

State methodology for collecting call volumes is unknown, and calls are not disaggregated by type, combining all police, fire and EMS records, so researchers cannot use this data to review how many police specific calls for service are made in a given state. Nor can they determine how call volumes are distributed between, for example, urban and rural areas or night and day. Without access to this type of data, important questions remain about states like Colorado, where in 2017 nearly 11 calls for service were made for every 10 residents. Other states with high call volumes, such as New York, have populations substantially affected by tourism and commuter traffic: New York City has approximately 8.6 million residents, but in 2018, 65 million tourists visited, and its population fluctuates substantially throughout the day because of workforce commuters.[79] Data about what time of day calls are made and whether they are made from business or personal phones could help establish whether local residents or commuters are driving call traffic and allow the New York City Police Department (NYPD) to allocate resources accordingly.

[79] For New York City's population, see Census Bureau, "Quick Facts," https://www.census.gov/quickfacts/fact/table/newyorkcitynewyork,US/PST045218. For tourism estimates, see Patrick McGeehan. "N.Y. Draws a Record 65 Million Tourists (in Spite of Trump's Trade War, Many Were Chinese)," *New York Times*, January 16, 2019, https://www.nytimes.com/2019/01/16/nyregion/nyc-tourism-record.html. For an overview of how New York City's population varies because of workforce commuting, see Mitchell L. Moss and Carson Qing, The Dynamic Population of Manhattan (New York: New York University Wagner School of Public Service, 2012), 1, https://perma.cc/P2TQ-QEKM.

Examining call volume, with additional data for location and time, can yield useful predictive information about when PSAPs are likely to be overburdened and how to plan for unexpected volumes as well as predictable ones. But as yet, this data has been sparsely examined by researchers and only at very local levels.

- Researchers in 2015 examined NYPD's 911 call volumes by time and location to help determine which communities or populations are driving call volume and to predict future call patterns to increase policing efficiency.[80] Using the model they developed, they were able to successfully "forecast" the heaviest concentrations of 911 calls on days with predictably high call volume such as the Fourth of July.[81]

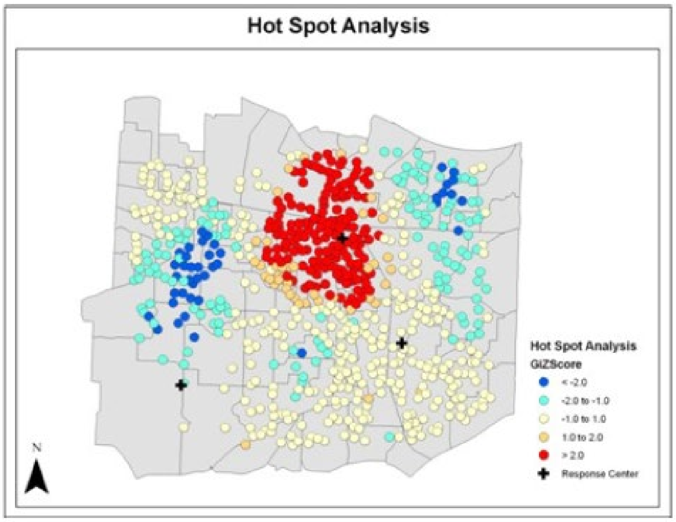
- Researchers analyzed 2,000 calls made to 911 between January 1 and May 31, 1998, in the Portland, Oregon, metro area to determine where "hot spots"—areas of concentration—of call volume occurred and what factors influenced high call volumes.[82] Figure 2.2 on page 35 provides a visual representation of the final hot spot analysis, where clusters of red dots represent areas with high call volumes (hot spots), and clusters of blue dots represent areas with relatively lower call volumes (cold spots). Equipped with this information, the researchers used regression analyses to investigate what factors influenced 911 call volumes for the city and found that neighborhood characteristics such as the number of people renting, the presence of businesses, the number of available jobs, the number of college graduates and those not in the labor force, and the proximity to an urban center all significantly predicted an area's call volume.[83] Businesses, job availability, people out of the labor force, and percentage of rentals all correlated to an increase in call volume; college graduates tended to correlate to a decrease in call volume.[84] However, the researchers cautioned that with only five months of data collected from a small geographic area, they were unable to state definitively that those correlations would hold true over time even for the city studied.[85]

- In 2007, researchers examined whether the data California uses to make staff allocation decisions for PSAPs could also be used to understand call trends and help emergency service providers respond to large-scale emergencies.[86] To do this, they analyzed data from emergency calls made between September 1, 2004, and August 31, 2006, in San Francisco.[87] The model they generated revealed that the volume of calls for service follows a cyclic pattern, which can be seen in

[80] Chohlas-Wood, Merali, Reed, and Damoulas, "Mining 911 Calls in New York City," 2015.
[81] Ibid., 7.
[82] Cramer, Brown, and Hu, "Predicting 911 Calls Using Spatial Analysis," 2011, 3, 6.
[83] Ibid., 5, 7-9.
[84] Ibid., 11.
[85] Ibid., 12.
[86] Jasso, Fountain, Baru, et al., *Prediction of 9-1-1 Call Volumes*, 2007.
[87] Ibid., 3.

Figure 2.3 on page 36. The researchers also closely examined trends that surfaced in response to two medium-to-large scale events (a fire and a hit-and-run incident in which a driver in an SUV struck 19 pedestrians across 20 blocks) to investigate whether the prediction model would still be effective at detecting unusually high call volumes that resulted from larger emergency incidents .[88] The study found that it was.

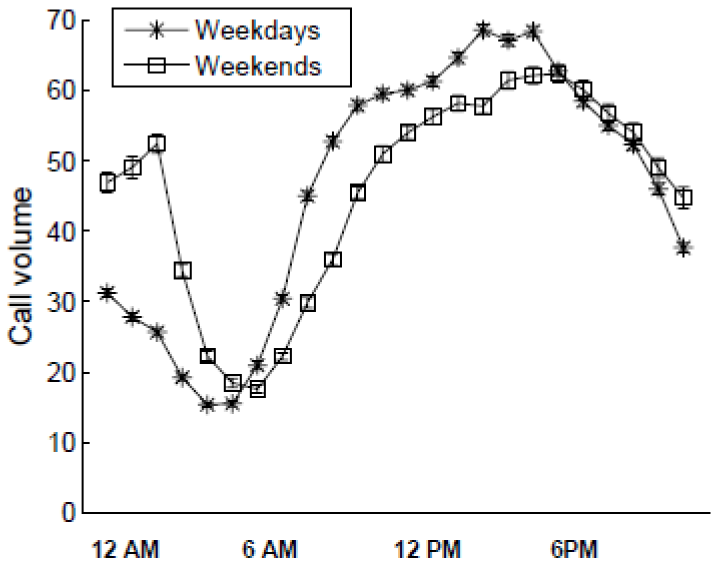
Figure 2.2 911 hot spots and cold spots, Portland, Oregon, January 1–May 31, 1998



Source: Adapted from Dan Cramer, Albert Arthur Brown, and Gongzhu Hu, "Predicting 911 Calls Using Spatial Analysis" (paper presented at the 9th International Conference on Software Engineering Research, Management and Applications, SERA 2011, Baltimore, MD, August 10-12, 2011), 8 (used with permission).

[88] Ibid., 5-7.

Figure 2.3 Average hourly call volume for San Francisco Emergency Communications Center PSAP, September 1, 2004–August 31, 2006



Source: Adapted from Hector Jasso, Tony Fountain, Chaitan Baru et al., *Prediction of 9-1-1 Call Volumes for Emergency Event Detection* (paper presented at the 8th Annual International Digital Government Research Conference, Philadelphia, PA, May 20-23, 2007), fig. 3 (used with permission), https://perma.cc/WC2D-HC55.

Similar studies in other jurisdictions could help unpack not merely how many calls are being made, but who is calling 911.

Call type

To understand 911 calls, it is important to know who is calling and what they need. But the local nature of 911 and its PSAPs presents special challenges for researchers attempting to analyze calls by type. Police calls for service must be separated from all other emergency calls. Then police calls for service must be broken down by priority, type of incident, and final assessment/disposition. But different jurisdictions categorize their police calls in different ways, making it difficult to compare call types across jurisdictions. Another issue is the evolving nature of emergencies: a call-taker may enter one call type code in the CAD system, but once officers respond to the call, they may discover that the emergency was of a different nature. For example, a call-taker may enter “burglary,” but when the officer arrives on the scene, he or she may learn that there is actually a raccoon in the caller’s attic. Or a “mugging” may turn out to be a drug deal gone wrong when the customer refused to pay.[89] Without call type data, however, it is even more difficult to analyze where police resources are being used and where they could be replaced entirely or bolstered by community resources.[90]

[89] Peter C. Moskos, “911 and the Failure of Police Rapid Response,” *Law Enforcement Executive Forum* 7, no. 4, 2007), 137-149, 145, https://perma.cc/ZUL6-X4WM.
[90] For example, researchers studying the implementation of 311 in Baltimore, Maryland, were able to identify trends in call type migrating to the new system. Although the number of noise complaints increased during the implementation period, the use of 911 for noise complaints declined 87 percent from 266 calls per week to only 34.

- A 1989 study of 265 randomly recorded phone calls over a 24-hour period delved into how call-taker behavior in police-related emergencies influences how the event is constructed before the call is even dispatched.[91] The researcher also performed 36 hours of participant observation and found that the type of questions asked by call-takers and their interactions with the callers went beyond information-gathering to serve an interpretive function and help callers construct a narrative of the event that made organizational sense.[92]

- A 2004 study surveyed 420 U.S. police departments on their CAD system practices, including whether the departments used CAD data to analyze department activities.[93] Eighty-eight percent of the agencies reported using CAD incident data recorded by the dispatcher for analysis, whereas 65 percent used the responding officers' final assessment, highlighting the potential differences in each type of data source.[94] The researchers also noted that the list of call types that communications centers employ may not be sufficient to describe issues that fall under community policing, citing the example of the "other" call category, which is the largest call volume for some departments.[95]

- A 2007 study of the Baltimore Police Department's calls for service over the course of the year 2000—approximately 113,000 dispatched calls—found that officers made significant assumptions about the legitimacy of 911 calls based on the sparse information provided by dispatchers, and that those assumptions often affected their responses.[96] Officers who perceived calls as legitimate were more likely to make response a priority—in fact, perceived legitimacy (whether police could provide a service that would be meaningful) was a greater influence on their behavior than what type of service was needed.[97]

- A 2018 study compared 20,000 mental health-related calls for service to 20,000 domestic violence-related calls for service in Surrey, British Columbia, and found that mental health-related calls for service occurred most often on weekdays (particularly Mondays), whereas calls for service related to domestic violence peaked on weekends (especially Sundays).[98] Although these results may not be generalizable to other jurisdictions, knowing that specific types of calls can follow predictable patterns has

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Alberto Gonzales, Tracy Henke, and Sarah Hart, *Managing Calls to the Police with 911/311 Systems* (Washington, DC: DOJ, 2005), 2, https://perma.cc/ESR2-QEBE.
[91] James Gilsinan, "They Is Clowning Tough: 911 and the Social Construction of Reality," *Criminology* 27, no. 2 (1989), 329-344, https://perma.cc/2RRV-39DW. The study sampled 265 randomly recorded calls.
[92] Ibid.
[93] McEwen, Ahn, Pendleton, et al., *Computer Aided Dispatch in Support of Community Policing*, 2002, 3, 5, 86-99.
[94] Ibid., 90.
[95] Ibid., 2.
[96] Moskos, "Failure of Police Rapid Response," 2007, 145.
[97] Ibid.
[98] Adam Vaughan, Kathryn E. Wuschke, Ashley N. Hewitt, et al., "Variations in Mental Health Act Calls to Police: An Analysis of Hourly and Intra-Week Patterns," *Policing* 41, no. 1 (2018), 58-69, 66.

value for police and public safety communications agencies interested in determining where—and when—to allocate appropriate and limited resources.

- A 2019 study of 514 calls to an anonymized call center in the United Kingdom found that the first substantive question asked by a call-taker carried "a diagnosis of the merits of the caller's case and an implication of the call's likely outcome."[99] The researchers were able to divide these substantive questions into four categories: "On a gradient of increasing skepticism, these are requests for the caller's location (which are treated as indicating that police action will be taken); open-ended requests for further information (treated as neutral); and queries of the relevance of the incident or legitimacy of the caller, and reformulations of the caller's reason for calling (both projecting upcoming refusal of police action)."[100]

Response time

Response time—the time between the call coming in and responders arriving at the scene—is one of the easiest metrics to review and compare either within a single jurisdiction or between jurisdictions. Response time in medical emergencies is critical: a 2002 study, for example, found that mortality rates in medical emergencies rose sharply beyond a response time of five minutes.[101] The value of response time in policing presents a more nuanced question.

Does response time affect case closure?

There are calls when response time would seem obviously critical: if a crime is ongoing at the time of the call, responding officers may have an opportunity to stop it. But, in the aggregate, response time appears to have little statistical relationship to the probability of making an arrest or even to closing the case.

- As early as 1976, researchers in Kansas City, Missouri, reviewed 1,106 response time surveys collected over a four-month period in the South Patrol District in 1973 and found that response time is barely, if at all, related to likelihood of positive case outcomes such as case clearance or property recovery.[102] They did, however, find a positive correlation between civilian perceptions of policing quality and short response times.[103]

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[99] Alexandra Kent and Charles Antaki, "Police Call-takers' First Substantive Question Projects the Outcome of the Call," *Applied Linguistics* amz002 (2019).
[100] Ibid.
[101] Thomas H. Blackwell and Jay S. Kaufman, "Response Time Effectiveness: Comparison of Response Time and Survival in an Urban Emergency Medical Services System," *Academic Emergency Medicine* 9, no. 4 (2002), 288-295, 293-95. Similarly, other researchers found that the odds of survival were higher for patients who had been responded to within four minutes. Peter T. Pons, Jason S. Haukoos, Whitney Bludworth, et al., "Paramedic Response Time: Does It Affect Patient Survival?" *Academic Emergency Medicine* 12, no. 7 (2005), 594-600, 596-598, https://perma.cc/QY7N-XKCG.
[102] Tony Pate, Amy Ferrara, Robert A. Bowers, and Jon Lorence, *Police Response Time: Its Determinants and Effects* (Washington, DC: Police Foundation, 1976), 48, https://perma.cc/Z9RM-68AV.
[103] Ibid. For the formal report completed a year later by the Kansas City Police Department, see Kansas City Police Department, *Response Time Analysis: Executive Summary* (Washington, DC: DOJ, 1978), https://perma.cc/JA66-J992.

- A 1980 study conducted in York, Pennsylvania, sampling approximately 31,000 calls for service in 1976, also found that the relationship between response time and clearance rate was tenuous, although researchers cautioned that the study should be repeated with more data and better information about which crimes were reported and cleared.[104] They expressed concern that breaking the jurisdiction's 38 call classifications for police service into three broad categories had oversimplified the study's results.[105]

- A 1984 DOJ study sampling 3,332 cases from call through completion between April 1979 and January 1980 from four jurisdictions—Peoria, Illinois; Rochester, New York; Jacksonville, Florida; and San Diego, California—confirmed the findings of the Kansas City study and advanced the hypothesis that the negligible difference in outcome was because in many cases crimes are not reported until they are over.[106] The researchers also found a correlation between the type of crime and whether police response time had a statistically significant impact on likelihood of arrest and noted that, in most cases, it did not.[107] Ultimately, the researchers concluded that chances of arrest were most influenced by civilian response time from incident to call, not police response time to a call for service.[108]

- A 1998 project discussed the potential for research made possible by the advent of CompStat, a tracking model for policing statistics developed in the 1990s by the NYPD.[109] The author suggested that the rich data available in a CompStat system could lend itself to the development of evidence-based policing procedures, using response time as one example. He proposed that rather than focusing solely on response time, police departments could be tracking call outcomes and repeat calls to see if the first response was effective.[110]

- A 2007 study of Baltimore's Eastern District, analyzing approximately 113,000 calls made in 2000, affirmed again that response time has a minimal effect on the likelihood

[104] Stevens, Webster, and Stipak, "Response Time: Role in Assessing Police Performance," 1980, 226.
[105] Ibid., 215.
[106] William Spelman and Dale K. Brown, *Calling the Police: Citizen Reporting of Serious Cri*me (Washington, DC: DOJ, 1984), 6-7 (sampling methodology), 61 (conclusions), https://perma.cc/BTY3-23NV. Researchers controlled for type of crime, category ("involvement" versus property crimes), and for whether a crime was in progress or not during the call. Calls resulting in on-scene arrests were oversampled to ensure enough of them were included in the study.
[107] Response time had the most significant, albeit slight, effect in what the researchers categorized as "involvement" crimes—assault, robbery, burglary, larceny, and motor vehicle theft—when those crimes were reported in progress. Ibid., 60-72.
[108] Ibid., 173-175.
[109] Lawrence W. Sherman, *Evidence-Based Policing* (Washington, DC: Police Foundation, 1998), https://perma.cc/7WQU-PFCT. For the development of CompStat, see U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Assistance, Police Executive Research Forum, *CompStat: Its Origins, Evolution, and Future in Law Enforcement Agencies* (Washington, DC: Police Executive Research Forum, 2013), 2-6, https://perma.cc/UX84-VNPP.
[110] Sherman, *Evidence-Based Policing*, 1998, 5.

of arrest.[111] The study also examined whether response time has a deterrent effect on crime and concluded that it did not.[112]

Recent research has reexamined the link between response time and likelihood of arrest, and the results have been more mixed.[113] This may be partly because the newer studies had access to more data—that is, rather than simply reviewing response time, category of crime, and whether an arrest was made, the researchers could readily add data points like where the call was coming from to match neighborhood characteristics and see if there were more factors at play in achieving a particular outcome than just response time.[114] Being able to study neighborhood characteristics to see how they affect response time may finally yield an answer to whether—and under what circumstances—response time matters for police.

What factors affect response time?

With richer pools of data to draw from, researchers can now study not only how fast police respond to calls for service, but what factors may be affecting their speed.

- Studies in the United Kingdom in 2001 and 2005 suggested that faster response times by two-officer vehicle patrols increased the likelihood of making an arrest for in-progress burglaries.[115] However, the authors declined to extend their research to conditions in the United States, noting the significantly different challenges of policing in a U.S. jurisdiction. Another United Kingdom study in 2017 found that in Manchester, improving response time by 10 percent led to a 4.7 percent greater chance that a case would be "cleared," or resolved with an arrest.[116] Faster response time was correlated with a larger increase in the chance of arrest in cases involving theft and a smaller increase in cases involving violent crime.[117]

[111] Moskos, "Failure of Police Rapid Response," 2007.
[112] Ibid.
[113] Under specific conditions in the United Kingdom, response time correlates to a slightly increased chance of apprehending a suspect for an in-progress burglary. Laurence Blake and Richard Timothy Coupe, "The Impact of Single and Two-Officer Patrols on Catching Burglars in the Act: A Critique of the Audit Commission's Reports on Youth Justice," *British Journal of Criminology* 41, no. 2 (2001), 381-396; and Richard Timothy Coupe and Laurence Blake, "The Effects of Patrol Workloads and Response Strength on Arrests at Burglary Emergencies," *Journal of Criminal Justice* 33, no. 3 (2005), 239-255. Another study in the United Kingdom demonstrated a positive correlation between improved response time and percentage of cases cleared. Jordi Blanes i Vidal and Tom Kirchmaier, "The Effect of Police Response Time on Crime Clearance Rates," *Review of Economic Studies* 85, no. 2 (2018), 855–891. Although researchers for the United Kingdom studies declined to extend their results to the United States, a 2012 study in Houston, Texas, also found a slight correlation between response time and arrest for in-progress burglary calls. Abdullah Cihan, Yan Zhang, and Larry Hoover, "Police Response Time to In-Progress Burglary: A Multilevel Analysis," *Police Quarterly* 15, no. 3 (2012), 308-327.
[114] See generally Cihan, Zhang, and Hoover, "Police Response Time to In-Progress Burglary," 2012.
[115] Blake and Coupe, "Catching Burglars in the Act," 2001, 381-396 (sampling 441 cases from an anonymized police force serving 2.6 million people between July and December 1996); and Coupe and Blake, "Arrests at Burglary Emergencies," 2005, 239-255 (sampling 406 cases from an anonymized police force serving 2.6 million people between July and December 1996). In both studies, researchers controlled for number of officers (one versus two); prior activity; day versus nighttime; and zulu (i.e., rapid response) versus panda (i.e., primarily nonemergency and routine) patrols.
[116] Blanes i Vidal and Kirchmaier, "Crime Clearance Rates," 2018. Burglary characteristics were used as control variables; researchers also controlled for area size, workloads, and basic command unit.
[117] Ibid.

- A 2012 study in Houston analyzing 5,290 in-progress burglary calls for service in 2007 found correlation between response time and likelihood of arrest.[118] The study also examined neighborhood characteristics, finding police calls for service had faster response times in disadvantaged neighborhoods than in more affluent ones, as determined by census tract data.[119]
- A 2014 follow-up study comparing 5,898 in-progress burglary calls for service in Houston and 7,746 in Dallas in 2006 found that concentrated disadvantage, immigrant concentration, and residential stability were important predictors of the distribution of police response time patterns for in-progress burglary calls in both cities, although the results were not consistent for the two locales.[120] For example, police response was slower to neighborhoods with more concentrated disadvantage in Dallas and faster in Houston.[121] In both cities, however, response time was faster for neighborhoods with more immigrants and less stability.[122]
- A 2017 study in Houston of 10,000 cases from September 2010 to August 2013 explored the factors that affect response time for a different narrow category of calls: intimate partner violence.[123] They found that the race of the caller, whether a weapon was involved, and the day and time of incidents were all significantly correlated with response time—predictably, in the case of a weapon, which raised the priority code of the call.[124] Latino callers experienced the fastest response times.[125] At a neighborhood level, concentrated disadvantage, immigrant concentration, and residential instability were also significantly associated with faster response times.[126]

[118] Cihan, Zhang, and Hoover, "Police Response Time to In-Progress Burglary," 2012. A limitation of the study was that it controlled only for significant incident characteristics, looking at one type of crime, in one jurisdiction. Researchers were not able to control for deployment density, traffic congestion, police workload, and police behavior—all of which are likely to contribute to response time.
[119] Ibid.
[120] Cihan, "A Tale of Two Cities," 2014, 344. Researchers controlled for source of the call (e.g., burglar alarm, automated call, or civilian-initiated call) and for effects of calls for service rates at the census tract level (as a way of controlling for the distribution of calls across service neighborhoods).
[121] Ibid., 351.
[122] Ibid.
[123] Lee, Lee, and Hoover, "What Conditions Affect Police Response Time?" 2017, 61-80. The fixed effect model for this study completely controlled for census tract level variation but could not control for deployment concentration of police units and geographic concentration of incidents, which may influence response time.
[124] Ibid., 71-72.
[125] Ibid., 72.
[126] Ibid.

How can police behavior be altered to improve response time?

By using demographic data, researchers have also attempted to model police behavior that will reduce or optimize response time in police calls for service.

- A 2007 study in Manchester, United Kingdom, modeled how call congestion and increased demands on policing resources affected response time and made suggestions for reaching an "optimal" number of alarms per officer per shift to increase productivity.[127] Treating alarms as a "disruption" in normal service patterns, they developed a system using the officer's experience and location to predict how long an alarm call would take, and the likelihood that a given alarm would be "false."[128]
- A 1982 study of an unnamed "large city" in the United States explored how routinely collected data could be used to monitor and improve patrol response functions.[129] The study focused not on collecting additional data, but how the data already in the system could inform researchers about delay factors.[130] The study was designed to demonstrate how individual departments could structure their own studies, rather than to return a specific result.
- In 2018, a researcher at Stanford compared data from 40 jurisdictions' CAD systems to derive a "Maximum Covering Model," which would determine the optimal place for stations and vehicle patrol routes in a jurisdiction to improve response time.[131] However, the researcher found that decreasing response time for one priority type of call produced a concurrent increase in response time for other priorities.[132]

How does response time affect community relations?

Regardless of the effect of response time on crime or arrest, it is clear that response time has a significant impact on people's satisfaction with police.

- The same 1976 study of Kansas City 911 call outcomes that found a weak correlation between response time and outcomes found a strong correlation between response time and civilian satisfaction.[133]
- A 1984 study attempted to link objective and subjective measures of performance to help police determine which objectively measurable markers they could use to set policing

[127] Erwin A. Blackstone, Andrew J. Buck, Simon Hakim, and Uriel Spiegel, "The Disturbance Model and Congestion in Emergency Response," *Manchester School* 75, no. 1 (2007) 104-121, https://perma.cc/7LJ2-N4V3. Researchers controlled for normal call volume, industrial versus residential neighborhoods, and prior alarm behavior.
[128] Ibid., 118.
[129] Michael G. Maxfield, "Service Time, Dispatch Time, and Demand for Police Services: Helping More by Serving Less," *Public Administration Review* 42, no. 3 (1982), 252-263.
[130] Ibid.
[131] Bennett, "Police Response Times," 2018.
[132] Ibid., 33.
[133] Pate, Ferrara, Bowers, and Lorence, *Police Response Time*, 1976, 48.

goals.[134] The researcher reviewed survey data from Los Angeles, California, and Tuscaloosa, Alabama, regarding both objective (empirical measures like response time) and subjective (civilian satisfaction) performance rankings.[135] Although inconclusive, the study noted that response time was conceptually linked to subjective measures of performance.[136]

- A 1999 study sampling a primarily Black population found a strong relationship between respondents' evaluation of response time and their positive evaluation of overall police performance.[137] The researchers used survey data from 338 people in Charlotte, North Carolina, and noted that their results were significantly different from previous surveys sampling primarily white populations—suggesting that similar surveys might not contain findings that should be extended beyond the surveyed communities.[138] They collected data about age, gender, neighborhood, education, income, and employment status to examine the survey results in more depth and found that, for example, higher levels of educational attainment in the community studied correlated with more positive civilian perceptions of police, whereas in previous, white-focused studies it had a negative correlation.[139]

- A 2003 study of police and fire department management strategies in 50 U.S. localities, however, found little link between the measures commonly used to establish performance on an administrative level, such as number of arrests, and civilian satisfaction.[140] The researcher noted, however, that she had experienced significant difficulty in developing a sampling strategy because the inconsistent descriptions for measures across the locations studied resulted in so many missing values and variables.[141]

Studies analyzing more granular 911 datasets

A number of studies suggest not only what data could be collected and used to inform policing practice, but how to better use the data already automatically collected. As early as 1987, researchers recognized the improved data collection capabilities of E911 and envisioned how this data could shape police response to emergencies.[142] Although computers at the time were limited in their ability to manipulate large datasets or develop predictive models, many of the researchers' ideas have since been explored. Police are already using this data on a local level to

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[134] Roger B. Parks, "Linking Objective and Subjective Measures of Performance," *Public Administration Review* 44, no. 2 (1984), 118-127.
[135] Ibid., 118-119.
[136] Ibid.
[137] Thomas B. Priest and Deborah Brown Carter, "Evaluations of Police Performance in an African American Sample," *Journal of Criminal Justice* 27, no. 5 (1999), 457-465.
[138] Ibid.
[139] Ibid., 460-463.
[140] Janet Kelly, "Citizen Satisfaction and Administrative Performance Measures: Is there Really a Link?" *Urban Affairs Review* 38, no. 6 (2003), 855-866, https://perma.cc/J3XC-CWQB.
[141] Ibid., 859.
[142] Patricia Kuhn and Thomas Hoey, "Improving Police 911 Operations in Washington, D.C.," *National Productivity Review* 6, no. 2 (1987), 125-133.

inform administrative decisions and monitor departmental practices and their effects.[143] (See "Using 911 data: Examples from the field" on page 47.) Although in the past researchers might have to make a Freedom of Information Act request to obtain this data, some jurisdictions are making their data public and accessible on the Internet. For example, New Orleans has released calls for service data on its own initiative.[144] This database and others like it can help realize the vision that researchers have had for decades: the ability to predict demand for police resources so well that the right responders can be where they are needed at the right time.

- A 2002 study reviewed the universe of rich basic data collected by U.S. CAD systems and discussed its utility in policing.[145] Researchers noted that the largest call volume for many jurisdictions was simply coded "other" and described the greatest weaknesses of CAD systems as their insufficient categorization system and dependence on caller—rather than call-taker or responder—assessment for description.[146] In fact, the study found that "less than 20 percent of the citizen calls in a CAD system are for serious crime incidents—the rest are for incidents that affect the callers' quality of life to such an extent that they believe police intervention is necessary."[147]

- A 2005 DOJ report discussing the advantages of managing civilian calls and expectations when duties are shared between 911 and 311 (nonemergency) systems discussed how patterns of calls could be used to alter how policing resources are distributed.[148] The report focused on Baltimore, Maryland's 311 implementation, and noted that capturing more data about how each line is used could help other departments successfully implement nonemergency lines to ease the burden on PSAPs.[149] (See "Emerging alternatives to 911" on page 49.)

- Another 2005 study explored how gathering data from call through outcome—rather than stopping at response—could inform call-taker training for types of calls such as those related to intimate partner violence.[150] The study found, among other things, that only half of departments required specialized training for call-takers and dispatchers regarding intimate partner violence.[151] More study is needed, and the researchers called for additional data collection as well as for the development of model policies that could then be studied to determine their effectiveness.[152]

- A 2006 study of 448 Seattle women who had been victimized by a male intimate partner investigated how data being gathered about calls related to intimate partner violence

[143] See for example Center for Public Safety Management, *Police Operations and Data Analysis Report: Roswell, Georgia* (Washington, DC: Center for Public Safety Management, 2017), https://perma.cc/S6VN-YTWY.
[144] City of New Orleans, "Calls for Service 2017," 2018.
[145] McEwen, Ahn, Pendleton et al., *Computer Aided Dispatch in Support of Community Policing*, 2002.
[146] Ibid., 2.
[147] Ibid., 22.
[148] Gonzales, Henke, and Hart, *Managing Calls to the Police*, 2005.
[149] Ibid., 8.
[150] Meg Townsend, Dana Hunt, Sarah Kuck, and Caity Baxter, *Law Enforcement Response to Emergency Domestic Violence Calls for Service* (Washington DC: DOJ, 2005), https://perma.cc/C4ZN-F2A8.
[151] Ibid., 48.
[152] Ibid., 49.

could be used to inform police about the callers themselves.[153] The study delved into commonalities between frequent callers, and mapped different call patterns to severity of violence.[154] Researchers found that women were more likely to call police repeatedly if they had children, experienced severe violence, or were injured by their partner.[155]

- The 2011 study of Portland, Oregon, that analyzed hot spots demonstrated that it is possible to use this data not only to put policing resources where they are needed, but also to add call center capacity during times of predictably high call volumes.[156]
- In 2014, researchers analyzed a year of CAD data for the Lorain, Ohio, police department including calls for service type and call location in order to develop an optimized districting system for police resources.[157]
- In 2015, researchers used 911 data to examine the "broken windows" theory, which posits that order-maintenance policing is the best deterrent of crime.[158] The study used location data from more than 200,000 911 calls for service made in Boston, Massachusetts, and found that private conflict was more highly correlated with crime than was public disorder.[159]
- Also in 2015, researchers reviewed New York City police calls for service data to detect patterns in call type and to determine how to remove "noise" from data samples.[160] Although the researchers were unable to develop conclusions from the dataset they had, they established procedures for data manipulation and have planned future studies to incorporate richer datasets and add factors like weather and humidity.
- A 2015 study of San Francisco's CAD data from May 2011 through February 2015 highlighted additional data challenges experienced by researchers after the deployment of a new CAD system in 2014.[161] The new and old systems did not use exactly the same codes, and analysts had to find a way to compare similar but nonmatching data fields.[162] However, researchers were able to readily identify not only the top 20 incident codes for

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[153] Amy E. Bonomi, Victoria L. Holt, Diane P. Martin, and Robert S. Thompson, "Severity of Intimate Partner Violence and Occurrence and Frequency of Police Calls," *Journal of Interpersonal Violence* 21, no. 10 (2006), 1354-1364, 1354.
[154] Ibid., 1358.
[155] Ibid.
[156] Cramer, Brown, and Hu, "Predicting 911 Calls Using Spatial Analysis," 2011.
[157] Philip Stinson, Steven Brewer, and John Liederbach, "Lorain Police Department: A Study to Improve Patrol Deployment," *Review of Economic Studies* 85, no. 2 (2018), 855-891, https://perma.cc/NJK3-GUAG.
[158] James Q Wilson and George L. Kelling, "Broken Windows: The Police and Neighborhood Safety," *Atlantic*, March 1982, https://perma.cc/C2R6-AKDE. The "broken windows" policing model has justifiably been criticized for disproportionality targeting poor inner-city neighborhoods and contributing to overpolicing of communities of color.
[159] Daniel Tumminelli O'Brien and Robert J. Sampson, "Public and Private Spheres of Neighborhood Disorder: Assessing Pathways to Violence Using Large-Scale Digital Records," *Journal of Research in Crime and Delinquency* 52, no. 4 (2015), 486-510, https://dash.harvard.edu/bitstream/handle/1/17553309/JRCD_O%27Brien_Sampson%202015.pdf?sequence=3&isAllowed=y.
[160] Chohlas-Wood, Merali, Reed, and Damoulas, "Mining 911 Calls in New York City," 2015.
[161] Dankert, Driscoll, and Torres, *San Francisco's 911 Call Volume Increase*, 2015.
[162] Ibid., 10.

police calls in a given year, but also to demonstrate that the system's two "other" codes made up more than 30 percent of logged calls (the next most common code, a dispute without weapons, made up only 6 percent of calls).[163] The study recommended adding additional functions to the CAD system to more efficiently deal with duplicate calls, dropped calls, and accidental calls in the face of increasing call volume to the city's PSAPs.[164]

- A 2018 study that mapped different types of calls to day and time in Surrey, British Columbia, found that these calls followed predictable patterns within the jurisdiction studied.[165] However, because of the decentralized nature of 911 data, it was not possible to compare those patterns to other jurisdictions within the scope of the study.

[163] Ibid., 14.
[164] Ibid., 21.
[165] Vaughan, Wuschke, Hewitt, et al., "Variations in Mental Health Act Calls to Police," 2018.

Using 911 data: Examples from the field

Because 911 data is not uniformly collected, it is difficult to compare jurisdictions except on very broad levels such as response time or call volume. There are no multi-city studies analyzing calls from intake to outcome to develop training or systems that would establish not only how well police are doing their job, but also whether police response is necessary at all.[a] By collecting data from intake through outcome on each 911 call and comparing this information across jurisdictions, it is likely that patterns will develop that can help shape every aspect of emergency response from call-taker training through dispatching the right team through ensuring community safety and health.

Some departments are already doing this work. In 2007, the Houston police department responded to 15,122 calls for mental health issues; by 2014, the number had more than doubled to 37,032 calls.[b] Identifying this surge in *call type*, rather than merely treating it as an increase in *overall volume*, resulted in the 9-1-1 Crisis Call Diversion (CCD) program, by which dispatchers identify and refer qualifying nonemergency mental health-related calls for immediate connection to a phone counselor.[c] Implementation of the CCD has resulted in hundreds of thousands of dollars in cost savings as well as the promotion of more appropriate mental-health—rather than criminal justice—responses to crisis situations.[d] In 2017 alone, CCD counselors handled 7,264 calls for service, resulting in 2,151 diversions away from responses by patrol officers.[e]

Other jurisdictions have been able to use data about specific call types or patterns to implement alternate programs for people in crisis. In this regard, police can follow the examples of medical and fire personnel in establishing community partnerships that ease the burden on scarce resources. In Washington, DC, where one in four calls received is not a public safety emergency, a triage program has helped reduce the use of 911 resources.[f] Triage nurses sit alongside 911 dispatchers and can set up medical appointments and arrange rides for callers if they deem the situation to be nonemergency (e.g., sprained ankles or coughs).[g] Another program was created by the Baltimore City Fire Department to connect repeat callers with nurses and case managers.[h] The program was developed after the department realized that the majority of calls for service were coming from people who didn't need the fire department, but who were instead calling with questions about issues such as medical and food insecurity problems or insurance.[i]

[a] One study does show positive correlation between 911 call-taker behavior and call outcome. Alexandra Kent and Charles Antaki, "Police Call-takers' First Substantive Question Projects the Outcome of the Call," *Applied Linguistics* amz002 (2019).

[b] Houston Police Department, Mental Health Division, "Crisis Call Diversion Program," October 18, 2017, https://perma.cc/XW5L-TCXB.

[c] Ibid.

[d] Ibid.

[e] Ibid.

[f] Selena Simmons-Duffin, "Can Triage Nurses Help Prevent 911 Overload?" NPR, April 19, 2018, https://perma.cc/K8YG-SDMF.

[g] Ibid.

[h] Carolina Cournoyer, "Reducing Repeat 911 Callers," *Governing*, April 28, 2011, https://perma.cc/C7LZ-UJ2E.

[i] Ibid.

New options within police departments

Some calls for service, even though they are not emergencies, genuinely do require a response from police—either for documentation (e.g., traffic accidents) or community relations purposes. But these calls can strain PSAPs and police departments and do not require *immediate* response by sworn personnel. Some police departments have already established methods to promote efficiencies in police response by creating alternative ways for community members to report issues when sworn personnel are not (or are not immediately) necessary.

The Tucson Police Department (TPD) has pioneered initiatives to expand its menu of alternative responses for dealing with large calls for service volumes.[166] Some of these alternatives include

Crisis Call Diversion (CCD) program residential and commercial burglary (in cases where the victim has already checked the premises);

- nonsworn personnel to handle calls for service for incidents such as
  - residential and commercial burglary (in cases where the victim has already checked the premises),
  - found property/evidence pickups,
  - shoplifting/larceny incidents where evidence is present,
  - traffic collisions involving no or minor injuries,
  - disorderly or disobedient children,
  - code enforcement/quality of life issues, and
  - traffic point control (e.g., when traffic lights are out);
- encouraging community members to report a variety of lower-level crimes through the department's Internet reporting tool;
- establishing a Collision Reporting Center, where individuals involved in a minor crash can avoid waiting at the scene and report property damage accidents with TPD and their insurance companies;
- encouraging community members to come to TPD stations to file reports and ask crime-related questions and extending front desk service until 10:00 p.m. seven days a week;
- utilizing nonsworn Community Service Officers to respond to a plethora of nonurgent calls (e.g., blocked driveways or runaway juveniles);
- establishing an appointment-based response for calls for which it is mutually convenient for police to respond at a later, less busy time;[167]
- eliminating certain calls for service by transferring them to more appropriate services or simply not generating a call for service, including;
  - barking dogs (redirected to animal control);

[166] Chris Magnus, "Tucson Police Department Meeting the Challenges of a Growing Call Load," Arizona Daily Star, June 11, 2018, https://perma.cc/LV7W-NA4D.
[167] Ibid.; and personal communications between the authors and the Tucson Police Department, September 7, 2018, on file with Vera.

- loose livestock (redirected to Tucson's livestock board);
- stalled vehicles (no call for service generated if vehicle is not a hazard or blocking traffic);
- lost electronic devices (if the device is lost and the owner locates it via GPS, no call for service is generated);
- establishing a Theft Reduction Apprehension Program where the police department trains store loss prevention personnel to process shoplifters, complete forms, and write a trespass letter and direct the person found shoplifting to respond to the substation to receive a citation (no call for service generated); and
- status offenses (police personnel do not intervene in any juvenile status offenses other than runaway incidents or underage drinking).

Similarly, Camden County Police Department (CCPD) (New Jersey) has implemented a variety of departmental changes to effectively deal with large volumes of calls for service. For instance, the department implemented a call deferral policy where communications operators instruct callers to fill out self-reporting forms at the police department for certain types of calls, including motor vehicle accidents (except accidents that involve injuries), nondrivable cars, deployed air bags, or drivers who are believed to be under the influence of drugs or alcohol, as well as calls involving reports of theft or lost/missing property.[168] Additionally, CCPD established an alarm verification response protocol: police units will not be dispatched to reports of alarms that have not been verified (with the exception of holdup, duress, and panic alarms).[169]

Emerging alternatives to 911

A significant burden on the 911 system is created by individuals seeking information or resources that fall outside the scope of crisis intervention. For these calls, two alternatives already exist: 211 and 311 information services. And crisis hotlines, a third nonemergency service, can help connect community members with the resources they need in a mental health crisis.

211. The 211 service can be used to connect callers with community health and human services resources.[a] A community resource specialist assists callers with identifying local services and resources (e.g., shelter and housing options, employment and education opportunities, veteran services, addiction and rehabilitation programs, various support groups, etc.).[b] 211 services are available to 94 percent of the population across all 50 states and Washington, DC, and millions of people make use of them already.[c] In 2017, nearly 13 million 211 calls were placed; the callers were most frequently referred to physical and mental health services, employment opportunities, homelessness prevention services, and housing assistance.[d] Because of this, 211 has been regarded as a service that promotes early intervention and helps avoid the use of 911, highlighting the need to raise awareness of the service.[e]

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[168] Ibid.; and personal communications between the authors and the Tucson Police Department, September 7, 2018, on file with Vera.

[169] Ibid. To verify an alarm, the alarm company contacts the person associated with an alarm to confirm that there is an emergency. If they cannot reach the person, they may dispatch a private guard to the alarm location before dispatching emergency responders. Ring, "Guard Response Verification Service," https://perma.cc/TD2R-GRVJ.

311. 311 is a nonemergency public services line people can use to file complaints about issues such as noise, potholes, and graffiti, as well as obtain public information on a variety of topics.[f] 311 call centers are still relatively rare compared to 911 call centers. An article published in *Governing* in 2014 reported that just 300 U.S. municipalities had operational 311 call centers at that time (compared to the more than 6,000 PSAPs servicing 911 calls in 2017).[g] Although this number has likely since increased, 311 is far from operating at a national scale. In locations where it has been adopted, however, its popularity is evident: a 2001 study of 311 implementation in Baltimore, Buffalo, Dallas, and Phoenix, showed that low-priority calls migrated to the 311 call center in significant numbers.[h]

Crisis hotlines. Another alternative response to calls for service—one centered on providing mental health crisis response in lieu of or in coordination with police, is the crisis hotline. These specialized hotlines provide services to individuals experiencing mental health issues.[i] Community members can use such hotlines to request help for themselves or others without notifying the police.[j] Research demonstrates that hotline services are effective at reducing psychological distress in both suicidal and nonsuicidal callers.[k] Crisis services can also coexist with enforcement responses. Some law enforcement agencies collaborate with mental health crisis facilities to link calls from mental health providers directly to dispatch.[l] And, in some communities, residents have become familiar enough with the availability of crisis intervention teams that they will explicitly request them—instead of police—during 911 calls.[m]

[a] 211, "About ," https://perma.cc/6Q5B-L8EU.

[b] Ibid.

[c] Ibid.

[d] Ibid.

[e] Matthew L. Saxton, Charles M. Naumer, and Karen E. Fisher, "2-1-1 Information Services: Outcomes Assessment, Benefit–Cost Analysis, and Policy Issues," *Government Information Quarterly* 24, no. 1 (2007), 186-215, 201; Nancy Shank, "A Review of the Role of Cost–Benefit Analyses In 2-1-1 Diffusion," *American Journal of Preventive Medicine* 43, no. 6 (2012), S497-S505, S501 & S502, https://perma.cc/8D8R-LBY5. Westchester County, New York, provides residents with a resource outlining whether 911 or 211 services are appropriate for their situation. Westchester County, "Do I Call 9-1-1 or 2-1-1?," https://perma.cc/23CR-7FJD.

[f] Rebecca Tuhus-Dubrow, "Who is Most Likely to Dial 311?," Next City, April 8, 2014, https://perma.cc/HK63-CZB7.

[g] Tod Newcombe, "Is the Cost of 311 Systems Worth the Price of Knowing?" *Governing*, March 2014, https://perma.cc/D996-BU77. For the number of PSAPs see NENA, "9-1-1 Statistics," https://perma.cc/RS7Y-SZEJ.

[h] The study of call patterns was limited to Baltimore and Dallas. In Dallas, although calls migrated to the 311 number, the 311 and 911 call centers were integrated to the extent that adding the nonemergency line had little effect on policing practice. In Baltimore, however, nearly all low-priority calls migrated to 311, correlating with a decrease in dispatched calls of 3,700 per month. This contrast shows how different implementation strategies can affect results as much as civilian behavior. Lorraine Mazerolle, Dennis Rogan, James Frank et al., *Managing Citizen Calls to the Police: An Assessment of Non-Emergency Call Systems* (Washington, DC: DOJ, 2003), iii-vi, https://perma.cc/4R7D-NL2P.

[i] Fox News, "Broome 911 Dispatch Utilizing Faster Care for Mental Illness," WICZ, April 24, 2018, https://perma.cc/LQ4K-97BS.

[j] Sometimes these hotlines are exclusively for people experiencing a crisis (1-800-SUICIDE), whereas others provide services for community members who know someone experiencing a crisis. See for example Baltimore Crisis Response Inc., "Telephone Crisis Hotline," https://perma.cc/Z65C-9PQB; and Clara Martin Center, "Community Crisis Response," https://perma.cc/CY6Q-K7AH.

[k] For an example of crisis response systems that provide services for individuals in crisis, see Anne Arundel County Mental Health Agency, Inc., "Crisis Services," https://perma.cc/ZG5Y-F5BC. For research showing the effectiveness of crisis hotlines, see Madelyn S. Gould, John Kalafat, Jimmie L. Harris Munfakh, and Marjorie Kleinman, "An Evaluation of Crisis Hotline Outcomes. Part 2: Suicidal Callers," *Suicide and Life-threatening Behavior* 37, no. 3 (2007), 338-352; John Kalafat, Madelyn S. Gould, Jimmie L. Harris Munfakh, and Marjorie Kleinman, "An Evaluation of Crisis Hotline Outcomes. Part 1: Nonsuicidal Crisis Callers," *Suicide and Life-threatening Behavior* 37, no. 3 (2007), 322-337; and Wayne K. Rhee, Michael Merbaum, Michael J. Strube, and Susan M. Self, "Efficacy of Brief Telephone Psychotherapy with Callers to a Suicide Hotline," *Suicide and Life-Threatening Behavior* 35, no. 3 (2005), 317-328, 325, 327.

[l] Melissa Reuland, *A Guide to Implementing Police-based Diversion Programs for People with Mental Illness* (Rockville, MD: SAMHSA GAINS Center, TAPA Center for Jail Diversion, 2004), 14-16, https://perma.cc/EX67-XBMJ.

[m] Personal communications between the authors and Tucson Police Department, September 7, 2018. On file with Vera.

Conclusion

The 911 call processing system has undergone significant growth and development since its inception: from its birth in the late 1960s, through the professionalization of the emergency communications field during the 1970s, to the development of new technology in E911 and what ultimately grew to be NG911. Nonetheless, there is a pressing need for more innovation in this space and for research exploring key features of the system, including call volume, type, and outcomes at the national, state, and local level. Analysis of calls for service data provides a huge and largely untapped opportunity for researchers and practitioners to inform and transform policy and practice. And understanding the landscape of 911 call processing at a deeper level gives stakeholders across the board the chance to develop sound alternatives beyond police responses to calls for service. To this end, further studies should be done to develop knowledge or aggregate existing data in the areas set out below.

- **Coding and protocols**. In the absence of research into the protocols in place for 911 call-takers and dispatchers, as well as the processes by which information is gathered and communicated between and among call-takers, dispatchers, and responding officers, it is difficult to determine if current protocols are adequate and effective.

- **Adequacy of coding**. Studies are needed to examine the nature and volume of "other" types of calls (and call types in general) to determine how call types are used to inform agencies' decision making and practice, and whether new categories for call type should be included in CAD systems.

- **Metrics other than response time**. Given that a substantial number of calls for service are unrelated to crimes in progress, there is a real question whether a rapid response is necessary or even effective. Researchers should explore whether slower responses where the *most appropriate* officer is dispatched (one who has the appropriate training, skills, tools, demeanor, etc.) produce more favorable outcomes than prioritizing rapid response by the *first available* officer, which typically results in a lights and sirens response that can cause undue anxiety and adrenaline for officers and community members alike at the scene.

- **Call outcomes based on type of response.** Researchers have not examined the nature and outcomes of calls that are answered with police responses, precluding an understanding of whether police responses are the most appropriate way to deal with certain call types.
- **Frequent caller protocols.** Although there is some research on frequent 911 callers, there is a need for more studies that go beyond the types of calls that the literature is currently limited to (researchers could, for example, look at frequent callers for nuisance complaints to determine whether there are more appropriate ways to address those types of calls). The ways in which data is—and is not—collected currently make analyses of frequent callers very difficult. Enhancing data collection capabilities in this area is key to better understanding the frequent caller population and to assessing what factors contribute to—and ultimately can prevent—future calls.
- **Alternative response options.** Overall, despite the increase in alternative responses, there is still a need for additional innovation to both reduce calls for service and to improve the quality of responses, as well as for studies to evaluate the prevalence and effectiveness of each of these options. Although it is a promising sign that programs exist, it is important to understand where there are opportunities for growth and expansion. The efforts in agencies such as the Tucson Police Department and Camden County Police Department are just the beginning—for this endeavor, both agencies partnered with Vera's Policing Program to help expand alternatives locally and nationally by identifying gaps in research and practice. It is efforts like these that are necessary to fully understand the landscape of emergency communications with the goal of ultimately recognizing areas where there are opportunities to respond beyond applying enforcement.

911 and 911 call-takers play a vital role in U.S. law enforcement. As the United States continues to evaluate the role of its police in the community, understanding these critical components will be crucial to developing a system that best serves the nation.

Appendix 1: Summary of research

	Authors	Date	Summary of findings
1	Bennett	2018	CAD data from 40 police departments from 2015-2016 was used to study response time. Researchers found that CAD and location data can be used to generate models of optimal coverage. However, decreasing response time in one priority category increased response time in other categories.
2	Blackstone, Buck, Hakim et al.	2007	This Manchester, UK, study modeled traffic patterns in automated alarm calls for service and response and explored ways to optimize behavior. After determining what "normal" looked like, the study treated alarms as a "disruption" and developed a model for ideal numbers of alarms per officer per shift depending on officer experience and location, including the possibility of false alarms.
3	Blake & Coupe	2001	In Manchester, UK, two-officer patrols were more successful in apprehending in-progress burglary suspects than single-officer patrols under specific circumstances because of faster response times. The study sampled 441 911 cases between July and December 1996 from an anonymized police force serving 2.6 million people.
4	Blanes i Vidal & Kirchmaier	2017	This study of the 2008–2014 internal records of the Greater Manchester Police found that for certain crimes in the UK, response time has a statistically significant effect on clearance, with a 10% faster response time leading to 4.7% increase of likelihood of clearance, overall. The effects of a faster response time were stronger for theft, less for violent crime.
5	Bonomi, Holt, Martin et al.	2006	The study explored frequent caller behavior among 448 Seattle, Washington, women who had been involved in intimate partner violence (IPV) and found that women were more likely to contact police if they experienced severe physical or psychological IPV, had injuries, or lived with children.
6	Braga	2001	This study used 911 data from nine selected studies of Houston, Jersey City, Kansas City, Minneapolis, St. Louis, and Beenleigh (Queensland, Australia) to locate "hot spots" and found that focused police actions can prevent crime and disorder in crime hot spots without necessarily resulting in crime displacement.
7	Chohlas-Wood, Merali, Reed et al.	2015	Researchers mined 911 and 311 data from 2013–2014 in New York City and disaggregated calls by type to detect patterns in types such as "noise" and "crime." Researchers suggested that other data like weather and humidity could be included to refine results and better detect patterns.

8	Cihan, Zhang & Hoover	2012	This study of Houston 911 data for 5,290 in-progress burglary calls for service in 2007 found correlation between response time and likelihood of arrest for in-progress burglaries. The study also examined neighborhood characteristics, finding police calls for service had faster response times in disadvantaged neighborhoods than in more affluent ones, as determined by census tract data.
9	Cihan	2014	As a follow-up to the 2012 study by the same authors, this study compared 5,898 in-progress burglary calls for service in Houston and 7,746 in Dallas in 2006. Concentrated disadvantage, immigrant concentration, and residential stability were important predictors of the distribution of police response time patterns in Dallas and Houston, although not always in the same ways.
10	Coupe & Blake	2005	This study of two-officer patrols and 911 response sampled 406 911 cases between July and December 1996 from an anonymized police force serving 2.6 million people and found that quicker response times elevated the likelihood of an arrest being made in the UK, although the authors specifically declined to extend those results to U.S. policing.
11	Cramer, Brown & Hu	2011	Researchers analyzed 2,000 calls made to 911 between January 1 and May 31, 1998, in the Portland, Oregon, metro area to determine where areas of concentration of call volume occurred and compared these hotspots to neighborhood data to see what factors influenced call volumes.
12	Dankert, Driscoll & Torres	2015	Researchers analyzed CAD data from San Francisco from May 2011 to February 2015 and collected data on 475 calls by shadowing dispatchers to examine whether the city's CAD system was adequate to deal with increases in call volume. They recommended small changes to increase efficiency as well as to increase transparency into "unknown type" calls.
13	Famega, Frank & Mazerolle	2015	Researchers studied Baltimore dispatch data gathered over 1,304 hours of observation in 1999 to see how it could be used to assess efficiency and manage patrol officers' time. They concluded that analyzing call patterns and adjusting patrol routes to include predicted high call volume areas and times could increase efficiency.
14	Gardett, Clawson, Scott et al.	2016	A literature review of 149 studies of emergency dispatch research. Common topics of study were first point of contact care, professional status and consistency/protocols/training, resource allocation, and best practices for dispatch. Additional emerging topics that are ripe for study include using CAD/algorithms to determine the best response to an emergency.

15	Gilsinan	1989	This study used 265 recorded 911 calls to examine the interpretive function of call-takers in event construction before the call is dispatched and found that the types of questions asked help callers determine their narrative (and description) of the event.
16	Gonzales, Henke & Hart	2005	This DOJ report discusses the type of data gathering necessary to ensure that certain policy changes are effective in separating emergency and nonemergency policing response in the context of Baltimore, Maryland's 311 implementation.
17	Jasso, Fountain, Baru et al.	2007	Researchers developed and tested models with data from emergency calls made between September 1, 2004, and August 31, 2006, in San Francisco, then used them to predict high call volumes as a result of anomalous occurrences. "Predictions" were tested with anomalous occurrences already in the system.
18	Kansas City Police Department	1978	The Kansas City Police Department studied three years of internal records and found that overall response time was statistically unrelated to arrest probability. In addition, civilian satisfaction was more closely related to expectation and perception of response than to actual response time.
19	Kelly	2003	A study of 50 U.S. locations including both police and fire department data found that the link between objectively measurable data and subjective measures of satisfaction is tenuous at best. The researcher experienced significant difficulty in developing a sampling strategy because of inconsistencies in identifiers across the locations studied.
20	Kent & Antaki	2019	This UK study of 514 emergency calls found that the call-taker's first substantive question already carried a diagnosis of the merits of the caller's case, and an implication of the call's likely outcome.
21	Kuhn & Hoey	1987	During the implementation of E-911 in the U.S., researchers examined the ways the system could improve police response, including what data collection is possible and how the system can match demand with deployment.
22	Lee, Lee & Hoover	2017	This study focused on a narrow band of IPV calls in Houston, analyzing 10,000 cases from September 2010 to August 2013 to find factors that influence response time on a personal and neighborhood level. Researchers found that the race of the caller, whether a weapon was involved, and the day and time of incidents were all significantly correlated with response time—predictably, in the case of a weapon, which raised the priority code of the call. Latino callers experienced the fastest response times. At a neighborhood level, concentrated disadvantage, immigrant concentration, and residential instability were also significantly associated with faster response times.

23	Maxfield	1982	This paper examines how information routinely collected by urban police departments may be used to monitor the performance of the patrol response function. Data from one anonymized large city is used to examine the problem of delay in responding to civilian requests for police service.
24	McEwen, Ahn, Pendleton et al.	2002	A study combining national surveys of 420 police departments and case studies in San Diego, the District of Columbia, and Aurora, Colorado, found that CAD systems collect rich basic data that can and should be used to support community policing, and that less than 20 percent of the civilian calls in a CAD system are for serious crime incidents. The rest are for incidents that affect callers' quality of life to such an extent that they believe police intervention is necessary." The major identified weaknesses in CAD data are insufficient list of call types (largest call volume is "other") and dependence on caller assessment (e.g., is it burglary or robbery?).
25	Moskos	2007	The study examined approximately 113,000 calls made in 2000 in Baltimore's Eastern District to determine whether response time has a positive effect on odds of arrest or a deterrent effect on crime and found that the effect in either case was minimal at best.
26	O'Brien & Sampson	2015	Researchers re-examined "broken windows" policing as a paradigm and found that it doesn't hold up to large-scale data analysis. A study of 200,000 calls for service from Boston showed that private conflict is a better predictor of crime than public disorder.
27	Parks	1984	Survey data from Los Angeles, California, and Tuscaloosa, Alabama, shows that objective and subjective measures of police performance aren't necessarily exclusive: conceptually linked objective and subjective measures return correlated results. More data is needed to confirm the results of this study.
28	Pate, Ferrara, Bowers et al.	1976	This Kansas City, Missouri, study of 1,106 response time surveys collected over a four-month period in the South Patrol District in 1973 showed that short response time is likely to be unrelated to positive results but can be related to civilian satisfaction. Setting and meeting expectations was more important to satisfaction than actual response time.
29	Priest & Carter	1999	This study surveyed 338 people in Charlotte, North Carolina, most of whom were Black, and found a strong relationship between respondents' evaluations of police response time and their evaluations of overall police performance. Respondents' evaluations of the service their neighborhood receives also influenced their evaluations of overall police performance. The authors noted that previous studies had significantly different results but sampled a populations consisting mostly of white people.

30	Sherman	1998	This project discusses the research potential of CompStat in developing evidence-based policing methods, including what evidence is necessary all the way through case outcome. At the time of the study, current data practices were to collect only time of response rather than quality of service or repeat call data.
31	Spelman & Brown	1984	This U.S. Department of Justice study of four jurisdictions— Jacksonville, Florida; Peoria, Illinois; Rochester, New York; and San Diego, California—confirmed work by Kansas City Police Department that improved response time to crime calls does not significantly increase odds of arrest. The researchers hypothesized that this is because callers delay reporting until crime is over—even with access to instantaneous reporting via 911. The researchers found a slight correlation between the type of crime and whether police response time had a statistically significant impact on likelihood of arrest, noting that, in most cases, it did not.
32	Stevens, Webster & Stipak	1980	A study of York, Pennsylvania, data, sampling approximately 31,000 calls for service in 1976 found little if any correspondence between response time and likelihood that a crime will be "cleared." Researchers noted that more study is needed with more variables such as call type: response time almost certainly makes a difference for some calls but not others, and this was lost when aggregating all calls into three categories in the overall sample.
33	Stinson, Brewer & Liederbach	2014	Researchers analyzed a year of call for service type and location data from the Lorain, Ohio, CAD system to optimize police districting to better serve hot spots and balance workload.
34	Townsend, Hunt, Kuck et al.	2005	This study of IPV call handling from intake to outcome shows how call-taker training can be part of an early intervention to shape IPV call procedure. The study found, among other things, that only half of the 368 departments surveyed required specialized training for call-takers and dispatchers regarding IPV.
35	Vaughan, Wuschke, Hewitt et al.	2018	This study mapped 20,000 mental health-related and 20,000 IPV calls for police service in Surrey, BC, and found that they have a distinct temporal pattern for both days of the week and hours of the day. Specifically, mental health calls for police service peak during the middle of the week and in the midafternoon, while IPV calls peak on Saturday and Sunday between 6:00 pm and 2:00 am.

Chapter 3: 911 System Processing Map Report

Megan O'Toole, Mawia Khogali, Sarah Scaffidi, and S. Rebecca Neusteter

Hundreds of millions of calls are made each year to 911, but little is known about the nature and scope of these calls or how they are processed.[170] For example, many people believe that 911 operators are actually police officers, when in fact, call center employees often do not even work directly for police departments. Another common misconception is that call-taking and dispatching are done by the same person, but this workload often requires two or more employees to complete it successfully. Further, from childhood onwards, community members are taught to call 911 in case of emergency, but in practice, 911 systems are sometimes inefficient or lack the appropriate response for a variety of situations (e.g., alarms or lost pets).

The lack of public understanding about 911 call processing is surprising, given that all states have been required to have a 911 service since the 1990s.[171] Although each jurisdiction adopts a slightly different call processing system to reflect its unique resources and needs, a general pattern of call progression from receipt to response can be observed across localities. However, the general flow of 911 calls is not well documented or understood outside of law enforcement and public safety communications.[172] Because 911 calls require translation of information from initial 911 callers to call-takers, then to dispatchers, then to responding police, and finally to community members at the scene, it is important to consider the role of each key actor, how that person communicates information, and the decisions that result. Some models examined in the literature review attempt to trace the call-processing trajectory but reflect written procedure and not necessarily practice. Others thoroughly outline discrete steps in the call-taking process but impose a rigidity that fails to account for local variation.

A clear and research-informed map of 911 system processing is imperative to the field's ability to adopt best practices, correctly use resources, educate community members, and develop alternatives. Further, this type of resource will allow researchers, practitioners, and policymakers alike to identify intervention points in 911 call for service workflows where innovative alternatives might be implemented to enhance law enforcement practices and outcomes. For example, it may be the case that more resources are needed for community members in crisis, or that more detailed protocols are needed to reduce the frequency of miscommunications among key personnel. In this way, a 911 system processing map will allow stakeholders to visually identify strengths, weaknesses, and opportunities to reengineer traditional practices.

[170] NENA, "9-1-1 Statistics"; 911.gov, "Review of Nationwide 911 Data Collection: National 911 Program," 2018, https://www.911.gov/pdf/National_911_Program_Review_of_Nationwide_Data_Collection_2017.pdf.
[170] Police Data Initiative, https://www.policedatainitiative.org/about/
[171] iCert, *History of 911*, 2015.
[172] National 911 Program, *Review of Nationwide 911 Data Collection*, (Washington, DC: National 911 Program, 2013), 2, https://www.911.gov/pdf/National_911_Program_Review_Nationwide_Data_Collection_2013.pdf.

Research questions

This chapter seeks to answer the following research questions:

- How are 911 calls processed, from placement to final outcomes—including key personnel, responsibilities, means of communication and prioritization, data entry points, and decision points?
- What types of training, protocols, standardizations, management practices, and alternatives exist relative to 911 call processing at each level (e.g., call-takers, dispatchers, and responding officers)?

Methods

To advance the field's understanding of 911 call processing, Vera conducted a mixed-methods study examining two law enforcement agencies and their corresponding communications centers. Vera selected Camden County Police Department (CCPD) in New Jersey and Tucson Police Department (TPD) in Arizona because: (a) they are both prioritizing innovation around 911 call processing and exploring alternatives to traditional police responses, and (b) they are notably different in the communities they serve and their access to resources. For example, in 2016, Tucson's population size was over 500,000, 43 percent of its residents were Hispanic and 44 percent were non-Hispanic white, and its policing budget was nearly $190 million.[173] Conversely, in 2016 Camden's population size was roughly 76,000, 48 percent of its residents were Black, and its policing budget was nearly $65 million.[174] In 2016, Tucson's city budget was $1.37 billion, compared to Camden's 2017 budget of $196.5 million (for complete site profiles, see Appendix 3A). These differences suggest that most similarities observed in this report reflect recurring patterns in 911 call response, rather than demographic or geographic characteristics shared by the sites. Together, these departments allow for an informed perspective of trends in how 911 calls are received and processed across different communities (see Appendix 3A).

To learn about CCPD's and TPD's call processing procedures and develop 911 system processing maps, Vera conducted multiple qualitative research activities, including: (a) documentation review, (b) site visits, and (c) focus groups. At the start of the study, Vera collected all 911 call processing-relevant documentation from both police agencies and their corresponding communications centers. This documentation included training materials, protocols, standard operating procedures (SOPs), and more. Vera researchers then reviewed the documentation to understand 911 call flow and job responsibilities (for a complete document index and overview of their contents, see Appendix 3B). Ultimately, this documentation was coded based on employee role (e.g., call-taker, dispatcher, or responding officer), and its relevance to:

- information flow;
- incident type classifications;
- protocols and procedures;
- training materials;
- current alternatives to traditional call for service law enforcement responses; and
- management practices.

[173] Census Bureau, "ACS Demographic and Housing Estimates: 2013-2017 American Community Survey 5-Year Estimates,"https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk
[174] Census Bureau, "ACS Demographic and Housing Estimates: 2012-2016."

For CCPD's and TPD's document matrices, see Appendices 3C and 3D, respectively.

After reviewing this documentation, Vera researchers conducted site visits at the Camden and Tucson call-taking centers and police departments, with the goal of validating and supplementing the information learned through the jurisdictions' written documentation. On these site visits, researchers conducted observations with call-takers, dispatchers, officers, sergeants, police department and communications leadership teams, and information technology employees. Throughout this process, researchers accumulated more than two weeks of time on site observing, participating, facilitating, going on ride-alongs, and listening in on dozens of hours of call-taking and dispatching.

While on the site visits, researchers also facilitated semi-structured focus groups and interviews with 100 people, including call-takers, dispatchers, responding officers, supervisors, agency and communications leadership, and community members. Questions covered topics such as roles and responsibilities of 911 system actors, system strengths and weaknesses, existing and recommended alternatives to traditional police responses, perceptions of call trends, and trainings and protocols. In total, Vera researchers spoke to approximately 50 participants at each site.

During the study, Vera researchers also visited and observed other police departments and call centers across the United States, to which they were granted access due to separate ongoing projects. Although not a formal research activity featured in the study's methodological design, these opportunities allowed Vera to confirm that the 911 system processing trends discovered in CCPD and TPD were relevant and upheld across various departments, thus increasing their validity and generalizability. Collectively, these engagements with 911 stakeholders informed Vera's creation of one general system map for the field, and two specific system processing maps that are specific to CCPD and TPD.

Limitations

Though this research adapted a rigorous methodological approach, several structural limitations must be recognized before examining the findings. First, Vera's use of convenience sampling precludes this study from generalizability. Vera spoke to a self-selecting group of police departments that were willing to grant researchers access, and who consider themselves innovators in the field of public safety. Taken together, this predisposes them to operate with greater efficiency and efficacy than other police departments throughout the country. However, the diversity of the sites indicates that the commonalities observed across them is likely common across police departments and 911 call-takers nationally. Furthermore, this study set out to determine alternative policing strategies, so departments that consider themselves to be innovators and are on the cusp of implementing other significant related reforms were a natural fit.

Vera researchers were granted access to call-takers, dispatchers, and officers by the executives of their respective agencies. It may be that the executives chose high performers to be observed, so that findings would reflect positively on their organizations. This is worth recognizing, but may not be a problem, as this research aims to identify best practices, and learning from consummate professionals is a strategic way to achieve that. Similarly, the behavior observed may be different from the norm precisely because Vera staff were observing, thereby incentivizing participants to be on their best behavior. This observation bias is unavoidable, but the longer researchers spend time in the presence of their subjects, the more likely the subjects are to become accustomed to researchers' presence and behave normally.[175] Over the course of several site visits, Vera researchers spent multiple days establishing their presence, so it is likely that call-takers, dispatchers, and officers acclimated to their presence.

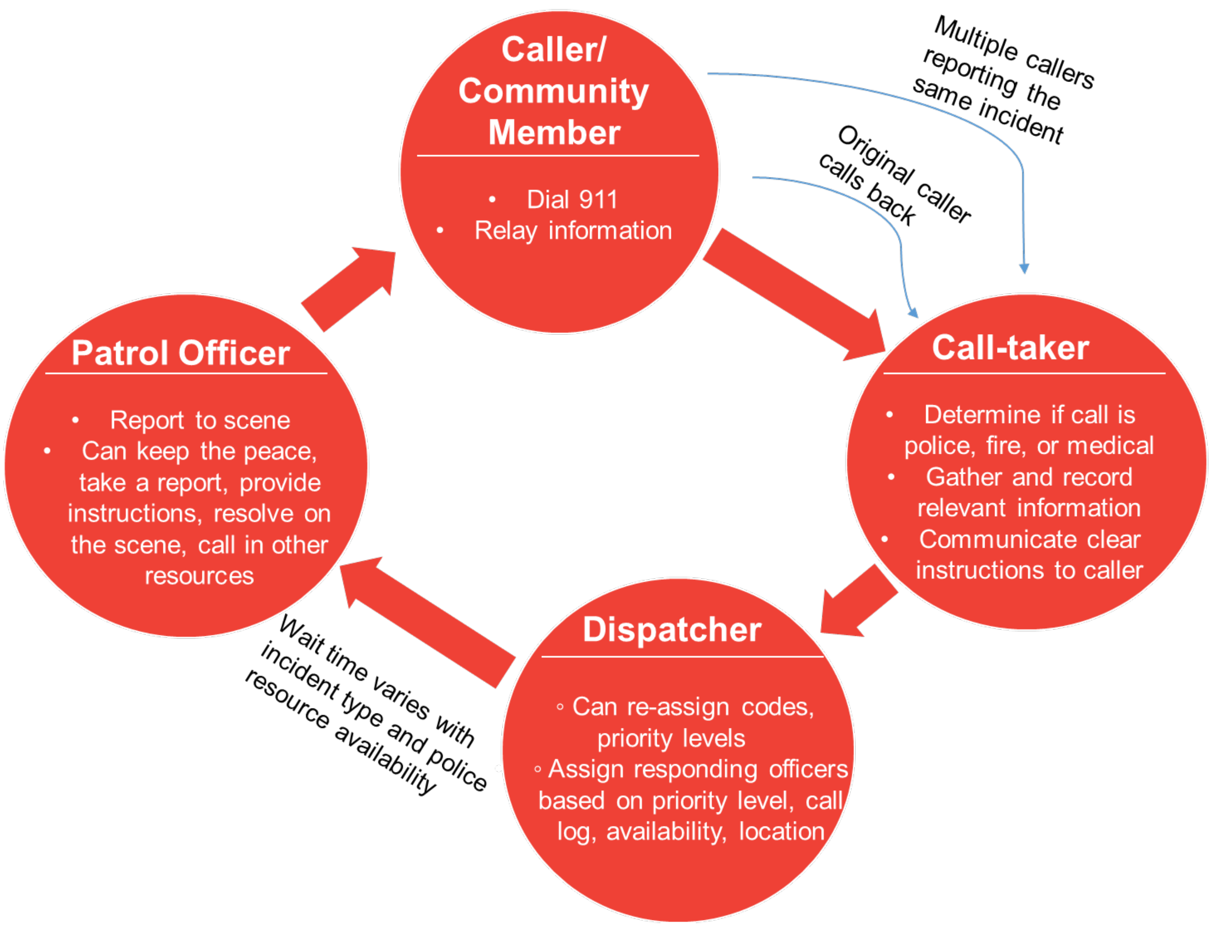
When conducting this research, Vera staff were only present on-site during business hours. This means that weekend, late evening, and early morning call procedures were not observed. Though researchers may not have observed those times firsthand, they did have access to a great deal of documentation (see Appendix 3B) to supplement this information. Similar studies at other research sites in the future could benefit from additional direct observation during off hours.

911 system processing maps

General 911 system processing map

To advance public understanding of 911 system processing, Vera developed a general map—based on empirical research in CCPD and TPD and supplemented with additional site visits to other jurisdictions—to demonstrate what happens when a person calls 911, denoting the flow of information, key people, roles and responsibilities, and available resources (see Appendix 3G).

Figure 3.1: An overview of 911 call processing



[175] Kathy Baxter, Catherine Courage, and Kelly Caine, "Field Studies," in *Understanding Your Users: A Practical Guide to User Research Methods*, 378-428, (San Diego, CA: Elsevier Science, 2015).

As Figure 3.1 demonstrates, the key people, in sequential order, include callers, call-takers, dispatchers, patrol officers, and community members. First, a caller dials 911 and relays information to a call-taker, who is typically responsible for (a) determining if the call is relevant to police, fire, or medical; (b) gathering and recording information in the computer- aided dispatch (CAD) system; and (c) determining and recording the call type, priority level, and narrative. Next, a dispatcher assigns patrol officers to report to the scene via CAD and/or radio, based on priority-level, officer availability, and incident location. Dispatchers can also override the assigned call type and/or priority or request a callback for more information. The assigned patrol officers then read CAD information and, if needed, send questions to dispatch (via phone, radio, or electronically via the CAD system), change the call type, or request a callback. Once on scene, officers can keep the peace (e.g., prevent violence from occurring), take a report (e.g., of auto accidents or thefts), resolve on the scene (e.g., advise involved person), use enforcement (e.g., citations or arrests), or call in other resources (e.g., social services or mental health counselors). Finally, the community member(s) at the scene ideally receive(s) the services necessary, but can also provide responding officers with information, and if the situation requires enforcement, they can either cooperate or resist.

The resolutions or outcomes of each 911 call may differ. For example, a caller might hang up the phone, resulting in a call-back or an officer being dispatched to the scene. Call-takers may reroute a call to a more appropriate emergency dispatcher (e.g., fire or medical) or location; inform the caller of another resource (e.g., nonemergency reporting numbers, animal control, 311 for information about city services, or 211 for information about social services); or inform them of a no-response policy (e.g., some agencies do not send officers for incidents like alarms or minor auto accidents). The call center and/or law enforcement supervisors might choose to manually end or defer a call if no-response policies deem it ineligible for officer dispatch. Finally, officers may not be required to arrive on the scene if an incident is resolved before they are able to get there. If an incident is not adequately resolved through this process, community members can visit a police station, call 911 again, seek other non-police support (e.g., family, friends, community organizations, and/or social services), or submit a complaint.

Although this system processing map describes the general flow of 911 calls, the 911 system is operated by local and state governments, so it is likely that there are differences across agencies based on available resources, geography, and state and local policies and rules. Call-takers are employed by a variety of local and state agencies, including law enforcement, fire departments, emergency management agencies, and information technology services.[176] However, given the consistency in 911 call processing across CCPD and TPD, as well as the three other jurisdictions observed during this research period, much of this map likely applies to many communities, thereby making it a vital tool in understanding and advancing 911 call processing as a whole. Below, site-specific maps are detailed for Camden and Tucson to demonstrate how the general map of 911 call processing can be adapted to more closely reflect individual agencies' practices. As discussed in the following sections, Camden and Tucson's system maps are largely similar to the general map and to each other, with the exception of more detailed information about each person's roles and responsibilities and relevant protocols. These more specific maps are helpful, though—especially at a community level—as they allow for a deeper exploration of available resources, strengths, gaps, and areas of opportunity.

Camden 911 system processing map

To contextualize CCPD's 911 system processing map, it is important to understand that CCPD serves Camden *city* exclusively, but its 911 calls are processed through *Camden County's*

[176] 911.Gov, "Frequently Asked Questions," https://www.911.gov/frequently_asked_questions.html

Communications Center. Prior to December 2017, CCPD's 911 call center was operated by and within the police department. In December 2017, the Camden County Communications Center took over this responsibility, effectively shifting CCPD's 911 call processing out of the department and into a separate public safety communications organization that serves most of the county. Within the Camden County Communications Center in the Public Safety Department, CCPD/Camden city's calls are processed in what they refer to as the "Metro" room, where call-takers and dispatchers are trained on CCPD-specific SOPs, CAD systems, etc. The CCPD 911 system processing map featured in Appendix 3F reflects its current procedures, post-the 2017 call center shift.

Compared to the general 911 system processing map, CCPD's map features more specific staffing descriptions and responsibilities (see Camden County 911 Call Processing System Map on page 74 for details). At any given time, there are two main (channel one) radio operators, two National Crime Information Center (NCIC)(channel two) radio operators, two specialty (channels 3 and 4) radio operators, two call-takers, and one supervisor available in the Camden County Public Safety Communications Center's "Metro" room. Callers who dial from a landline located in Camden city are routed directly to call-takers in the "Metro" room, whereas callers who dial from a cell phone are routed to the general county call-taker, who then reroutes the call to a metro-specific call-taker. Call-takers first establish whether the call is CCPD, Camden County non-metro police, fire, or medical-specific. "Metro" room dispatchers process CCPD-specific calls exclusively and reroute the others.

Dispatcher responsibilities are coordinated between the Camden County Public Communication Center and the police department and are divided among staff, with two dispatchers covering the city's four geographic divisions and four alternating between:

(a) call-taking surplus (i.e., assisting when all other lines are full);
(b) directed patrols (i.e., assigning officers to engage in proactive community policing);
(c) shot spotting (i.e., deploying officers based on gunfire detections);
(d) warrants (i.e., assigning officers to execute warrants);
(e) National Crime Intelligence (NCI) lookups (i.e., researching criminal histories of community members involved in stops and incidents), and
(f) Real-Time Tactical Operations and Intelligence Center (RTTOIC) communications (i.e., dispatching officers based on city camera footage).

RTTOIC Commanders can also manually end or defer calls. In terms of officer resources available, CCPD currently has access to Crisis Intervention Team (CIT) officers (i.e., those trained in responding to mental health crises). Beyond these specifications, CCPD's map reflects the general 911 system processing map.

In Camden, participants highlighted a variety of 911 system processing successes, including law enforcement's ability to address high priority and repeat incidents efficiently, build relationships between community officers and community members, and implement alternative reporting processes. Some of the challenges raised include conflicts between proactive and reactive policing, staff turnover, and inconsistencies in CAD priority level assignments.

Tucson 911 system processing map

In 2017, TPD's 911 call center merged the city's fire and medical call centers with the police call center to create the Tucson Public Safety Communications Department. In the fall of 2019, Tucson PSCD implemented a series of innovations intended to strengthen 911 call processing and police responses to calls for service, including:

- cross-training of all call-takers and dispatchers, so that they are equipped to process police, medical, and fire calls;
- CAD system upgrades (e.g., ability to color code certain types of information, streamlining of incident types);
- Criteria Based Dispatching (CBD), which will provide call-takers with guided instructions and questions to inform incident coding and narrative text drafting, with the goal of making communications more efficient and improving community outcomes;
- 311 system, a longer term initiative that is currently in review and development, where community members can access information about city services; and
- mental health clinicians staffed in the call center, to assist with processing and responding to mental health related calls for service.

The map discussed here and presented in Appendix 3G reflects 911 call processing prior to CBD implementation in November 2019, which includes Tucson PSCD, but not the innovations described briefly above.

Compared to the general call processing map, TPD's also features more specific details. Tucson's staffing is designed to meet the 911 call answering standard defined by the National Emergency Numbers Association (NENA). At any given time, there are between four and 12 call-takers, five dispatchers, and one supervisor on duty. Presently, some of communications' staff is cross-trained and equipped to process all three types of calls (police, fire, and medical), but others are trained only in one specific call type. Thus, some call-takers can process any incoming call, and others triage and reroute the calls accordingly. The four dispatchers are each responsible for deploying officers in a specific geographic division. This system results in 95 percent of 911 calls being answered in 10 seconds or less.

In terms of officer resources available, TPD currently has access to (a) Crisis Intervention Team (CIT) and Mental Health Support Team (MHST) officers (those who are trained in responding to mental health crises); (b) a Mobile Crisis Team (units staffed by Arizona Complete Health (ACH) that can respond with or without TPD, depending on the circumstances); (c) a Crisis Response Center (CRC) (a clinic with 24/7 access where community members can walk in, and officers can drop off people in need of behavioral health services and support); and (d) Community Bridges Inc. (CBI) (a community-run organization that assists people with mental health and substance use problems, and to which TPD often makes referrals).[177] Beyond these specifications, TPD's map reflects the general 911 system processing map. In Tucson, participants highlighted successes, including collegial relationships across key personnel, friendly call-takers, and an eagerness to explore new ideas and areas for

[177] Although TPD's use of community clinician partners and specialized mental health officers within the department is often viewed as progressive, these approaches do not provide comprehensive solutions to mental health needs in the community and may increase contact with law enforcement for people who require health services. To further reduce law enforcement's role with people with mental health needs, departments should move toward well-integrated models, such as CAHOOTS, a mobile crisis response program run by the White Bird Clinic in Eugene, OR. See White Bird Clinic, "CAHOOTS," https://whitebirdclinic.org/cahoots/.

improvement. Some common challenges noted include important information not always being logged and inconsistencies in call triaging practices, including changes to priority level assignments.

Conclusion

As the initial point of contact for many people in crisis, 911 call systems are a critical part of Intercepts 0 and 1 of the Sequential Intercept Model–the first line of defense to connect people with systems and services before contact with the criminal justice system.[178] The success of this system impacts officer resources and effectiveness, community vitality, perceptions of the police, and more. As discussed further in Chapter 4 (see page 78), the 2014 officer-involved shooting of 12-year-old Tamir Rice demonstrates the importance of the 911 call system. In that case, though the caller told the call-taker several times that he believed the gun in Rice's possession was fake, that information was never relayed by the call-taker to the dispatcher, who in turn was unable to share it with the responding officer.[179] This tragic outcome demonstrates just how crucial it is to have a well-functioning call system. As such, it is critical that researchers, funders, community advocates, and police practitioners explore this avenue as an early opportunity to improve policing in the United States and implement alternative emergency responses that can better serve all stakeholders. Before this area of opportunity can truly be explored, however, it is imperative that all of the aforementioned stakeholders have a clear and research-informed understanding of how 911 call processing systems work, including key resources, protocols, and off-ramps—and lack thereof. Only by understanding how these systems currently operate, can strengths, gaps, and potential alternatives be identified. As such, these system maps, and the research that informed them, will serve as key resources to this growing field.

[178] Dan Abreu, Travis W. Parker, Chanson D. Noether, et al., "Revising the Paradigm for Jail Diversion for People with Mental and Substance Use Disorders: Intercept 0," *Behavioral Sciences & the Law* 35, no. 5–6 (2017), 380–95.
[179] Timothy J. McGinty, *Cuyahoga County Prosecutor's Report on the November 22, 2014 Shooting Death of Tamir Rice* (Cleveland, OH: Office of the Prosecuting Attorney), 1-70, http://prosecutor.cuyahogacounty.us/pdf_prosecutor/en-US/Rice Case Report FINAL FINAL 12-28a.pdf.

Appendix 3A: Site profiles

	CCPD[180]	TPD
Estimated population[181]	76,005	527,586
Median household income[182]	$26,214	$37,973
Median age[183]	28.9	33.2
Hispanic ethnicity[184]	48%	43%
Race[185]		
White alone (non-Hispanic or Latino)	5%	46%
Black or African American alone	42%	5%
Asian alone	3%	3%
Other race/ethnicity combinations	50%	46%
Number of sworn police officers[186]	261	850
Number of authorized professional staff[187]	62	323
Agency budget[188]	$63.4 million	$188.6 million
Violent crime rate (per 100,000 inhabitants)[189]	1,977	657
Property crime rate (per 100,000 inhabitants)[190]	3,632	6,659
Arrest rate (per 100,000 inhabitants)[191]	10,345	6,312

180 Camden County Police Department is the primary law enforcement agency for the City of Camden; thus, the census data here represents the city. Further, census data is an imperfect estimator of jurisdictional demographics (e.g., local data suggests far more racial diversity), especially in Camden, where the reliability of available data has been questioned.
181 Census Bureau, "ACS Demographic and Housing Estimates: 2012-2016 American Community Survey 5-Year Estimates," https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk.
182 Census Bureau, "Median Income in the Past 12 Months."
183 Census Bureau, "ACS Demographic and Housing Estimates: 2012-2016."
184 Ibid.
185 Ibid.
186 City of Tucson, Arizona, "Adopted Budget Fiscal Year 2018," 2017; and Laday, "Two Years of the Camden County Police Department," 2015 ; Laday, "County Police Officially Take Over," 2013.
187 City of Tucson, Arizona, "Adopted Budget Fiscal Year 2018," 2017; Laday, "Two Years of the Camden County Police Department,"2015; and Laday, "County Police Officially Take Over," 2013.
188 City of Tucson, Arizona, "Adopted Budget Fiscal Year 2018," 2017; Laday, "Two Years of the Camden County Police Department,"2015; and Laday, "County Police Officially Take Over," 2013.
189 FBI, "Offenses Known to Law Enforcement: Arizona, 2015," https://ucr.fbi.gov/crime-in-the-u.s/2015/crime-in-the-u.s.-2015/tables/table-8/table-8-state-pieces/table_8_offenses_known_to_law_enforcement_arizona_by_city_2015.xls; and FBI, "Offenses Known to Law Enforcement: New Jersey, 2015," https://ucr.fbi.gov/crime-in-the-u.s/2015/crime-in-the-u.s.-2015/tables/table-10/table-10-state-pieces/table_10_offenses_known_to_law_enforcement_new_jersey_by_metropolitan_and_nonmetropolitan_counties_2015.xls.
190 FBI, "Offenses Known to Law Enforcement: Arizona, 2015,"; and FBI, "Offenses Known to Law Enforcement: New Jersey, 2015."
191 FBI, *Uniform Crime Reporting Program Data,"* 2016.

Part I crime clearance rate[192]	19%	13%
City budget[193]	FY 2017: $196.5 million	FY 2016: $1.37 billion FY 2017: 1.43 billion

Note: Fiscal years (FYs) run from July of the previous year to June of the reporting year.

[192] FBI, *Uniform Crime Reporting Program Data: Offenses Known and Clearances by Arrest, 2015* (Ann Arbor, MI: Inter-university Consortium for Political and Social Research, Uniform Crime Reporting Program Data: Offenses Known and Clearances by Arrest, 2014), https://www.icpsr.umich.edu/icpsrweb/NACJD/studies/36391/version/1.
[193] City of Camden, *2016 Municipal Budget of State Fiscal Year*, https://www.ci.camden.nj.us/wp-content/uploads/2016/04/Budget-FY-2016.pdf; and City of Tucson, Arizona, "Adopted Budget Fiscal Year 2017," 2016, https://www.tucsonaz.gov/files/budget/17Book-Op.pdf.

Appendix 3B: Document index

Camden documents

1. *911 call processing*: PowerPoint of call processing in CCPD and current alternatives
2. *Association for Public Safety Community Officials (APCO) Public Safety Telecommunicator (PST) 7th edition final review*: communications training quiz PowerPoint
3. *APCO PST 1 7th edition manual*: complete communications training manual
4. *APCO PST 1 7th edition modules*: communications training modules PowerPoint
5. *APCO PST 1 7th edition student update*: list of communications training updates/in-services
6. *Camden County communication training binder sign in sheet*: sign in sheet for communications training sessions
7. *Camden County Department of Public Safety and Juvenile Justice nondisclosure policy*: communications nondisclosure form
8. *Camden County Department of Public Safety communications center training milestones*: communications training syllabus
9. *Camden County Department of Public Safety training department*: personal file form
10. *Camden County road tour for trainees*: two-day training route of north and south ends of county for communications staff
11. *CCPD Vol 5, Ch 3*: call for service priority-response protocols
12. *CCPD Vol 5, Ch 4*: communications function protocols
13. *CCPD Vol 5, Ch 15*: Real-Time Tactical Operations and Intelligence Center (RTTOIC) protocols
14. *CCPD Vol 5, Ch 23*: field reporting system protocols
15. *County map*: Camden County map with districts color coded
16. *County of Camden employment application*: communications employment application
17. *CritiCall candidate score reports*: examples of communications assessment failures and passes
18. *CritiCall software list*: links to CritiCall software resources
19. *Daily observation report*: communications training observation score card
20. *Daily observation report short form*: communications training observation score card, short version
21. *Daily observation report spreadsheet*: communications spreadsheet version of training observation score card
22. *District map*: color coded map of CCPD districts and sectors
23. *Emergency medical dispatch (EMD) instructor guide*: EMD trainers manual and curriculum
24. *EMD trainee guide*: EMD trainee handbook and modules
25. *Emergency medical services (EMS) fire and police codes*: list of Camden County's EMS, fire, and police (10) codes and their descriptions
26. *Employee ID, phone, and computer-aided dispatch (CAD) login information*: communications new hire form to generate ID, badge, computer, and phone logins
27. *Evaluation criteria list, Camden County*: communications scorecard short version rating criteria
28. *Evaluation criteria list, Camden County*: communications scorecard rating criteria
29. *Grid map*: map of CCPD districts and sectors
30. *Neighborhood map*: color coded map of CCPD districts and sectors, with neighborhoods labeled
31. *New employee orientation*: new hire training contract

32. *New hire letter*: communications welcome and informational employment letter
33. *Outside employment update*: outside employment authorization form
34. *Sector map, November 2015*: Map of 2013 CCPD sectors
35. *Standard operating manual uniform dress code*: communications dress code protocols
36. *Standard operating manual 9-1-1 training*: communications 911 training protocols
37. *Standard operating procedures manual form*: communications form confirming that person is familiar with standard operating procedures manual
38. *State of New Jersey EMD guidecards*: PowerPoint of medical emergency types, details, questions, and instructions
39. *Town codes*: Camden County towns and numeric codes
40. *Trainee timeline*: itinerary for communications staff training
41. *Training manual*: communications training manual

<u>Tucson documents</u>

1. *Addendum to TPD communication division rules and procedures*: amendment to several components of Communications rules and procedures, relative to Tucson and South Tucson
2. *Alarm chart*: web diagram of alarm types, codes, and definitions
3. *Alarm questions*: list of questions to ask regarding alarm calls
4. *Call-taking process flow chart*: 911 call-taking flow chart, including general information to obtain
5. *Chapter 700 dispatcher operations*: dispatcher policy manual
6. *Chapter 800 calls for service May 2016*: CAD incident codes, including incident sub-types
7. *Chapter 800 calls for service August 2017*: CAD incident codes
8. *Chapter 800 call types*: Spreadsheet of call codes, types, subtypes, descriptions, and priorities
9. *Command list*: list of communications computer shortcuts
10. *Commonly misspelled words in law enforcement*: list of commonly misspelled police words
11. *Communications Division procedures Chapter 1*: Communications manual, introduction/values
12. *Communications Division procedures Chapter 2*: Communications manual, personnel policies
13. *Communications Division procedures Chapter 3*: Communications manual, job duties and responsibilities
14. *Communications Division procedures Chapter 4*: Communications manual, TPD organization
15. *Communications Division procedures Chapter 5*: Communications manual, division/specialized training
16. *Communications Division procedures Chapter 100*: Communications manual, telephone equipment
17. *Communications Division procedures Chapter 100 January 2018*: Communications manual, telephone equipment section revised
18. *Communications Division procedures Chapter 200*: Communications manual, radio equipment
19. *Communications Division procedures Chapter 300*: Communications manual, computer equipment
20. *Communications Division procedures Chapter 400*: Communications manual, other (voice logging, storage, headsets, etc.) equipment

21. *Communications Division procedures Chapter 500*: Communications manual, general operations
22. *Communications Division procedures Chapter 600*: Communications manual, call taking procedures
23. *Communications Division procedures Chapter 700*: Communications manual, dispatcher operations
24. *Communications Division procedures Chapter 900*: Communications manual, other agencies
25. *Event status/alarm codes*: list of CAD alarm codes
26. *Hispanic surnames*: list of common Latino surnames
27. *Intergraph call-taker cheater sheet*: list of query commands / acronyms and their definitions
28. *Intergraph cheat sheet*: spreadsheet of old and new query commands and their definitions
29. *Intergraph event status/alarm codes*: list of CAD alarm codes and their definitions
30. *Intergraph unit status list monitor*: unit status monitor icons, acronyms, and descriptions for dispatch
31. *Law enforcement lingo, terminology & codes*: list of common police terms and their definitions
32. *Liability*: document outlining liability definition, basics, laws, issues, responsibility, and concerns
33. *Liability issues*: policy on Communications liability policy
34. *Managing stress inside and outside the communications center*: sources of stress for Communications staff and strategies for mitigating
35. *Police operations and data analysis report*: ICMA report of TPD operations, with emphasis on staffing, effectiveness, and IT
36. *Primary 911 public safety answering point (PSAP) call transfer algorithm*: 911 call processing flow chart, with call transfer algorithm
37. *Simplified 911 system overview*: Flow chart of 911 call processing, including non-law-enforcement agencies and average response times
38. *Subtype worksheet*: Spreadsheet of incident sub-types
39. *Ten code event types, pre-November 2017*: list of 10-codes and their plain English call types
40. *TPD 10-codes*: training presentation of 10-codes and plain English definitions
41. *TPD Communications Division procedures*: outlines protocols for generating calls of various types
42. *TPD ODE sector map*: operation division east sector map
43. *TPD ODM sector map*: operation division midtown sector map
44. *TPD ODS sector map*: operation division south sector map
45. *TPD ODW sector map*: operation division west sector map
46. *TPD school incident reporting decision matrix*: steps for classifying and responding to school incidents
47. *South Tucson boundaries*: geographic boundaries of South Tucson (separate jurisdiction from Tucson)
48. *Split ear exercise*: Spreadsheet used for call taking training exercise
49. *Unit status list monitor*: list of CAD unit status codes and icons
50. *Uniform crime classification codes:* uniform crime reporting codes and definitions

Appendix 3C: CCPD document matrix

Type of documentation	Call-takers	Dispatch	Responding officers
Information flow	• State of New Jersey EMD guidecards • Standard operating manual	• State of New Jersey EMD guidecards • Standard operating manual	• 911 call processing
Incident types	• EMS fire and police codes • Town codes	• EMS fire and police codes • Town codes	• CCPD Vol 5, Ch 3
Protocols	• Camden County Department of Public Safety and Juvenile Justice non-disclosure policy • County of Camden employment application • Employee ID, phone, and CAD login information • Outside employment update • Standard operating manual uniform dress code • Standard operating manual 9-1-1 training • Standard operating procedures manual form	• Camden County Department of Public Safety and Juvenile justice non-disclosure policy • County of Camden employment application • Employee ID, phone, and CAD login information • Outside employment update • Standard operating manual uniform dress code • Standard operating manual 9-1-1 training • Standard operating procedures manual form	• CCPD Vol 5, Chs. 3, 4, 15, 23
Trainings	• APCO PST 7th edition final review • APCO PST 1 7th edition manual, modules, student update • Camden County communication training binder sign in sheet • Camden County Department of Public Safety communications center training milestones • Camden County Department of Public Safety training department • Camden County road tour for trainees • EMD trainer and trainee guides • New employee orientation • New hire letter • Standard operating manual 9-1-1 training • Trainee timeline • Training manual	• APCO PST 7th edition final review • APCO PST 1 7th edition manual, modules, student update • Camden County communication training binder sign in sheet • Camden County Department of Public Safety communications center training milestones • Camden County Department of Public Safety training department • Camden County road tour for trainees • EMD trainer and trainee guides • New employee orientation • New hire letter • Standard operating manual 9-1-1 training • Trainee timeline • Training manual	• N/A
Alternatives	• N/A	• N/A	• 911 call processing
Management practices	• County map • CritiCall candidate score reports • CritiCall software list • Daily observation report (short and long form, spreadsheet, and scoring criteria) • District map • Grid map • Neighborhood map • Sector map, November 2015	• County map • CritiCall candidate score reports • CritiCall software list • Daily observation report (short and long form, spreadsheet, and scoring criteria) • District map • Grid map • Neighborhood map • Sector map, November 2015	• District map • Grid map • Neighborhood map • Sector map, November 2015

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Appendix 3D: TPD document matrix

Documentation	Call-takers	Dispatch	Responding officers
Information flow	• Call-taking process flow chart • Command list • Hispanic surnames • Intergraph call-taker cheater sheet • Intergraph cheat sheet • Primary 911 PSAP call transfer algorithm • Simplified 911 system overview • TPD communication division procedures	• Chapter 700 dispatcher operations Command list • Commonly misspelled words in law enforcement • Hispanic surnames • Intergraph cheat sheet • Intergraph unit status list monitor • Law enforcement lingo, terminology & codes • Primary 911 PSAP call transfer algorithm • Simplified 911 system overview • TPD communication division procedures • Unit status list monitor	• Police operations and data analysis report • Simplified 911 system overview
Incident types	• Chapter 800 calls for service May 2016 • Chapter 800 calls for service August 2017 • Chapter 800 call types • Event status/alarm codes • Intergraph event status/alarm codes • Ten code event types, pre-November 2017	• Chapter 800 calls for service May 2016 • Chapter 800 calls for service August 2017 • Chapter 800 call types • Event status/alarm codes • Intergraph event status/alarm codes • Ten code event types, pre-November 2017	• Uniform crime classification codes
Protocols	• Communications division procedures chapters 1-5, 100-400, 600 • Liability issues	• Communications division procedures chapters 1-5, 100-400, 700 • Liability issues	• Communications division procedures chapters 500 and 900
Trainings	• Subtype worksheet • TPD 10-codes • Split ear exercise	• Subtype worksheet • TPD 10-codes	• TPD field training officer program manual • Field services bureau community service officer handbook
Alternatives	• Alarm chart • Alarm questions	• Alarm chart • Alarm questions	• N/A
Management practices	• Addendum to TPD communication division rules and procedures • Liability • Managing stress inside and outside the communications center • TPD school incident reporting decision matrix	• Addendum to TPD communication division rules and procedures • Liability • Managing stress inside and outside the communications center • TPD Operations Division East (ODE) sector map • TPD Operations Division Midtown (ODM) sector map • TPD Operations Division South (ODS) sector map • TPD Operations Division West (ODW) sector map • TPD school incident reporting decision matrix • South Tucson boundaries	• TPD ODE sector map • TPD ODM sector map • TPD ODS sector map • TPD ODW sector map • TPD school incident reporting decision matrix • South Tucson boundaries

Appendix 3E: General 911 system processing map

General 911 call processing system map

Possible endpoints	Key people	Roles and responsibilities	Resources
• Hang up (may result in call back or officer being dispatched to scene)	Caller	• Dial 911 • Relay information	• Can sometimes report non-emergencies by phone or by visiting a police station
• Sometimes reroute call to more appropriate department based on location and/or incident type • Sometimes inform of no response policy and/or direct to other resource/procedure for select low-level incidents (e.g., alarms)	Call-taker	• Determine if call is police-, fire-, or medical-relevant • Gather information (5 Ws [who, what, where, when, weapons]) • Record information (apply codes to call type and priority level) in CAD drop downs and narrative text	• Communications supervisor available to assist with high-priority emergencies, ambiguous situations, breaks
• Manually end/defer if directed by command staff in accordance with agency policies	Dispatcher	• Assign responding officers over computer/radio based on priority level, call log, availability, location • Can override call type, priority, or request call back • Sometimes also manage other responsibilities (e.g., National Crime Index look-ups, warrants, directed patrols)	• Communications supervisor available to assist with high-priority emergencies, ambiguous situations, breaks
• No action may be required if incident is resolved before an officer is able to respond	Patrol officer	• Sent (or volunteered to go) to scene • Review CAD information (emphasis on priority level and narrative) • Computer message or radio questions to dispatch • Can change call type, request call back • At scene, can keep the peace, take a report, provide instructions/resolve on scene, use enforcement (citation, arrest, etc.), call in other resources	• Supervisors can change priority levels • Fire/medical can assist • Sometimes mental health/substance use resources can be mobilized: Crisis Intervention Team (CIT) officers, co-responders (social workers)
• Problem resolved on scene • If unresolved, visit station, call 911 again, seek other non-police support, or submit a complaint	Community member	• Provide information/tips • Cooperate or refuse	• Sometimes mental health/substance use resources are available: CIT officers, co-responders (social workers)

[1] This may be the original caller or a different member of the community to whom the call is relevant.

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Appendix 3F: Camden 911 system processing map

Camden County (Metro), NJ 911 Call Processing System Map[1]

Possible endpoints	Key people	Roles and responsibilities	Resources	Protocols
• Hang up (may still result in officer being dispatched to scene)	Caller	• Dial 911 • Relay information	• Can report non-emergencies by phone, or by visiting any substation	• N/A
• Route to other department if Camden County (CC) non-metro, fire, or medical • Inform of no-response policy and/or direct to other resource / procedure if select low-level incident (e.g., alarms, thefts, traffic accidents without injuries)	Call-taker	• 2 metro-specific and 1 CC-general available at a time • Determine if CC non-metro police, fire, or medical • Gather information (5 Ws [who, what, where, when, weapons]) • Provide clear instructions to caller (e.g., stay in a safe place) • Record information in CAD drop downs and narrative text	• Communications supervisor is available to assist with high priority emergencies, ambiguous situations, breaks	• Policy 306
• One of the two closest officers can respond directly to the call	Automated emergency dispatch (AED)	• All priority 1 calls go to AED • AED calls are geolocated to the 2 closest available officers • Closest officer has 30 seconds to acknowledge the call before it switches to second closest officer • If neither responds in their 30-second window, call is rerouted to the front of the dispatch queue	• Dispatched through the AED system. Dispatcher can override the system and select two units	• Volume 5, Chapter 3
• Call can be manually ended/deferred if directed by Sergeants or RTTOIC Commander, in accordance with CCPD policies	Dispatcher	• 2 primary dispatchers, cover all 4 divisions • 4 additional dispatchers, alternate between call-taking, directed patrols, shot spotting, warrants, NCI lookups, and RTTOIC communications • Assign responding officers over computer/radio, based on priority level, call log, availability, location • Can override call type, priority, or request call back	• Communications supervisor is available to assist with high priority emergencies, ambiguous situations, breaks	• Policy 306
• No action may be required if incident is resolved before an officer is able to respond	Patrol officer	• Response units sent (or volunteer) to scene • Scan CAD information (emphasis on priority level and narrative) • Computer message or radio questions to dispatch • Can change call type, request call back • At scene, can keep the peace, take a report, provide instructions/resolve	• Sergeants/supervisors can change priority levels • Fire/medical can assist • Mental health/substance use resources can be	• Volume 5, Chapter 3, 4

		on scene, use enforcement (citation, arrest, etc.), call in other resources	mobilized: CIT officers	
• Resolved on scene • If unresolved, visit Police Administrative Building, call 911 again, seek other non-police support, or submit a complaint form.	**Community member[2]**	• Provide information/tips • Cooperate or refuse	• Mental health/substance use resources are available: CIT officers	• N/A

[1] In December 2017, Camden County Public Safety assumed full call-taking and radio communication responsibility. Prior to that date, all communications were handled by Metro. This map reflects current practices.

[2] This may be the original caller or a different member of the community to whom the call is relevant.

Appendix 3G: Tucson 911 system processing map

Tucson, AZ 911 call processing system map

Possible endpoints	Key people	Roles and responsibilities	Resources	Protocols
• Hang up (results in callback)	**Caller**	• Dial 911 • Relay information	• Can report non-emergencies by phone, online, or by station visit	• N/A
• Re-route to fire or medical department • Inform of no response and/or direct to other resource / procedure if select low-level incident (e.g., alarms, thefts, traffic accidents without injuries)	**Call-taker**	• 911 triage (i.e., determine authority having jurisdiction and if police, fire, or medical are needed, and transfer as necessary) • Gather information (5 Ws [who, what, where, when, weapons]) • Provide critical pre-arrival instructions (e.g., stay in/seek safe place, CPR, evidence protection) • Record information in CAD drop downs and narrative text • Verify priority level (threat to life vs. standard 911 call; can override CAD-deemed priority)	• Communications supervisor is available to assist with high priority emergencies, ambiguous situations, breaks	• Chapter 800
• Call can be manually ended/deferred if directed by sergeants, due to limited units/long response times	**Dispatcher**	• 4 divisions, 1 dispatcher each • Assign responding officers over computer and/or radio, based on priority level, call log, available units, location • Can override call type, priority, or request call back	• Communications supervisor is available to assist with high priority emergencies, ambiguous situations, breaks	• Chapter 700
• No action may be required if incident is resolved before an officer is able to respond	**Patrol officer**	• Sent (or volunteer) to scene • Scan CAD information (emphasis on priority level, narrative, and sector) • Computer message or radio questions to dispatch • Can change call type, request call back • At scene, officers can keep the peace, take a report, provide instructions/resolve on scene, use enforcement (citation, arrest, etc.), call in other resources	• Sergeants/supervisors can change priority • Specialized Units (Air Support, Canine, etc.) • Other Agencies (fire, medical, other federal, state, and local law enforcement) can assist • Mental health/substance use resources can be mobilized: Mental Health Support Team (MHST), Crisis Intervention Team (CIT) officers, Crisis Response Center (CRC), Community Bridges Inc. (CBI)	• General Orders (GO) 2400 Field Procedures • GO 2412 Response to Calls for Service • GO 2421 Incident Command • GO 2431 Air Support Unit • GO 2432 Service Dog Unit • GO 2435 Explosives and Hazardous Devices Detail • GO 2440 Agencies

• Resolved on scene • If unresolved, call 911 again, or make a complaint by phone, online, or TPD HQ	**Community member**[1]	• Provide information/tips • Cooperate or refuse	• Mental health/substance use resources are available: MHST, CIT, CRC, CBI	• N/A

[1] This may be the original caller or a different member of the community to whom the call is relevant.

Chapter 4: 911 Audio Analysis Report

Megan O'Toole, Sarah Scaffidi, Hennesy Pineda, and S. Rebecca Neusteter

911 calls for service are the entry point for a vast amount of criminal justice system contact each year. As such, 911 call-takers play an integral role in ensuring the delivery of safe, accurate, and efficient police services to community members. The call-takers are the gatekeepers of the criminal justice system, yet most Americans who know to call 911 in case of emergency know little to nothing about them. When a call comes in, call-takers and dispatchers must work quickly to gather pertinent information and categorize the incident, so it receives the proper action. Categorizing something as more threatening than necessary can lead to an increase in perceived threat and may escalate a situation (e.g., the shooting and death of Tamir Rice). However, underestimating the level of threat may also have dire consequences, with police arriving on the scene unprepared for the severity of the incident and perhaps without the appropriate backup. How a call-taker treats callers, solicits information, and communicates details to dispatchers and officers all impact public safety outcomes—yet there is a notable lack of research on this topic to date.

This chapter sought, in part, to develop a methodology for examining trends in call-taking. This pilot study applied a combination of qualitative methods to evaluate the quality of information recorded by call-takers and how that information is coded. Researchers examined how much information call-takers solicit from callers, how reliably call-takers communicate key information to dispatchers and eventually to responding officers, and what degree of customer service is upheld. Given the sensitive nature of all the data contained in this study, but particularly that contained in the narrative fields and audio files, it is important to note that the data securely transferred to Vera researchers under the IRB guidelines and other research protocols guiding this study.[194] The following sections of this report outline the piloted methodology, preliminary results, and recommendations for next steps in refining and applying this methodology moving forward.

Research question

This chapter of the report examines the following research question:

- Is 911 call data entered reliably into CAD systems (i.e., are different call-takers likely to record information similarly), and does this vary by call type?

Methods

To explore trends in 911 call-taking and the reliability and consistency with which calls for service are classified, Vera researchers conducted qualitative analyses of 911 audio records. For the purposes of this methodology-refining pilot study, Vera obtained and analyzed samples of 911 audio records from the Camden County Police Department (CCPD) and the Tucson Public Safety Communications Division (PSCD) and Police Department (TPD)—the two research site jurisdictions. Each agency provided Vera with a random sample of 25 audio records of real 911 calls, along with call-taker protocols, training materials, and computer-aided dispatch (CAD)

[194] All datasets were encrypted and securely transferred and stored.

coding keys.[195] To begin assessing variations in 911 call-taking by key call types, Vera collected and analyzed an additional 25 calls per site—stratified random samples (*n*=5) of the following categories: (1) most frequent call type (CCPD disturbance of the peace; TPD check welfare); (2) domestic violence; (3) mental health-related; (4) use of force-eliciting; and 5) repeat callers for a total of 94 calls across the two sites.[196] Corresponding CAD records with incident type code, priority level assigned, and completed narrative fields were separately provided for each audio record.

Vera researchers carefully reviewed each agency's trainings, protocols, and CAD coding keys, and then followed up with Camden's and Tucson's public safety communications teams to discuss any questions. During this time, Vera researchers also developed three-point scales for assessing the call-taker's quality of service and information gathering based on agency protocols and site visits (see Appendix 4A).[197] Randomized call recordings were reviewed by multiple researchers and assessment metrics were based on the three point scale mentioned above. Next, a Vera researcher listened to each of the provided 911 audio records and coded the following:

(a) primary and secondary incident types (Camden refers to these as "CFS codes" and "Descriptions;" Tucson refers to these as "Types" and "Subtypes");
(b) priority level;
(c) narrative text; and
(d) 3-point scores for service and information gathering.

Researchers determined incident types and priority levels by referring to each agency's CAD coding key (Chapter 5.3) and selecting the most applicable codes. The decision on what information from the call to include in the narrative text field was informed by focus groups, interviews, ride-alongs, and observations at each agency's communications center and police department. During these observations, researchers inquired about the crucial types of details (e.g., weapons, mental-health concerns, visual identifiers, and other steps taken/resources informed) call-takers capture from callers to best prepare dispatchers and responding officers. Service and information gathering scores were determined based on the three-point scoring sheet provided in Appendix 4A (see page 85). Finally, 18 of those calls (nine from each site) were coded by a second Vera researcher to assess interrater reliability, or the rate with which two people would assign the same incident type and priority level to the same call.

Call-taking reliability was then assessed by comparing Vera researcher-assigned incident codes and narrative text with each call's CAD records. If this information did not match, the researcher indicated whether the difference was related primarily to incident-type ambiguity (e.g., coding an incident as "suspicious person" versus "suspicious vehicle," when the caller is referring to someone in a vehicle), training (e.g., when to utilize "Department of Corrections" versus "Court Order" incident types), or varying levels of detail (e.g., specific type of response requested or mental health concerns raised). Refer to Appendices 4B and 4C for detailed tables of 911 audio coding and reliability comparisons in Camden and Tucson, respectively.

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[195] The date range of Tucson's audio records matches the overall study period (2016-2017). However, Camden's audio records reflect calls placed in 2018, as the department's call records are not systematically saved for longer than 90 days. All referenced protocols, training materials, and CAD coding keys are featured as appendices in the project's corresponding 911 System Processing Map and Descriptive Analyses chapters.
[196] Given Camden's 90-day timeframe for accessing saved 911 audio records, the agency was only able to share four use of force-eliciting calls and no repeat callers.
[197] Though formal assessments of service and information gathering were not originally scoped research activities, Vera included these factors after Camden and Tucson's communications and police leadership teams expressed a vested interest in understanding the quality of callers' first interactions with initial law enforcement representatives.

Limitations

Because the reliability of call-taking and dispatching in the 911 call system is an under-researched area, Vera researchers acted as pioneers in developing a methodology, which is piloted in this study, that might be employed by future researchers examining this topic. Due to the exploratory nature of the study, Vera faced multiple limitations, several of which may inform the design of future studies of the 911 call-taking system.

To eliminate some of the differences between the experience levels of a trained call-taker and a Vera researcher, Vera performed interrater reliability tests by having two researchers code the same audio record and then comparing codes. However, this study did not include an inter-call-taker reliability test, with two call-takers coding the same call. This would have been beneficial, as call-takers have similar levels of training and contextual knowledge of the geographic and socioeconomic factors in the community. Though this was a limitation in this iteration of the study, identifying improvement areas is one marker of a methodological pilot's success. Future researchers examining call-taker reliability can learn from Vera's pilot and adapt this method.

Another limitation of the study is that Vera researchers were not under the same time constraints as call-takers when assigning codes to the audio recordings. Call-takers must work quickly to gather as much information as possible and assign the correct priority and incident types so that community members receive the appropriate level of service. They do not have the luxury to ponder more than 100 incident type codes before selecting the most applicable option because they must prioritize timely service to the community member. The researchers did not have this restriction, and therefore went about the coding process differently, meaning that comparisons between codes from the two are imperfect. While the research approach contains a sole focus on accuracy, the 911 space is judged by efficiency, and therefore the thought process for assignment is different. The code assigned to the call may differ between call-taker and researcher slightly, for example an assignment of assault with a weapon compared to domestic abuse with a weapon, but the time it takes for this more specific qualification could in turn waste valuable time and be the difference between life and death, this is key distinction that is not accounted for using this assignment method. However, the purpose of this study was to gain an understanding of the complexities facing call-takers, so a lack of perfect comparability does not harm the validity of the findings.

Results

To understand the reliability with which calls are entered into the CAD system, Vera conducted an audio analysis of 94 phone calls from across the two sites. As presented in the system processing map, these initial codes and descriptions influence how many officers are dispatched, the actions they take, the speed with which they respond, and numerous other factors that influence the communities they serve. It is important to note the exploratory nature of this study—all data presented reflects preliminary trends that require further research to validate their significance and prevalence. Nonetheless, these findings help to contextualize this crucial part of the public safety system and the challenges call-takers face.

General findings

The figure below summarizes Vera's analysis of the combined 911 calls, including the incident type and narrative matches.

Figure 4.1: Summary of audio analysis, Camden and Tucson combined

CAD call type	N	Priority level match	Call type match	Narrative match	Differences			Average scores	
					Incident type ambiguity	Training-based	Detail-based	Service	Information gathering
Randomly selected	50	70%	54%	76%	45%	5%	30%	Moderate	Excellent
Most frequent call type	10	40%	30%	70%	100%	14%	43%	Excellent	Excellent
Domestic violence	10	90%	60%	60%	67%	0%	50%	Moderate	Moderate
Mental health	10	50%	40%	80%	88%	25%	0%	Moderate	Excellent
Use of force eliciting	9	67%	44%	67%	50%	17%	50%	Moderate	Moderate
Repeat callers	5	40%	80%	100%	100%	0%	0%	Moderate	Moderate
Interrater reliability test	18	67%	56%	72%	46%	44%	54%	71%	53%

As Figure 4.1 shows, researchers and call-takers assigned the same incident type to just over half (54 percent) of the 50 randomly selected calls analyzed across Camden and Tucson. Narratives matched more often (76 percent of the time), demonstrating that, even when capturing the same salient details in the narrative field, designating the CAD event to the correct incident type code can be challenging. Vera researchers and trained call-takers assigned calls the same priority level 70 percent of the time, suggesting that they perceived similar levels of urgency, even when they applied different incident type codes. This makes sense, as there were five functional priority levels in Camden and nine in Tucson, whereas each site uses more than 100 incident type codes that call-takers must quickly choose from.[198] Though priority level variation is lower than incident type variation, it is still substantial. If these findings are reflective of practice, this misalignment could lead to a perceived threat level that is not in line with the situation.

Across both sites, repeat callers, those who called multiple times for the same kind of incident, had the highest incident type assignment reliability, with 80 percent of cases receiving the same incident type designation from both researcher and call-taker. Domestic violence calls had 60 percent incident type assignment reliability, which is just below the interrater reliability test's 59 percent reliability of matching codes between two raters. Frequent call types (disturbance of the peace in Camden and check welfare in Tucson) had the lowest call-taker to researcher incident type matching, with researchers and call-takers designating the same code a mere 30 percent of the time. This may be explained by the prevalence of such calls—call-takers have plenty of experience with them and thus may have a system of practice rather than protocol that informs their categorization, an area in which Vera researchers were entirely inexperienced. In general, call-takers demonstrated moderate to excellent service and information gathering, handling calls with professionalism and compassion while still covering the five Ws (who, what, where, when, weapon). Call-takers scoring highly in information gathering, but producing codes different from those of the Vera researchers highlights that these discrepancies are not due to

[198] In Camden, the priority scale is equivalent to 5 levels, with level 1 needing the most immediate and serious response, and 4 needing the least urgent attention. Because relatively few calls are placed for incidents in levels 5 through 9, these categories are collapsed into one for the purpose of dispatch. For more information on the priority level scales, see Section 5.3 on page 187.

poor practice, but one of three other explanations unearthed during Vera's analysis: incident type ambiguity, differences in training, and temporal constraints.

In nearly every sample—both random and stratified in Camden and Tucson—differences in researchers' and call-takers' incident type assignments and/or narrative text were explained primarily by issues regarding incident type ambiguity. Incident type ambiguity occurs when similar incident types (e.g., "vice complaint" and "vice complaint (drugs)" are used interchangeably. This discrepancy highlights the need for a coding protocol that would allow for a more accurate and standardized capture of information. However, it should be noted that call-takers received training that Vera researchers did not; thus, it would be useful to have two call-takers perform this exercise to more fully understand the nature of discrepancies. Furthermore, call-takers must act quickly when categorizing incidents into the CAD system, whereas Vera researchers were not under any time pressure when applying their codes and priority levels. The differences in training and background, as well as the difference in timing, likely account for some of the observed disparities.

Camden findings

The table below summarizes Vera's analysis of the Camden 911 calls, including differences in how calls were coded by researchers and call-takers. For a full account, refer to Appendix 4B.

Figure 4.2: Summary of Camden 911 call audio analysis

CAD call type	N	Priority level match	Call type match	Narrative match	Differences			Average scores	
					Incident type ambiguity	Training-based	Detail-based	Service[199]	Information gathering[200]
Randomly selected	25	80%	60%	72%	33%	11%	33%	Moderate	Moderate
Most frequent call type	5	0%	0%	80%	100%	25%	50%	Excellent	Moderate
Domestic violence	5	100%	60%	40%	75%	0%	100%	Moderate	Moderate
Mental health	5	40%	40%	80%	75%	50%	0%	Moderate	Excellent
Use of force eliciting	4	50%	50%	75%	33%	33%	33%	Moderate	Moderate
Repeat callers	0	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Interrater reliability test	9	56%	56%	67%	17%	33%	33%	88%	25%

As Figure 4.2 demonstrates, researchers coded only 60 percent of the randomly selected calls the same way that professional call-takers did, though both groups included the same salient details in the narrative field when processing 72 percent of those calls. The higher narrative match than call type match indicates that researchers were likely to record the same salient details as call-takers, but the inclusion of those details did not lead them to classify the calls under the same type code. As seen in the combined data, researchers and call-takers were more consistent in their priority level coding, assigning the same level to 80 percent of randomly

[199] For the details of scoring criteria for the service variable, see Appendix 4A.
[200] For the details of scoring criteria for the information gathering variable, see Appendix 4A.

selected calls. Domestic violence calls, followed by use of force eliciting calls, had high incident type assignment reliability, with 60 percent and 50 percent of researcher and call-taker incident code types matching, respectively. Disturbance of the peace, Camden's most frequent call type, had the lowest call-taker to researcher incident type matching, with no calls matching in either incident type or priority level. This suggests that Camden call-takers' categorization may be influenced by a shared contextual understanding to which Vera researchers were not privy.

Once again, most of these discrepancies were explained primarily by issues regarding incident type ambiguity and/or disparities in how much detail was recorded. Service and information gathering scored moderately in most instances, though service was excellent for disturbance of the peace calls, and information gathering was excellent for mental health calls. This may reflect Camden call-takers' emphasis on getting their calls to dispatch as soon as possible while maintaining professionalism.

Tucson findings

The figure below Vera's analysis of the Tucson 911 calls, including differences in how the calls were coded by researchers and call-takers. For a full account, refer to Appendix 4B.

Figure 4.3: Summary of Tucson 911 call audio analysis

CAD call type	N	Priority level match	Call type match	Narrative match	Differences			Average scores	
					Incident type ambiguity	Training-based	Detail-based	Service[201]	Information gathering[202]
Randomly selected	25	60%	48%	80%	55%	0%	25%	Excellent	Excellent
Most frequent call type	5	80%	60%	60%	100%	0%	33%	Excellent	Excellent
Domestic violence	5	80%	60%	80%	50%	0%	0%	Excellent	Excellent
Mental health	5	60%	40%	80%	100%	0%	0%	Moderate	Excellent
Use of force eliciting	5	80%	40%	60%	67%	0%	67%	Excellent	Excellent
Repeat callers	5	40%	80%	100%	20%	0%	0%	Moderate	Moderate
Interrater reliability test	9	78%	56%	78%	71%	43%	29%	56%	78%

As Figure 4.3 shows, researchers coded only 48 percent of the randomly selected calls the same way that professional call-takers did, though both groups included the same salient details in the narrative field for 80 percent of those calls. Priority level match was higher than incident type match, with 60 percent of call-taker and Vera researcher assigned classifications aligning, but it was still lower than the rate of narrative match. The higher narrative match than call type and priority level match indicates that researchers were likely to record the same salient details as call-takers, but those details did not lead them to classify the calls under the same type codes with the same levels of urgency. Once again, call-takers have contextual knowledge of their landscape of calls for service that position them to better understand the

[201] For the details of scoring criteria for the service variable, see Appendix 4A.
[202] For the details of scoring criteria for the information gathering variable, see Appendix 4A.

levels of urgency required by certain incidents. Repeat callers, followed by domestic violence calls and check welfare calls (Tucson's highest frequency incident type), had high incident type reliability, with 80 percent, 60 percent, and 60 percent of researcher and call-taker incident code types matching, respectively. Once again, most differences in researcher and call-taker incident type assignments and/or narrative text entries were explained primarily by issues regarding incident type ambiguity. Call-takers in Tucson, like those in Camden, demonstrated mostly excellent service and information gathering, though in Tucson, information gathering scored slightly higher than service, highlighting the relative importance of securing accurate information from callers.

Interrater reliability

	N	Priority level match	Call type match	Narrative match
Camden	9	56%	56%	67%
Tucson	9	78%	56%	78%
Cross-site combination	18	67%	56%	72%

Interrater reliability tests consist of two researchers coding the same call and then comparing their categorizations. This method was used as a check to understand differences in coding. In both Camden and Tucson, these tests produced 56 percent incident type coding reliability. However, there seems to be more variation for the narrative match (67 percent and 78 percent, respectively) and slightly larger variation for the priority level match (56 percent and 78 percent, respectively). This highlights the need for future interrater reliability research, in which two call-takers who received the same training and have a shared contextual knowledge of the district rate the same call. Further, this suggests the discordance between researcher and call-taker coding is likely to result from ambiguity of research-assigned codes.

Conclusion

Preliminary analyses indicate that at least half of all CAD records may be subject to limited reliability. As such, standardization in terms of incident type identification and narrative text inclusion should be further refined. Most differences in CAD coding seem to be accounted for by call type ambiguity—especially for high volume incident types. If this trend is upheld in future analyses, agencies ought to consider refining their incident type lists to reflect a narrower listing of only the necessary call types. This may mean that vague incident types, such as check welfare and keep the peace, are occurring in high frequency, when designating other incident types may be more informative and accurate for that call. It may be helpful to further unpack what types of calls are being classified under those incident types, and whether more incident types are needed to define those cases, or more training is needed to filter some of them out from that category. These findings highlight the importance of training to the call-taking process. Tucson is implementing a criteria-based dispatching model, with step-by-step instructions and decision trees to standardize coding across call-takers. Innovation like this may reduce or eliminate differences in the assignment of priority level and incident type.

This was a methodological pilot, and as such, many lessons can be learned to guide future research. In the future, it may make more sense for another call-taker to code these calls, rather than a researcher, as researchers have not undergone call-taker training, nor do they have the same on-the-job experience and exposure. This could help to remove further confounds and improve the accuracy of findings. Additionally, service and information gathering scoring systems can be further developed and refined beyond the three categories shown in Appendix 4A's score sheet. Conducting studies with larger sample sizes would also improve the robustness and accuracy of findings and provide an indication of how the trends observed in Camden and Tucson do or do not translate to police departments across the country.

Appendix 4A: Customer service and information gathering scoring sheets

Customer service	Information gathering
1/Poor: Call-taker was unprofessional (e.g., cut the caller off, blamed the victim, rude)	1/Poor: Covered <4 of the 5 Ws (who, what, where, when, weapons)
2/Moderate: Call-taker was professional (e.g., polite, respectful)	2/Moderate: Covered 4 of the 5 Ws
3/Excellent: Call-taker was professional and compassionate (e.g., thanked the caller, acknowledged their experience)	3/Excellent: Covered all 5 Ws

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Appendix 4B: Camden audio analysis detailed coding table

Vera				Communications				Comparison			Call quality	
CFS code	*Description*	*Priority*	*Narrative*	*CFS code*	*Description*	*Priority*	*Narrative*	*Incident*	*Narrative*	*Difference*	*Service*	*Information gathering*
35CA	CRIME (CHILD ABUSE)	2	Male caller's 11yo daughter assaulted by mother, ran to grandfather's house, father would like to make report	17	MEET COMPLAINANT	4	**** 2ND FLR APT SIDE ENTRANCE //SEE CALLER STATES THAT HIS 11Y/O DAUGHTER WAS ASSAULTED BY HER MOTHER // CALLER STATES THAT THE CHILD IS THERE WITH HIM NOW	No Match	No Match	Detail-based	Moderate	Poor
15	DISTURBANCE OF THE PEACE	2	White man, 5'4", keeps running in and out of Dunkin Donuts daily, has called police before	15	Disturbance of the peace	2	White male gray shirt bald head harassing employees and customers; ongoing issue	Match	Match	None	Moderate	Moderate
52OT	EMS CALL NON-EMERGENT (OTHER)	2	Employee having heart palpitations; transferred to EMS	520T	EMS call non-emergent	2	Employee in the lobby having heart palpitations// pt located at the garage entrance coming to the building	Match	Match	None	Moderate	Moderate
31OT	CRIME IN PROGRESS (OTHER)	2	Black male in lobby harassing and threatening caller over piece of paper; unclear whether weapons present	15	Disturbance of the peace	2	Imperial checking blk male wearing blk shirt harassing worker…no weapons…male in lobby	No Match	No Match	Detail-based	Moderate	Excellent

74CR	SERVICE ASSIGNMENT (CLOTHING REMOVAL)	5	Clothing removal; already called once; needs to return for more items; wants to pick up everything	17	Meet complainant	4	caller states that he just there with a police escort//female called him to state that she was holding some of his work clothing//male is on his way back the residence needs to retrieve his work clothes//would like for police to meet him there//he is walking on Fairview street approx eta 20 mins	No Match	Match	Training-based - OR- incident type ambiguity	Moderate	Moderate
35BU	CRIME (BURGLARY)	2	Next door neighbor (white male) broke into caller's garage, thinking it was his, and threw everything away, last Wednesday. He's next door now, & she'd like to file a police report	35BU	CRIME (BURGLARY)	2	CLR'S NEIGHBOR BROKE INTO GARAGE/THREW ITEMS AWAY; TRESPASSED IN YARD//CLR WANTS TO MAKE REPORT	Match	Match	None	Excellent	Excellent
16NPIP	DOMESTIC NO INJURIES & OFFENDER NOT PRESENT (IP)	2	Daughter's father threatening to shoot her, trying to hit her; Black male wearing black turban and coat, brown khakis; staying at house on corner; weapons unknown	16NP	DOMESTIC NO INJURIES & OFFENDER NOT PRESENT	2	CHILD'S FATHER MAKING THREATS TO KILL CLR//STS HE WILL GET TO CLR BEFORE POLICE DO//SUBJ [NAME] BLK MALE LSW BLK TURBAN BLK COAT BRN KHAKIS//POSS IN HOUSE ON CORNER//UNK WEAPONS	No Match	Match	Incident type ambiguity	Moderate	Excellent

3132	PERSON WITH A FIREARM	1	Spanish caller; using Language link to translate; 5-6 gunshots heard 5min ago; no visual	3132	PERSON WITH A FIREARM	1	LANGUAGE LINK OPER#/CALLER HEARD 5-6 GUNSHOTS	Match	Match	None	Excellent	Excellent
52OT	EMS CALL NON-EMERGENT (OTHER)	2	Requests ambulance	520T	EMS call non-emergent	2	VOA…43 YOM not feeling well due to chest discomfort; HX: Unknown medical conditions; transferred to psap 65 for medical	Match	Match	None	Moderate	Moderate
11	ANIMAL COMPLAINT	4	Hospital security officer asked to call on behalf of nurse, notified of a dog bite in ER	35	Crime (other)	4	ER…victim with a dog bite…NFI	No Match	Match	Training-based	Excellent	Moderate
3118 MC	MISSING CHILD	1	Son (black shorts tank top and black and white Jordans) cut off electronic monitoring ankle bracelet; needs to file missing person report; first time he's cut off bracelet	17	MEET COMPLAINANT	4	THE SON CUT OFF HIS ANKLE BRACLET….BLK SPORT SHORTS AND BLK TANK TOP BLK AND WHITE JORDANS	No Match	No Match	Detail-based	Moderate	Moderate

17	MEET COMPLAINTANT	4	Caller's brother would like officers to visit home; ex dropped off their 8mon old baby with a note saying to take care of his child	17	MEET COMPLAINANT	4	SEE MALE CALLER IN REF TO CHILDS MOTHER LEAVING THEIR 8 MONTH OLD BABY WITH A NOTE SAYING SHE NO LONGER WANTS THE BABY AND WANTS HIM TO KEEP THE BABY PERMANTLY….BABY IS ON SCENE AND IN GOOD HEALTH; REFUSED EMS	Match	Match	None	Moderate	Excellent
3116AD	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1 (could be downgraded)	Call back request to remove intoxicated adult daughter from house; harassing; can hear yelling; officers previously came once and "calmed her down;" now wants her out	3116AD	Domestic involving two adults with injury or offender present	1	caller's daughter is back and screaming and cursing at the mother. Daughter is 43 yo. Fem is high and mom wants her removed	Match	Match	None	Moderate	Moderate
94	TRAFFIC COMPLAINT	4 (maybe up-grade)	Vehicle blocking handicap spot at parents' house; provided vehicle type and tag number	94	Traffic complaint	4	blue Chrysler blocking callers handicap//NJ tag [ID]	Match	Match	None	Moderate	Moderate
15	DISTURBANCE OF THE PEACE	2 (maybe up-grade)	Request for police to remove black male in blue jersey from bar	15	Disturbance of the peace	2	Inside of crystals lounge blk male inside causing a disturbance; wearing blue basketball jersey	Match	Match	None	Moderate	Poor
15	DISTURBANCE OF THE PEACE	2	Noise complaint; neighbors playing music out on porch; suggests direction to come from	15	Disturbance of the peace	2	Loud music from outside	Match	No Match	Detail-based	Moderate	Moderate

35AR	CRIME (ARMED ROBBERY)	2	Cab manager calling because driver was robbed at gunpoint; no information on offender; cab driver speaks Spanish only	31RB	Crime in progress (robbery)	1	HIGH CLASS DELUXE//DRIVER [NAME]//CALLER STATES HIS DRIVER WAS ROBBED AT GUNPOINT//BY A MALE WHO RAN INTO APTS//ONCE HE PICKED HIM UP AND TOOK HIM TO HIS LOCATION//HE DID NOT PAY//AND PULLED THE GUN OUT.	No Match	No Match	Incident type ambiguity	Excellent	Excellent
13DC	VICE COMPLAINT (DRUGS)	4	Hispanic male with braids red shirt black pants and shoes; selling drugs from pocket to cars on street corner	13DC	VICE COMPLAINT	4	BETWEEN CARMAN AND MICKLE…1 HSP ML W/ BRAIDS WEARING A RED/BLK/WHT SHIRT BLK PANTS BLK SHOES…ML HAS CDS ON HIM…	No Match	Match	Incident type ambiguity	Excellent	Excellent
35	CRIME (OTHER)	4 (maybe upgrade)	Car window broken; looking through parking lot footage	35CM	CRIMINAL MISCHIEF	4	CM TO VEHICLE…PROPERTY HAS CAMERAS…2010 MAROON PONTIAC G6…CALLER WILL BE OUTSIDE IFO PROPERTY FOR POLICE	No Match	Match	Incident type ambiguity	Excellent	Moderate
DC	DEFERRED CALL	9	Neighbor locked out of car/house; request for assistance	DC	DEFERRED CALL	9	NEIGHBOR LOCKED KEYS IN CAR-NO ANIMAL OR CHILD IN VEH CALLER WAS ADVISED POLICE WILL NO RESPOND	Match	Match	None	Excellent	Excellent

13DC	VICE COMPLAINT (DRUGS)	4	Hispanic male selling drugs from his porch/house over extended period of time; assisted by Black male on bike	13DC	VICE COMPLAINT (DRUGS)	4	CALLER STS ONE HISPANIC MALE UNK CLOTHING DESCRIPTION IS SELLING CDS//KEEPS CDS INSIDE HOUSEWE OR ON HIM//BLACK MALE ON WHT BIKE WEARING BLK JEANS ALSO SELLING CDS	Match	Match	None	Moderate	Moderate
3116AD	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	Mother attempted to hit caller/adult daughter with hot pot; mother pulling sister with Down syndrome's hair; CPS attempting to take sister; EMS not needed; caller hung up	3116AD	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	APT#J4/MOTHER VS. DAUGHTER	Match	No Match	Detail-based	Moderate	Excellent
18MA	MISSING ADULT	1	Requesting wellness check for ill grandmother with child; hasn't heard from her in days; cousins have tried knocking/no response; no one has key; unavailable to meet police	4ORC	PROPERTY CHECK (RESIDENCE)	5	WELL BEING CHECK ON 80 YEAR IKD GRANDMOTHER CLR IS VERY CONCERNED//LAST TIME SHE HEARD FROM HER WAS IN A COUPLE OF DAYS//NO CONTACT MADE VIA PHONE//CLR STATED OFC STILL KNOCKED ON THE DOOR AS WELL NO CONTACT MADE/ /CLR WOULD LIKE A CALL BACK WITH FINDINGS	No Match	Match	Incident type ambiguity	Poor	Moderate

3116AD	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	Son following her with bat; wants money for drugs; has weapons	3116AD	Domestic involving two adults with injury or offender present	1	CLR STATED//MOTHER VS SON//[NAME] IS THE MALE INTOX AND HAS A BAT TRYING TO BREAK HER PROPERTY//MALE IS INSIDE TRAILER//CLR IS OUTSIDE TRAILER	Match	Match	None	Excellent	Moderate
3118MC	MISSING CHILD	1	5 year old daughter missing; realized when picking her up from school; father does not have custody; waiting in school	3118MC	MISSING CHILD	1	[SCHOOL]***CLR STATED//5YOF//[NAME]//LAST SEEN [SCHOOL] UNIFORM//LAST SEEN AT 4:15PM//CLR IS IFO LOC//SPOKE TP TEACHERS//UNABLE TO LOCATE CHILD//CLR WILL BE IN MAIN OFFICE	Match	No Match	Detail-based	Moderate	Excellent

Camden 911 call audio analysis: Disturbance of the peace (i.e., most frequent call type) subsample												
Vera				**Communications**				**Comparison**			**Call quality**	
CFS code	*Description*	*Priority*	*Narrative*	*CFS code*	*Description*	*Priority*	*Narrative*	*Incident*	*Narrative*	*Difference*	*Service*	*Information gathering*
31OT	CRIME IN PROGRESS (OTHER)	4	Native American male wearing black leather coat entered caller's home uninvited and refuses to leave; requesting police removal and transport to shelter; "he's not a bad guy, he just needs help"	15	Disturbance of the peace	2	MALE WALKED INSIDE HIS HOME / HSP ML BLUE JEANS / PER CALLER MALE IS NOT A BAD GUY / JUST NEEDS HELP / NEEDS A SHELTER	No Match	Match	Incident type ambiguity	Excellent	Moderate

17	MEET COMPLAINTANT	4	Neighbor put garbage on caller's property; officer came yesterday and problem persists; neighbor not home	15	Disturbance of the peace	2	NEIGHBOR IS PUTTING TRASHCANS INFRONT OF HIS HOUSE...ONGOING ISSUE...SEE CALLER	No Match	Match	Incident type ambiguity	Excellent	Moderate
35TH	CRIME (THEFT / LARCENY)	4	Cashier in corner store did not result $10 change to caller	15	Disturbance of the peace	2	[NAME] GROCERY STORE / CUSTOMER VS. EMPLOYEE OVER PROPER CHANGE NOT BEING GIVEN BACK	No Match	No Match	Detail-based	Excellent	Excellent
11	ANIMAL COMPLAINT	6	Noise complaint; dog barking since 9AM	15	Disturbance of the peace	2	HAS THERE DOG OUTSIDE AND HES BEEN BARKING SINCE 9AM THIS MORNING THE CALLER IS ELDERLY AND SHE WANTS TO SLEEP...	No Match	Match	Training-based - OR- incident type ambiguity	Excellent	Moderate
3116A DIP	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT (IP)	1	Caller's niece and her boyfriend are fighting; wants the police to separate them; no injury or weapons; individuals do not want officers to come	15	Disturbance of the peace	2	X // M V F // NO INJ NO WEAP	No Match	Match	Incident type ambiguity and detail-based	Poor	Moderate
Camden 911 call audio analysis: Domestic violence subsample												
Vera				**Communications**				**Comparison**			**Call quality**	
CFS code	*Description*	*Priority*	*Narrative*	*CFS code*	*Description*	*Priority*	*Narrative*	*Incident*	*Narrative*	*Difference*	*Service*	*Information gathering*
3116A DIP	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT (IP)	1	Black hispanic male attempting to kick in caller's door; restraining order	3116A D	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	APT 7s / MALE IS KICKING THE FRONT DOOR OF THE APARTMENT	No Match	No Match	Incident type ambiguity and detail-based	Poor	Moderate

3116A DIP	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT (IP)	1	Caller's sister and boyfriend fighting; sister separated from boyfriend and crying; no ambulance needed	3116A D	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	SISTER AND BOYFRIEND ARE ARGUING	No Match	Match	Incident type ambiguity	Moderate	Moderate
3116A D	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	Money dispute; male choked and scratched caller; still in house; caller states "I don't want to have to kill him"	3116A D	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	MALE VS FEMALE..VERBAL AND PHYSICAL NO WEAPONS	Match	No Match	Detail-based	Moderate	Poor
3116A D	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	Male won't leave caller's house; audible yelling	3116A D	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	FEMALE WANTS MALE REMOVED	Match	Match	None	Moderate	Poor
3116A D	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	Request for police; mother fighting sister in front of caller's children; audible screaming and cursing occuring; hang up	3116A D	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	SISTER FIGHTING MOTHER	Match	No Match	Detail-based	Moderate	Moderate
Camden 911 call audio analysis: Mental health subsample												
Vera				**Communications**				**Comparison**			**Call quality**	
CFS code	*Description*	*Priority*	*Narrative*	*CFS code*	*Description*	*Priority*	*Narrative*	*Incident*	*Narrative*	*Difference*	*Service*	*Information gathering*
15	DISTURBANCE OF THE PEACE	2	Transfer call; male sleeping in middle of street; EMS in route	3196	EMOTIONALLY DISTURBED PERSON	1	MALE SLEEPING IN THE MIDDLE OF THE STREET / CALLER: UNKNOWN FM [#] / EMS NOTIFIED / NO FURTHER INFO OR DESCRIPTIONS PROVIDED	No Match	Match	Incident type ambiguity	Excellent	Moderate

15	DISTURBANCE OF THE PEACE	2	White male in brown hat and coat yelling and refuses to leave	3196	EMOTIONALLY DISTURBED PERSON	1	[CLINIC] BACK ENTERANCE**IRATE CONSUMER REFUSING TO LEAVE//WHI MALE WEARING BRN HAT BRN LEATHER TRENCH COAT//UNK WEAPONS//MALE CAN BE HEARD CARRYING ON IN BACKGROUND	No Match	No Match	Training-based - OR-incident type ambiguity	Excellent	Excellent
3196	EMOTIONALLY DISTURBED PERSON	1	Request for officer to assist with crisis outreach; client homicidal/suicidal; off psychotropic meds; no weapons; walking outdoors with no clothing;	3196	EMOTIONALLY DISTURBED PERSON	1	CALLER IS FROM A CRISIS CTR, SUBJECT OFF MEDS AND A DANGER TO SELF AND OTHER, SUBJECT INSIDE THE HOME, WITH DAUGHTER IN LAW, NO WEAPONS IN THE HOME CALLER WILL BE IN A SILVER SUBURU FORESTER	Match	Match	None	Moderate	Excellent
35	CRIME IN PROGRESS (OTHER)	4	Black female in gray sweatpants and dark jacket hitting vehicle with sticks; throwing bricks and trash bags	3196	EMOTIONALLY DISTURBED PERSON	1	EDP FM HITTING PEOPLE'S VEHICLES WITH STICKS AND THROWING BRICKS	No Match	Match	Training-based - OR-incident type ambiguity	Moderate	Excellent

3196	EMOTIONALLY DISTURBED PERSON	1	White male wearing white t-shirt black pants on drugs hitting things stick; screaming he's on fire	3196	EMOTIONALLY DISTURBED PERSON	1	REPORT OF A HIGHLY INTOXICATED WHITE MALE WEAIRING BLACK PANT WHITE SHIRT YELLING THAT HE'S HOT AND HOLDING A STICK.......HE HAS A HOODIE ON BUT HE TOOK IT OFF	Match	Match	None	Moderate	Moderate
Camden 911 call audio analysis: Calls resulting in use of force subsample												
Vera				**Communications**				**Comparison**			**Call quality**	
CFS code	*Description*	*Priority*	*Narrative*	*CFS code*	*Description*	*Priority*	*Narrative*	*Incident*	*Narrative*	*Difference*	*Service*	*Information gathering*
31AG	CRIME IN PROGRESS (ASSAULT)	1	Physical fight in auto repair show; car windows being broken; owner being chased; caller doesn't want to get involved	31AG	CRIME IN PROGRESS (ASSAULT)	1	AUTO REPAIR SHOP GARAGE NEAR ABOVE INTERSECTION//CLLR SAID THAT HE HEARD A LOT OF THINGS BREAKING LIKE WINDOWS SMASHING AND YELLING AND THEN SAW WHAT HE THINKS IS THE OWNER OF THE BUSINESS RUNNNG AWAY BEING FOLLOWED BY SOMEONE//UNK DESC//	Match	Match	None	Moderate	Moderate

3116A DIP	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT (IP)	1	Caller's boyfriend refuses to leave house; fearful of violence; will meet officer outside house; has somewhere else to go; does not want kids taken away	3116A D	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	CALLER WAS KICKED OUT OF THE HOUSE BY HER BOYFRIEND......SHE IS WAITING IN FRONT OF THE HOUSE IN A BLUE TOYOTA	Match	No Match	Detail-based	Moderate	Moderate
35TH	CRIME (THEFT / LARCENY)	4	Hispanic male in black hoodie and jeans (known to caller) stole caller's iPhone and ran away; no weapons; "put his hands on me"	31BU	CRIME IN PROGRESS (BURGLARY)	1	H/M 505 BLK HOODY BLK JEANS JORDAN SNEAKERS TOOK CLRS PHONE OUT OF CLRS HAND AND RAN DOWN BROADWAY//ASSA ULTED CLR // NO WEAPONS	No Match	Match	Training-based	Moderate	Poor
31OT	CRIME IN PROGRESS (OTHER)	2	Caller's daughter's girlfriend hit her and stole her purse; suspect currently in her house	35	CRIME (OTHER)	4	CALLER VS DAUGHTERS GF NO WEAPONS [NAME] STOLE CALLERS PURSE WITH HER WALLET AND HER KEYS	No Match	Match	Incident type ambiguity	Moderate	Moderate
Camden 911 call audio analysis: Interrater-reliability assessment												
Vera Researcher #1				**Vera Researcher #2**				**Comparison**			**Call quality**	
CFS code	*Description*	*Priority*	*Narrative*	*CFS code*	*Description*	*Priority*	*Narrative*	*Incident*	*Narrative*	*Difference*	*Service*	*Information gathering*
15	DISTURBANCE OF THE PEACE	2	White man, 5'4", keeps running in and out of Dunkin Donuts daily, has called police before	15	DISTURBANCE OF THE PEACE	2	There's a White man (approx. 5'4 named [Name], gray shirt) who frequents the [restaurant] location and threatens staff.	Match	Match	None	R1: Moderate // R2: Moderate // COMPARISON: Match	R1: Moderate // R2: Excellent // COMPARISON: No Match

3116AD	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1 (could be downgraded)	Call back request to remove intoxicated adult daughter from house; harrassing; can hear yelling; officers previously came once and "calmed her down;" now wants her out	3116AD	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	Caller is reporting her intoxicated daughter, who is verbally harassing her. This is the second time the woman called about the police to remove her daughter from the premises.	Match	Match	None	R1: Moderate // R2: Moderate // COMPARISON: Match	R1: Moderate // R2: Excellent // COMPARISON: No Match
18MA	MISSING ADULT	1	Requesting wellness check for ill grandmother with child; hasn't heard from her in days; cousins have tried knocking/no response; no one has key; unavailable to meet police	40RC	PROPERTY CHECK (RESIDENCE)	5	Caller is requesting a wellness check on her grandmother who she hasn't heard from in a couple of days (87-88 y/o.)	No Match	No Match	Detail-based	R1: Poor // R2: Poor // COMPARISON: Match	R1: Moderate // R2: Excellent // COMPARISON: No Match
35AR	CRIME (ARMED ROBBERY)	2	Cab manager calling because driver was robbed at gunpoint; no information on offender; cab driver speaks Spanish only	35AB	CRIME (ARMED ROBBERY)	2	Caller is reporting a gunpoint robbery by one of his cab drivers. There is no description of the robber.	Match	Match	Detail-based	R1: Excellent // R2: Excellent // COMPARISON: Match	R1: Excellent // R2: Excellent // COMPARISON: Match
31OT	CRIME IN PROGRESS (OTHER)	4	Native American male wearing black leather coat entered caller's home uninvited and refuses to leave; requesting police removal and transport to shelter; "he's not a bad guy, he just needs help"	15	DISTURBANCE OF THE PEACE	2	Caller is reporting a man (Asian, black jacket) who is on his property, and walked into his home.	No Match	No Match	Incident type ambiguity and detail-based	R1: Excellent // R2: Excellent // COMPARISON: Match	R1: Excellent // R2: Moderate // COMPARISON: No Match

3116AD	DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	1	Male won't leave caller's house; audible yelling	15	DISTURBANCE OF THE PEACE	2	Caller wants to remove a man from her home.	No Match	No Match	Training-based	R1: Moderate // R2: Poor // COMPARISON: No Match	R1: Poor // R2: Poor // COMPARISON: Match
3196	EMOTIONALLY DISTURBED PERSON	1	Request for officer to assist with crisis outreach; client homicidal/suicidal; off psychotropic meds; no weapons; walking outdoors with no clothing;	3196	EMOTIONALLY DISTURBED PERSON	1	Caller is requesting a crisis outreach because the client is walking around without clothes, threatening to harm herself and others, and is not eating or sleeping. All weapons have been removed from the client's home.	Match	Match	None	R1: Moderate // R2: Poor // COMPARISON: No Match	R1: Excellent // R2: Moderate // COMPARISON: No Match
3132	PERSON WITH A FIREARM	1	4-5 shots fired behind school; caller is school principal; school entering soft-lock down; everyone inside school safe	31OT	CRIME IN PROGRESS (OTHER)	2	There's a shooting behind a school, as reported by the school's principal. There were 4-5 shots. School is on lockdown.	No Match	Match	Training-based	R1: Excellent // R2: Excellent // COMPARISON: Match	R1: Moderate // R2: Excellent // COMPARISON: No Match
31AG	CRIME IN PROGRESS (ASSAULT)	1	Physical fight in auto repair show; car windows being broken; owner being chased; caller doesn't want to get involved	31AG	CRIME IN PROGRESS (ASSAULT)	1	Noises from inside autobody garage. Glass breaking, owner spotted walking across street with someone following him, in progress	Match	Match	None	R1: Moderate // R2: Excellent // COMPARISON: No Match	R1: Moderate // R2: Excellent // COMPARISON: No Match

Appendix 4C: Tucson audio analysis detailed coding table

Tucson 911 call audio analysis: Random subsample													
Vera				Communications				Comparison			Call quality	
Type	*Subtype*	*Priority*	*Narrative*	*Type*	*Subtype*	*Priority*	*Narrative*	*Type / Subtype*	*Narrative*	*Difference*	*Service*	*Information gathering*
10-36	Burglary	4	Assisted living resident returned to find his room was burglarized; wheelchair and clothing items stolen; manager reported his items were "picked up"	10-35	LARCENY	4	Comp is client in this boarding home, says while he was at TMC for 3 days, a wheelchair, RX, clothes, were stolen, staff is saying someone picked up his things when he was not23 Staff has further info on who stole items.	No Match	Match	Incident type ambiguity	Excellent	Excellent
SUICDLW	Suicidal with weapon	1	Therapist calling to report suicidal client with gun and medication; individual on way to work and said she'd visit therapist after	SUICDL	SUICIDAL PERSON	2	Client [NAME]/[DOB] called from [#] and or [#] called at [#] and said she wanted to kill herself	No Match	No Match	Incident type ambiguity and details-based	Excellent	Excellent
Threats	Threats of physical harm	3	Mom's boyfriend's friend (Mexican male mid 30s green shirt black pants gray car) threatening to steal caller's car, has a gun tucked in pants (didn't intentionally show weapon)	THREAT.	THREATS	3	10-15 ago, mothers boyf's friend H/M/30'S/GRN shirt/blk pants told comp that he was going to steal comps veh. Subj left in a gray 4dr wb. Subj took his shirt off and comp saw a gun tucked in his pants but never threatened him with it only told him he would be back.	No Match	Match	Incident type ambiguity	Excellent	Excellent

10-31O	Family fight/ domest ic vio lence over	4	Mom calling to report DV / requests restraining order against son who threatened mom and his girlfriend, chased them in car, threatened violence, destroyed mom's property	10-31O	FAMILY FIGHT/ DOMEST IC VIO-LENCE-OVER	4	Son [name] h/m/dob 0505 1986/wearing whi tshirt/blu jeans was at her home about 45 ago and was causing problems. Destroyed her room, made threat to his girlf who was in the house. Comp says she took her sons girlf to grandmother's home and son tried to stop the vehicle and was banging on the car. Comp says son was making threats towards her, comp told son to leave and told him she doesn't want him coming back to the house. All of this occurred about 45 ago. Comp just got back to the house and saw the damage her son did to her room. Son is not 23 right now/	Match	Match	None	Excellent	Excellent
SUSACT.	Suspici ous activity	3	2 Hispanic men 30-40 yo in black pickup truck banging on caller's house window and ringing doorbell; caller watching them from inside through camera	SUSA CT.	SUSPI-CIOUS ACTIVITY	3	A black/Ford/pickup is sitting on front of his house; 2 males are pounding on the windows he doesn't know them. Can't see the descrip on the male now at door except h/m/30-40's/short/chubby. Comp shares a house w/his girlf but she's at work. The males aren't saying his name of anything at all. 1 of the men is back in the truck and others are pounding on the windows.	Match	No Match	Detail-based	Excellent	Excellent

10-35	Larceny	4	Caller's mail and packages stolen; observed white male with glasses and beanie walking with backpack full of mail	SUSA CT.	SUPER-SUSPICIO US PERSON	3	U/m w/a backpack just tried to steal a package from comp's porch. Subj is a w/m/20/dbln/505/120-130/gry beanie/glasses/ gry/blk plaid shirt/gry baggy shorts. Comping is following subj & subj's backpack is now stuffed w/ mail. Subj is in an alley just n of Pima; he is walking toward 7-11 through alley. Comp not able to stand by has a dr's appt. Comp in a gry BMW. The subj didn't have mail spilling out of his backpack when comp 1st saw him at comp's house. When subj came up to comp's porch, comp asked if he could help him & subj walked away.	No Match	No Match	Detail-based	Excellent	Excellent
FIGHT	TRBCUS	3	Customer cursing and yelling; request to remove; Hispanic male 50yo green shirt blue jeans with female pink shirt black pants	FIGH T	TRBCUS	3	Comp is employee asked customer to leave store, is refusing is arguing with comp now. W/f/30s/600/short blk hair/yellow sweatshirt/jeans. Is heading towards front of store now. Has now exited the store will rc if she returns	Match	Match	None	Moderate	Excellent
MISPER	RUNAW AY	4	Group home client missing; Black female ~180lb; missing since 7PM	MISP ER	RUN-AWAY	4	Client [name] 5/22/01 b/f/503/180/blk hair/brn eyes, last seen wearing brn shirt, gry sweats, no dts/dto, habitual runaway. Comp recontacted, advised subj returned, cancelled call.	Match	Match	None	Moderate	Excellent

SUSACT.	SUSPER	3	Suspicious people parked across street from caller's home; in maroon sedan on bike path with no license plate; 2 males 1 female	SUSACT.	SUSVEH	3	Maroon red 4 door sedan no plate parked across the street on the bike path vehicle is occupied 2 males and a female, can hear the voices no description, no contact needed, gb	No Match	Match	Incident type ambiguity	Excellent	Moderate
FIGHT	TRBCUS	3	Customer with history of stealing won't leave Circle K; threatening cashier; white male with white plaid shirt and jeans; running away; don't send anyone because he left	THREAT	PHYSICAL HARM	3	Trespassed subj is threatening to assault comp w/m/whi and gry plaid shirt/jeans refusing to leave is inside the store is poss 10-41 or on 1801 subj is now running away because comp is on the phone with 911. Comp adv ok to cancel will rc if subj returns.	No Match	Match	Incident type ambiguity	Excellent	Excellent
10-31	Family fight/domestic violence	2	Male and female; neighbors physically fighting; no weapons; have newborn; neighbor going to get baby	10-31	FAMILY FIGHT/DOMESTIC VIOLENCE	2	Nbrs are fighting sounds physical. No weapons heard or seen. Thinks there is a newborn child in home. In rears of complex on second flr. Comp does not want contact will rc if escalates any further. Subjects heard fighting is a male and female. Nfd. Another event created at same location. Poss" [name]/[dob] and [name]/b/f/33yo. In previous event, male half stated he may have a 9mm in home.	Match	Match	None	Moderate	Excellent
DV	IN_PROGRESS	2	Neighbor's across street fighting; multiple individuals	FIGHTB	FIGHT-BREWING	3	Across from listed hears several people arguing, poss [address] comp refused, does not want ofcr contact.	No Match	Match	Incident type ambiguity	Excellent	Moderate

10-48	Runaway juvenile	4	Hispanic Black run away male; wearing jeans and hoodie; left last night 7PM; caller is runaway's mother	10-48	RUN-AWAY – JUVEN-ILE	4	B/m/03192004/508/120/bro/blu hoodie/jeans last night at 1900 yesterday. neg dts/dto. Neg ment/ med issues. Neg smts comp is mother.	Match	Match	None	Moderate	Excellent
LARCENY	RESIDENTIAL	4	Phone stolen from caller's apt by friend of friend; offender Hispanic male in camo hoodie	LARCENY	PROPER-TY THEFT	3	Comp's friend just took comp's property less than 5 ago. Ran off eb on speedway. Friend [name] h/m/20s/grn hoodie/unk pants. Subj was staying at comp's apt, took several handfuls of comp's belongings and took off on foot. Comp using borrowed 21. Comp just saw subj at intersection of Silverbell/Speedway. Subj actually wearing blu hoodie/denim shorts. Neg wpns for subj. Comp rcd says friend also took clothes and subj is running eb speedway.	No Match	No Match	Detail-based	Excellent	Excellent
DOC	LD-NOISE	4	Neighbor noise complaint; yelling and cursing slamming doors started at 6AM; suspected mental illness; request for restraining order	CKWLELF	CHECK WEL-FARE	3	Nbr at listed apt is slamming doors, banging on comps side of the wall and yelling obscenities ongoing issue for days now ongoing today since 0800, comp concerned, nbr lives alone. Only knows subj's first name, [Name]. Comp wants ofcr contact.	No Match	No Match	Incident type ambiguity and detail-based	Excellent	Excellent

DV	OVER	4	Wife's mother knocking on caller's door; police previously separated caller and his wife; thinks he's being set up for another police incident; left before end of call	DV	BREWING-DOMESTIC VIOLENCE BREWING	3	Says his mother in law is knocking at his door and refuses to go away. No wpns, nothing physical, mother in law [Name] nfd, mother in law from apt [#] may have gone back now.	No Match	Match	Incident type ambiguity	Excellent	Excellent
10-31O	FAMILY FIGHT/ DOMESTIC VIOLENCE OVER, PARTIES SEPARATED	4	Teenage stepdaughter (white, navy shirt jeans flip flops) punched biological mom and threw items; sped off in red sedan	10-31O	FAMILY FIGHT/DOMESTIC VIOLENCE OVER, PARTIES SEPARATED	4	Stepdaughter [name] w/f/113099/d blu shirt/jeans was arguing and throwing things left in red [name].	Match	Match	None	Excellent	Excellent
NARCOTICS	USE	4	Customers complaining about drugs being smoked from red jeep in store parking lot; offender white male 40s white hat	NARCOTICS	USE	3	Man in vehicle smoking unk substance off a piece of foil. Is inside a red jeep SUV in lot. W/m/40's/white baseball cap/nfd, parked in a corner of parking lot, SUV has black rims, unk wpns. Comp is customer.	Match	Match	None	Moderate	Excellent
THREAT.	HARASS	4	Maintenance man Hispanic 50s bald in yellow shirt yelling and threatening resident; offender with his family in silver car	FIGHT	BREWING-FIGHT BREWING	3	Office. Says maint man h/m/40-50, grn shirt and other males assco silver veh are in the parking lot trying to fight with comp and comps boyfr will wait at the office.	No Match	Match	Incident-type ambiguity	Excellent	Excellent
DV	IN_PROGRESS	2	Sister kicked door in; history of previous violence; Hispanic wearing boxers and white tank top; no weapons	DV	IN PROGRESS	2	Comp says sister kicked in his door. Sister is [name]/h/[dob]/507/175/nfi, no weapons, comp not sure is sister is still in house.	Match	Match	None	Excellent	Excellent

10-31 w	10-31 WITH WEAPON	1	Neighbor's engaged in violent fight over money; Asian woman (30yo thin) white man (50s cowboy hat); knife involved; no longer on property	10-31 w	10-31 WITH WEAPON	1	Female pulled knife on male in room 107; a/f/35-40/502-503/thin/unk clothing. W/m/50's/cowboy hat/nfd. Comp left room about 2 ago. Per comp, female had a kitchen.	Match	Match	None	Excellent	Excellent
10-31O	Family fight/domestic violence-over	4	Ex-boyfriend took car keys and phone; threatening he'll get 2yo child taken away if she doesn't do what he says; made hole in wall; may be on drugs ("BLACK" and pipes); wearing gray shirt black hat black shorts; no weapons	10-31	FAMILY FIGT/DOMESTIC VIOLENCE	3	Gry shirt, blk hat, gry bb shorts, comp thinks that he might be under influence of drugs..comp is calling from across the street comp says that he would not let her take her 2 yo, per comp subj does something called black..she does not know what that is..comp is calling from across the street..neg weapons that comp knows of.	No Match	Match	Incident-type ambiguity	Excellent	Excellent
ASSAULT	OVER	4	Fight happened outside of bank; Black man 20yo green shirt red shorts (was tackled, came into bank); white man buzz cut navy shirt jeans 25yo on bike; fear over white man returning; Black man running away	FIGHT	FIGHT	3	2 males fighting in parking lot. Comp manager. B/m/20yo/602/thin/grn shirt /red shorts vs w/m/24 yo/wearing blk shirt/jeans/ on a bike. Comp says w/m/tackled the b/male in the parking lot. B/m came into busn. Comp says his boss is talking to both of them. W/m/may have gone wb on bike from parking lot. Comp now saying the b/m/ is running off eb now.	No Match	Match	Incident-type ambiguity	Moderate	Excellent

SUSPER	SUSPICIOUS PERSON	3	Superintendent calling to report 2 suspicious people at apartment complex; 2 Hispanic people 20s (male Black sweater in shorts; female clothes unknown); in entrance	SUSPER	SUSPICIOUS PERSON	3	H/m/20-25/blk sweater/blk shorts and h/f/20-25 are hanging out by the entrance they were trying to reach into the office door where money orders are deposited.	Match	Match	None	Moderate	Excellent
FRAUD	FRAUD	4	Veteran caller was formerly housing two ex-marine males addicted to heroin; they stole her items and credit cards; threw them out last week; wants to press charges	FRAUD	FRAUD	4	Comp saying couple of months ago took into two ex-marines who ended up stealing from her accts and also stealing her items from house...has their info, they are not23, says threw them out, and has evidence, [name]/[dob] and [name]	Match	Match	None	Moderate	Moderate
Tucson 911 call audio analysis: Check welfare (i.e., most frequent call type) subsample												
Vera				**Communications**				**Comparison**			**Call quality**	
Type	*Subtype*	*Priority*	*Narrative*	*Type*	*Subtype*	*Priority*	*Narrative*	*Type / Subtype*	*Narrative*	*Difference*	*Service*	*Information gathering*
SUSACT.	SUSPER	3	Small child (Hisp, male, shaved head) attempting to sell chips at 12AM; suspicious because another apt was broken into last Thurs/Fri	CKWLF.	CHECK WELFARE	2	Less than 5 ago.. 7yo child came to comps apartment trying to sell comp chips; per comps adult grandson who is 23 child was h/m/7yo/shv head/unk clothing.. Comp only 107right the door a little so not a good visual; the nbr'ing unit was broken into about a week ago; unk what direction the child went once the door was closed; confirmed the child isn't currently outside; comps unit is located at the front at the exit gate on the lower level on the inside of the building; comp is expecting ofcr contact	No Match	No Match	Incident type ambiguity	Excellent	Excellent

SEXOFF	SEXOFF	3	Adult protective services reporting sexual abuse; 22yo developmentally disabled woman made to “pinch [father’s] penis until he got off;” father is her legal guardian	CKW LF.	CHECK WELFAR E	3	Comp is with aps; would like officers to check on [name]; states that she is developmentally disabled. [name] reported to her coworker at her day program that on [date] her father forced her to do sexual acts on him while they were home together; father is [name]	No Match	Match	Incident type ambiguity	Excellent	Excellent
CKWLF.	CHECK WELFA RE	3	White male (20s, t shirt and pants) attempting to get 108rights towed; seems mentally unstable; requested caller call 911 to tow bike	CKW LF.	CHECK WELFAR E	3	There is a w/m outside who has been asking comp for 21’s to towing companies to tow his 108rights. Subj is acting strangely, seems to be confused. W/m/20’s/510/170/tshirt/ pants. (yes, wants a tow truck for his bicycle. Not a motorcycle.)	Match	Match	Incident type ambiguity	Excellent	Excellent
CKWLF.	CHECK WELFA RE	3	Male (white, 50s, jeans, green shirt) by McDonalds bus stop very drunk or sick; afraid someone will steal from him	CKW LF.	CHECK WELFAR E	3	Reporting a w/m/50s/grn shirt/jeans passed out at the bus stop in front of listed; comp would like officers to check on him	Match	Match	Incident type ambiguity	Moderate	Excellent
CKWLF.	CHECK WELFA RE	3	Caller (white female, white dress) requesting safe ride home; cannot find uber app; people acting strange (gone now)/making her feel unsafe; feels unsafe in neighborhood; intoxicated; stating brother in law is TPD officer	CKW LF.	CHECK WELFAR E	3	Comp’s is w/f/[dob]/whi dress is 10-41; crying and saying she doesn’t feel safe; were people outside acting strange and making her feel uncomfortable; are goa now; adv she is standing outside with her sister, who is also 10-41. Keeps repeating she needs to find a safe way home and can’t reach brother in law	Match	No Match	Detail-based	Moderate	Excellent

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Tucson 911 call audio analysis: Domestic violence subsample												
Vera				Communications				Comparison			Call quality	
Type	*Subtype*	*Priority*	*Narrative*	*Type*	*Subtype*	*Priority*	*Narrative*	*Type / Subtype*	*Narrative*	*Difference*	*Service*	*Information gathering*
DV	FAMILY FIGHT	2	Request to remove son (37yo, white, thin, blond); yelling at himself and his mother; won't take medication; no violence; thinks someone is trying to kill him; wants court order; no weapons or court order; HOPE client; medical center released him; wants him taken to CRC	DV	FAMILY FIGHT	2	Comp said her son/ [name]/[dob] is yelling & talking to himself in background. Is yelling at her. Not taking his meds for mental health issues; she wants him taken somewhere; no weapons. No kids. No veh. W/m/37/ 511/thin-med/blond/unk clothes; has on gry-blu shirt/jeans. He thinks someone is trying to kill comp; he wants her to stay in bedroom; he's client of hope. Has been in tmc recently & was released within 24hrs. Comp would like him to go to crc. Has never been viol toward ofcrs before. [apt #] on se crnr, 109righ#1, first floor	Match	Match	None	Excellent	Excellent

MISPER	ADULT	4	Estranged husband took keys/caused scene at work; parents and boss now cannot reach her (knocked on door)	CKW LF.	CHECK WEL-FARE	3	45 is in office. Comp is mgr, 12 23 with employer of resident [name]/about 40yo/w/f/bln who is not answering her door or 21 and did not show up to work today after an altercation with her estranged husband at her work yesterday. [name] works at [company], and her employer [name] is waiting in the office. Was just 23 at [name's] door. [name] is neg veh. Estranged husband is [name]/unk dob	No Match	Match	Incident type ambiguity	Moderate	Moderate
DV	FAMILY FIGHT	2	Caller's neighbor (white 30s blank tank top shorts) requested she call; bloody face; husband (white 30s) assaulting her and kids; 3 children; went back to house	DV	FAMILY FIGHT	2	Comp is nbr; w/f/30's/blk tank top/shorts; asked comp to call police; says her husband is trying to leave with the kids; she has been assaulted, has blood on her face; husband is w/m/30's/unk clothing; couple poss has 3 children; unk weapons; female went back to listed, no longer at comps 23	Match	Match	None	Excellent	Excellent

DV	FAMILY FIGHT	2	DV 111 right sto at Valero Gas Station; yelling; male (white 20s then baseball cap gray shirt with backpack gray sweatpants) cornered female (dark skin and hair, green pants, 20s) in store; she pushed back; silver sedan	DV	FAMILY FIGHT	2	Comp was at 111right gas & said male & female are yelling at each other; their veh is a sil/Chev Lumina.... No kids. Unk on weapons. They went into the store.... He kept cornering the female, pushing/shoving; w-h/m/20's/600/thn/bb cap/gry shirt/gry sweat pants/backpack; drk complected female/20's/drk hair/grn pants/unk shirt	Match	Match	None	Excellent	Excellent
MISPER.	KIDNAP	2	Employee's ex-husband took car keys; female (Hispanic female, 30s, brown hair, blue shirt, tan pans) and male (Hispanic, 30s, dark brown hair, red tank top, basketball shorts) left in car (white sedan); unclear whether she went willingly; cursing and yelling up until car left	DV	FAMILY FIGHT	2	Employee's ex-husb came into the business, grabbed her vehicle keys, then left with employee. Unk if she went willingly with him, left her cellphone behind; subjs argued, man cursed at her; employee is [name] h/f/30's/brown hair/blue top/nfd; male subj h/m/30's/brown hair/red tank top/unk color basketball shorts; left white ford SUV, unk plate; husb is [name]; veh took off eb on Williams toward Craycroft; nfi. 45 comp at front desk	No Match	No Match	Incident type ambiguity	Excellent	Excellent
Tucson 911 call audio analysis: Mental health subsample												
Vera				**Communications**				**Comparison**			**Call quality**	

Type	*Subtype*	*Priority*	*Narrative*	*Type*	*Subtype*	*Priority*	*Narrative*	*Type / Subtype*	*Narrative*	*Difference*	*Service*	*Information gathering*
MHST	Mental health unit	3	Crisis line representative; client requesting police presence during mobile team client approach for safety reasons; male has history of violence; multiple personality disorder; no weapons	CKW LF.	CHECK WEL-FARE	3	Comp with crisis mobile team 23 rq- ofcr to respond for safety reasons; member has history of 112rightst, says 112rightst called cris line from a closet; says member suffers from multi personalities; member [name]/[dob]/u/m; as far as comp knows no wpn's in the house; rc'd by comp req to canx	No Match	Match	Incident type ambiguity	Moderate	Excellent
MHST	Mental health unit	3	Neighbor (late 20s, white) yelling another neighbor's name and random 112rightsto, continued problem, suspected mental health issues; requested officer contact	CKW LF.	CHECK WEL-FARE	3	Nbr yelling and screaming, at another nbr. Subj has mental issues, is yelling the name of the nbr across from her. Subj's [name]. Last night, subj ran inside, locked doors and turned off lights to hide from officers that responded out. Subj's w/f/27-20yo/unk clothing. Comp wants officer contact, is the mgr. He does leave for work by 1000. Wants something "done" to "help" the subj. Ongoing problem. The nbr that subj seems to be yelling about, is not outside	No Match	Match	Incident type ambiguity	Excellent	Excellent

CKWLF.	CHECK WELFARE	3	Adult protective services and nurse practitioner requesting welfare check; combative male (white, 72yo) may need medical attention; nurse was at male's house at 11AM; schizophrenia, seizures, diabetes, not taking medication, auditory, hallucinating; depressed; no shower for 1yr; cigarette burns on his clothes; not eating; requesting title 36 petition (assisted living denied 2x) and CRC	CKWLF.	CHECK WELFARE	2	Comp is nurse practitioner, was 23 here abt: 11:30 this morning for home visit with client [name] w/m/[dob]/age 75; hx schizophrenia, diabetes, seizures, depression, psychosis, hallucinating, not taking his rx meds, not caring for self properly, not eating, not bathing; comp went back to her office, discussed this with her supervisor then read his medical chart and saw he had hx of seizures; comp called adult protective services who xferred her to tpd; states he was somewhat argumentative and combative with her during the home visit; lives alone, unable to care for self; [name] with adult protective services wants a call at [#] by ofcr with outcome	Match	Match	Incident type ambiguity	Poor	Moderate

CKWELF.	CHECK WELFARE	3	Request for welfare check on Red Cross coworker (male, 60, white; gray shoulder length hair; former marine); address unknown; bipolar; on manic episode / upset because female friend sleeping with someone else; caller wishes to remain anonymous; explosive with coworkers; in office overnight; showed text messages with woman; threw rocks at her window; gray sedan and green 114right; weapons unknown; lives alone with dog	CKWLF.	CHECK WELFARE	3	Comp's co-worker [name]/60yo/w/m/about 510/about 170/gry shoulder length is bipolar and has been explosive recently with co-workers. Told comp this morning that he had spent the night in the office. Told comp had thrown rocks at ex-girlfr's window overnight. Left the office early this morning. Subj's 21 [#] works with comp at red cross [address]. Subj did not return to work, but he was scheduled to start vacation today; 20 is per ileads, comp does not know 20 but says he lives near Tanque Verde. Unk firearms... Per comp [name] was in the marine corps; has one dog; lives along; assoc with gry 114right 35ox and grn 114right 114rightst mc. Per ileads [dob]	Match	Match	Incident type ambiguity	Excellent	Excellent

SUSACT.	STALKER	3	Caller (I/brown hair/black jacket and blue jeans) being chased by 3 unknown men (1 Hispanic, 20s, red shirt; 1 Hispanic, 30s, black shirt; 1 light skin, age unknown, clothing unknown); in neighborhood behind Barnes and Noble; hiding behind vehicle; last seen 5 min ago	CKW LF.	CHECK WELFARE	2	Comp stating he was being chased by 3 men in the area of Broadway/ 115rightst unk where he is now. Doesn't know who they are and stating that he doesn't know where the subjs are; location is where cp is plotting with in 8 meters; comp is 1/m/[dob]/600/210/brow/ blk jacket/blu jeans; comp is hiding behind an unk vehicle; the subj's that were flowing him... 3 subs... H/m/20-30s/red shirt; unk/m/nothing further; comp last saw them 5 min ago; desk telling comp to keep an eye for the ofcr; still plotting in the same location within 8 meters; says he sees the ofcrs... Adv'ing him to wave them down	No Match	No Match	Incident type ambiguity	Moderate	Excellent
Tucson 911 call audio analysis: Repeat callers subsample												
Vera				**Communications**				**Comparison**			**Call quality**	
Type	*Subtype*	*Priority*	*Narrative*	*Type*	*Subtype*	*Priority*	*Narrative*	*Type / Subtype*	*Narrative*	*Difference*	*Service*	*Information Gathering*
DV	OVER	4	Caller's ex-boyfriend (black shorts, white, black hair, gray t shirt) pushed her downstairs; injured ankle; threatening mom; scared he has keys to her home; riding away on bike; crying; refusing medical attention; mother witnessed	DV	FAMILY FIGHT	2	Boyfriend [name] [dob] just pushed comp down the stairs; comp does not want med 115righ; boyfriend leaving on bike nb toward Miracle Mile; w/m/gray shirt/blk shorts; no weapons	No Match	Match	Incident type ambiguity	Moderate	Excellent

COURTORD	VIOLATION	4	Caller has order of protection against ex-boyfriend (39yo white male, black shirt black shorts); he's standing outside her house; on silver bike; has not yet been served; has keys to house	DV	FAMILY FIGHT	3	[Name] 39yoa h/m blk shorts in front of trailer and comp has protection order against him has not been served. [name] on silv bicycle has tape on the handlebars; per comp randy is sitting directly in front of her trailer	No Match	No Match	Incident type ambiguity and detail-based	Moderate	Moderate
DV	IN_PROGRESS	2	Daughter's ex-boyfriend (white; 39yo;) with restraining order (not yet served); present in house (family let him in); yelling; refusing to leave; stealing car and dog	DV	FAMILY FIGHT BREWING	3	Comp is reporting daughter's boyf is 23 and fighting with her. [name] w/m/39/505/120/blu top/blu pants. This has become a physical struggle. Comp has filed a restraining order on subj but it has not been served.	No Match	No Match	Detail-based	Poor	Moderate
COURTORD	VIOLATION	4	Daughter's ex-boyfriend (white/39yo/blue shirt with pattern/jean shorts) was served an order of protection yesterday and is now sitting on the back steps; might be trying to get his belongings	COURTORD	VIOLATION	4	Comp says [name] was served with an order of protection yesterday and today his is sitting on the back steps of this address. this address is listed; in the order of protection. comp has copy of the order; [name] is h/m/39/505/ 120/blue shirt with pattern/unk shorts...	Match	Match	None	Poor	Moderate
C OURTORD	V ISOLA-TION	4	Caller's ex-boyfriend (white male, black hair, 39, silver bike, blue jeans, blue pattern shirt) was going through her belongs and car; has a restraining order; second time she's had to call today; cursed at her	OURTORD	VIOLA-TION	4	Ex-bf was just at comps home, was going through her veh; looked at comp and called her names, was also sleeping on her property; subj is [name] h/m/39/505/120/blu shirt with writing/blue jeans	Match	Match	None	Moderate	Moderate

Tucson 911 call audio analysis: Calls resulting in use of force subsample												
Vera				**Communications**				**Comparison**			**Call quality**	
Type	*Subtype*	*Priority*	*Narrative*	*Type*	*Subtype*	*Priority*	*Narrative*	*Type / Subtype*	*Narrative*	*Difference*	*Service*	*Information gathering*
ASSAULT	OVER	4	Caller (117rightstown) was assaulted/hit requesting help; offender unknown (native 117rightst, female, 30s, heavy, pink shirt, green pants); at apartment; agitated/unwilling to answer questions	ASSAULT	OVER	4	Comp reporting that if30/510/165/heavy build/pink top/grn pants; comp was very uncooperative and seemingly annoyed with desk's questions and requested to send ofcr instead of giving further detail over the 21. Comp claimed to not know subj that assaulted him but assault occ'd inside comp's 20, without subj having broken in to listed.	Match	Match	None	Excellent	Moderate
FIGHT	WEAPONS	1	Resident (117rightst male, early 30s, blue jeans, black shirt, shaved head, boots) with knife making threats; claims they're calling him a child molester; "tripping out;" knife in right pocket; lives in the area	FIGHT	WEAPONS	1	H/m/30's blk shirt/jeans pulled out a knife and is yelling comp and others he knows they are talking to him in the alley behind comp and his crew are working on a job behind his home; making threats to take everyone out; per comp appears #6; knife now in his right pocket; thinks comp and others are talking about him being a child molester; subj is possibly [name] [dob] who lives at above; comp was advised	Match	Match	None	Moderate	Moderate

AGNAST.	NURSE WISE	3	Request officer assistant to serve petition; caller sitting outside in white Honda CR-V; attempting to trade/use food stamps to get a gun to shoot brother in law; sister called crisis line to report; schizophrenic; refuses medication; lives alone	AGN AST.	NURSEW ISE	3	Needs to have an emergency petition served on [name] [dob]. They are sitting outside in whi/Honda/CR-V on the se quad of Rillito/7th to 45 ofcrs; subj attempting to get a gun by using food stamps or trading property for a gun to shoot his brother in law; his sis/[name] called the crisis line to get the emerg petition going; he has history of violence toward himself & officers per the sister. Has mental issues. He refuses meds. They are sitting across from the above 20. He lives in a mobile home in lot #15 but trailer is parked across from the lot	Match	Match	None	Excellent	Excellent

SUICIAL	WEAPON	1	Caller (Hispanic male) suicidal with gun; near outhouse sees flag; lost multiple loved ones over a short period of time; formerly Christian; on foot; doesn't want to be taken to psych hospital; wants someone to pay attention; everyone's telling him to take meds; concerned about being arrested; would be a favor if officers shot him; requesting call taker not leave	SUICIAL	WEAPON	1	Has a gun; wants to kill self; near the outhouse at the end of the cemetery; doesn't want to live. Comp has 38 Geist gun. Says no one cares for him; comp crying; comp not answering questions; said would rather be shot then go to a hospital; comp doesn't want to give clothing description; he thinks officers will just throw him in a veh and take him to hospital; comp says helicopter is irritating him, doesn't want it above him; he's afraid he's going to be arrested; says he doesn't care if officers shoot him; comp asking desk not to leave him; comp [#] is comps 21; comp says he will answer the other line, doesn't want desk to disconnect	Match	Match	None	Excellent	Excellent

SHOOTING	SHOOTING	1	Armed robbery at fitness center caller is an officer working at the gym and is locking everyone inside for safety; robber outside with 2 shotgun and white shirt black ski mask and jeans (white, male, 6ft, 200lbs); trying to member a customer; robber is east bound; 10 shots heard	ROBBERY	ARMED	2	Comp reporting there is a subj outside with a shotgun poss a 43. W/m/whi shirt/blk mask/nfd; comp says there might be a second subj; there are 2 firearms involved; comp is making sure everybody safe/locked in the gym. This is occurring right out front. Subj is now eb, walking across Wrightstown. Subj no walking sb, sb on Pantano. On the w side of street. Whi shirt/jeans. Subj is firing at the gym now and running sb on Pantano. There were 10 shots fired. Subj in the complex on the nw corner of intersection. Neg injury. Comp is off duty ofcr. Subj thought to be wb behind the feed store. Blk ski mask/600/200/whi shirt/jeans; victim is 23 with comp.	No Match	Match	Incident type ambiguity	Excellent	Excellent

Tucson 911 call audio analysis: Interrater-reliability assessment												
Vera Researcher #1				Vera Researcher #2				Comparison			Call quality	
Type	*Subtype*	*Priority*	*Narrative*	*Type*	*Subtype*	*Priority*	*Narrative*	*Type / Subtype*	*Narrative*	*Difference*	*Service*	*Information gathering*
SUICIAL	WEAPON	1	Therapist calling to report suicidal client with gun and medication; individual on way to work and said she'd visit therapist after	SUICIAL	WEAPON	1	Therapist has client who called expressing suicidal thoughts. Client has gun but doesn't know where the bullets are and that she has medication when therapist asked if she had a plan. Client called at 9:01 pm. Client said she was going to work.	Match	Match	None	R1: Excellent // R2: Moderate // COMPAR-ISON: No Match	R1: Excellent // R2: Moderate // COMPARISON: No Match
LARCENY	MAIL	4	Caller's mail and packages stolen; observed white male with glasses and beanie walking with backpack full of mail	LARCENY	MAIL	4	Person stealing mail. Caller saw male carrying backpack full of mail. MALE/WHITE/25/5'5/130 LBS. Wearing glasses, a gray beanie, gray shorts, and plaid t-shirt. Going toward Circle K through the allies on Beverley.	Match	Match	None	R1: Excellent // R2: Moderate // COMPAR-ISON: No Match	R1: Excellent // R2: Excellent // COMPARISON: Match
SUSACT.	SUSPER	3	Suspicious people parked across street from caller's home; in maroon sedan on bike path with no license plate; 2 males 1 female	SUSACT.	SUSVEH	3	Suspicious vehicle parked across from caller's house in bike path. Maroon 4 door vehicle. No license plate. People keep getting in and out of car. Two males and one female. Caller doesn't want officer contact.	No Match	Match	Training-based - OR-incident type ambiguity	R1: Excellent // R2: Excellent // COMPARISON: Match	R1: Moderate // R2: Moderate // COMPARISON: Match
DV	IN_PROGRESS	2	Male and female; neighbors physically fighting; no weapons; have newborn; neighbor going to get baby	DV	IN_PROGRESS	2	Upstairs neighbors fighting. Male and female. Have newborn baby. No weapons.	Match	No Match	Detail-based	R1: Moderate // R2: Moderate // COMPARISON: Match	R1: Excellent // R2: Excellent // COMPARISON: Match

CKWELF.	CKWELF	3	Male (white, 50s, jeans, green shirt) by McDonalds bus stop very drunk or sick; afraid someone will steal from him	CKWELF.	CKWELF	3	There is a white man, approximately 50 years old, who appears to be physically and/or mentally unwell. He is wearing jeans, and a light green shirt. Caller says the man is laying down at the bus stop.	Match	Match	None	R1: Moderate // R2: Moderate // COMPARISON: Match	R1: Excellent // R2: Excellent // COMPARISON: Match
DV	IN_PROGRESS	2	DV occurring at Valero Gas Station; yelling; male (white 20s then baseball cap gray shirt with backpack gray sweatpants) cornered female (dark skin and hair, green pants, 20s) in store; she pushed back; silver sedan	DV	IN_PROGRESS	2	There is a domestic situation at a gas station between a man (About 6 foot tall, White or Hispanic, early-mid 20s, grey shirt and sweatpants) and a woman (unidentifiable race/ethnicity, wearing dark green.) The two appeared to be yelling at each other outside of the store, when the man cornered the woman, and pushed her into the wall.	Match	Match	None	R1: Excellent // R2: Moderate // COMPARISON: No Match	R1: Excellent // R2: Excellent // COMPARISON: Match
SUSACT.	STALKER	3	Caller (I/brown hair/black jacket and blue jeans) being chased by 3 unknown men (1 Hispanic, 20s, red shirt; 1 Hispanic, 30s, black shirt; 1 light skin, age unknown, clothing unknown); in neighborhood behind Barnes and Noble; hiding behind vehicle; last seen 5 min ago	SUSACT.	UNKTRB	2	Caller (Native American, 6'2, brown hair, black jacket/blue jeans) was being chased and followed by three men (first man: Hispanic, early 20s, red shirt; second man: Hispanic, 30s, black shirt; race/ethnicity, and age unidentifiable) on foot. He was hiding behind	No Match	Match	Incident type ambiguity	R1: Moderate // R2: Excellent // COMPARISON: No Match	R1: Excellent // R2: Excellent // COMPARISON: Match

COURTORD	VIOLATION	4	Daughter's ex-boyfriend (white/39yo/blue shirt with pattern/jean shorts) was served an order of protection yesterday and is now sitting on the back steps; might be trying to get his belongings	DOC.	UNWANT	4	Mother was calling concerning her daughter's ex-boyfriend (White, 39 y/o, 5'5, 120 pounds, blue shirt/jean shorts) because they have an order of protection against him, and he was sitting on their back-steps.	No Match	Match	Training-based - OR-incident type ambiguity	R1: Poor // R2: Poor // COMPARISON: Match	R1: Moderate // R2: Moderate // COMPARISON: Match
FIGHT	WEAPONS	1	Resident (Hispanic male, early 30s, blue jeans, black shirt, shaved head, boots) with knife making threats; claims they're calling him a child molester; "tripping out;" knife in right pocket; lives in the area	THREAT.	HARM	3	Resident (Hispanic, early 30s, black shirt/blue jeans/boots) is threatening caller, and other workers in an alley with a knife.	No Match	No Match	Incident type ambiguity and detail-based	R1: Moderate // R2: Moderate // COMPARISON: Match	R1: Moderate // R2: Excellent // COMPARISON: No Match

Chapter 5: Descriptive Analysis of 911 Calls for Service and Officer-Initiated Activity

Section 1: Overview and Top-Line Findings

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To improve contextual understanding of the nature of police activity, Vera researchers reviewed two years of computer-aided dispatch (CAD) entries across five cities, including both calls for service and officer-initiated incidents. These cities include Camden and Tucson—research partner sites that provided detailed case-level data directly to Vera for the purposes of this study—and Detroit, New Orleans, and Seattle—sites that make their CAD data available publicly through open data initiatives.

This chapter is divided into three sub-sections. The first, presented here, provides an overview of the research questions, approach, and top-line findings from the descriptive analysis. The second provides more detailed, site specific information relating to the research questions outlined below. The third provides supplemental findings from each of the research sites, including information that does not pertain directly to the proposed research questions, but provides useful context for understanding the nature of police activity and calls for service.

Research questions

Three key research questions guided this study:

- What is the volume/rate (per capita) of 911 calls received, and how does it vary by incident-type (e.g., nuisance complaint, crime in progress, medical emergency, domestic violence incident, officer involved shooting), time of day, and geographic location?
- How promptly are calls responded to—by a call-taker, dispatcher, and an officer on-scene—and how does this vary by call volume, incident-type, time of day, and geographic location?[203]
- What proportion of police activity—especially enforcement—is proactive (i.e., officer initiated, such as traffic stops and directed patrols) versus reactive (i.e., in response to 911 calls / reported incidents)?

Approach

Data analyses

The descriptive analyses presented below are based the following aggregation strategies and corresponding variables:

[203] Overall, response times may be an outdated/flawed metric of success, in that promptly addressed calls for service may be correlated with an increased likelihood of repeat and/or unresolved incidents. Both call receivers and officers respond slower when/where call volumes are high (e.g., weekends, nights, low SES geographic areas). Officers respond fastest to the scene when the incident involves a serious crime in progress.

- Frequency of CAD activity by
    - call source (e.g., 911 call for service or officer initiated)
    - priority level
    - incident type
    - day of week
    - time of day
    - hour of day
    - geographic sector/team

- 911 calls for service by
    - call source (e.g., 911 call for service or officer initiated)
    - priority level
    - incident type
    - day of week
    - time of day
    - hour of day
    - geographic sector/team

- Cross-tabulations were computed to examine the breakdown of priority levels at different categories/levels of the:
    - call source (e.g., 911 call for service, officer initiated)
    - incident type
    - time of day
    - day of week
    - hour of day

- Finally, average response times were calculated for call-takers, dispatchers, and officers, as well as average overall call processing time, at different categories/levels of the following variables:
    - call type
    - priority level
    - incident type
    - day of week
    - time of day
    - hour of day
    - geographic sector/team

To examine low priority calls more closely, seven calls were selected because of their priority level classification (either 4 or 5), and the narratives were extracted to better understand the reason for the call. For Camden, narratives are embedded in the CAD dataset, but for Tucson, narratives are contained in a separate file that was otherwise unused for this section of the project.

Response time calculations

Vera conducted several time analyses, by observing different average time metrics across variables of interest, in order to answer the research questions above. Researchers were able to assess time between events using similar criteria for the two research site jurisdictions and conduct a similar temporal analysis across both sites. However, this was not possible for the open data jurisdictions Vera examined, due to inconsistencies in record keeping procedures across sites.

It is important to note that each of the time variables was converted into seconds to allow for uniform analysis. Additionally, when running analyses on the response time measures, researchers excluded cases in which the response time was less than .00 seconds. This decision was made after observing several thousand cases with response times listed as negative numbers. Vera researchers examined those cases to determine a possible cause of these negative response times. It appears that numerous potential explanations may be relevant (e.g., some may be technical glitches in the system, whereas others may correspond to officer-initiated stops, which should technically not have a response time ; typically, the negative response time was less than 30 seconds and most often appears for self-initiated stops.

Camden and Tucson

For Camden and Tucson, response times for each actor (call-taker, dispatcher, and officer) and total call processing time were computed using the following formulas:

Figure 5.1.1: Camden and Tucson response time measures and calculations

Time measure	Calculation
Call-taker response time	Time call-taker answered (TX)- Time call was received (TR)
Dispatcher response time	Time call was dispatched (TD)- Time call-taker answered TX
Officer response time	Time officer arrived (TA)- Time call was dispatched (TD)
Call processing total time	Time call was marked as finished (FT) - Time call was received (TR)

Detroit

In contrast to Vera's research sites, Detroit's open 911 data, retrieved through the Detroit Open Data Portal, includes the following time variables, in which the times are already calculated. Therefore, there was no need to calculate the response times. However, "Call Receiver Response Time" was not available in the Detroit dataset and is thus excluded from the analysis.

Figure 5.1.2: Detroit response time measures

Time measure	Variable
Dispatcher response time	Dispatch time
Officer response time	Travel time
Call processing total time	Total time

New Orleans

Response times for each responder (call-taker, dispatcher, and officer) and total call processing time were computed using the following formulas for New Orleans:

Figure 5.1.3: New Orleans response time measures and calculations

Time measure	Calculation
Dispatcher response time	Time call was dispatched (TD)- Time call-taker answered TX
Officer response time	Time officer arrived (TA)- Time call was dispatched (TD)

Call processing total time	Time call was marked as finished (FT) - Time call was received (TR)

Seattle

The Seattle Police Department only includes "Time Created" and "Officer Arrival" in its 911 open dataset. As such, Vera researchers were able to produce the following calculation, unlike the other cities included in the comparative analysis.

Figure 5.1.4: Seattle response time measure and calculation

Time measure	Calculation
Officer response time	Officer Arrival – Time Created

It is also important to note that the city of Seattle has another call type: "Telephone Other, Not 911." Though an argument can be made to include these calls alongside the 911 calls, Vera researchers decided to keep these as two distinct call types, focusing only on 911 calls for the Officer Arrival Analysis.

Variables and recoding

To allow for more accurate comparison, Vera researchers recategorized both time and incident type variables. The following variables were extracted from the timestamp that is created when a call is entered into the CAD system by a call-taker:

- year call was received
- hour call was received
    - This variable was then recoded for the following times of day:[204]
        - Early Morning: 5:00 a.m. - 9:59 a.m.
        - Late Morning: 10:00 a.m. - 11:59 a.m.
        - Afternoon: noon - 4:59 p.m.
        - Early Evening: 5:00 p.m. - 9:59 p.m.
        - Night: 10:00 p.m. - 4:59 a.m.
- day of week call was received

The above recoding was applied to both Tucson and Camden. [205]

Incident types for both Tucson and Camden were consolidated in consultation with experts and representatives from each site. Tucson's data originally included nearly 500 different incident types, which were consolidated into 24 groups, and Camden's original data

[204] See "Limitations" on page 60 for acknowledged challenges with this type of categorization.

[205] A dataset containing CAD records, along with the source of the call (e.g., 911 call, officer initiated) was provided to the research team. For Tucson, the original file provided contained 2016 and 2017 data in one file. Researchers computed a variable for the year the call was received with the SPSS Date and Time Wizard. The data was then separated into datasets—one for 2016 and one for 2017. A separate dataset containing precalculated response times in seconds for dispatchers and officers was also provided to the research team.

included more than 100 incident types, which were collapsed into 17 groups. The following table presents the consolidated groups used in the current research.

Figure 5.1.5: Camden and Tucson consolidated incident types

Camden	Tucson
Incident type was recoded to consolidate 102 codes into 17 groups, which include: • alarms • behavioral health • complaints/environmental conditions • domestic violence • emergency call for help from police officer • hang ups and deferred calls • health • missing persons • other crimes • proactive • property check • property crimes • reports • service assignments/statuses • suspicion • violent crimes	Incident type was recoded to consolidate 495 codes into 24 groups, which include: ▪ accidents/traffic related ▪ alarms ▪ assisting the public ▪ behavioral health ▪ callback ▪ call-related issues ▪ complaints/environmental conditions ▪ domestic violence ▪ drugs ▪ fire ▪ liquor violations ▪ medical emergencies ▪ missing persons ▪ officer needs help ▪ officer status ▪ other (not crime) ▪ other crimes ▪ property crimes ▪ sex offense ▪ status offense ▪ suspicion ▪ violent crimes ▪ warrants

Limitations

The current research attempts to understand 911 call-taking in ways that have not been rigorously explored to date. Although these descriptive analyses provide important insights, there are several limitations of the research and the resultant findings. These included:

- absence of variables, coupled with lack of uniformity in variable structure and definition across jurisdictions;
- variation in measurements of total call processing time;
- inability to capture and examine seasonality across year and across jurisdictions in different time zones;
- difficulty determining geographic location due to the prevalence of cell phone calls for
- differences in documentation practices and accountability protocols across jurisdictions;[206]

[206] In contrast to Tucson, Camden employs the CAD system to document all service assignments and officer activity, consistent with this department's CAD system, documentation practices, and accountability protocols.

- variations in level of use and severity for priority levels across the study sites; and[207]
- scarcity of data (across all sites) on the characteristics and demographics of callers and people identified by callers, as well as whether someone is a resident or visitor, especially in places like New Orleans, where understanding the resident population is particularly relevant given the high tourism rate.

The open data jurisdictions (Detroit, New Orleans, and Seattle) also include a number of limitations, which are as follows:

- discrepancies between information published online and internal agency data;[208]
- lack of uniformity in variables across jurisdictions;
- variation in the level of detail and quality of data across jurisdictions; and
- inability to consolidate incident types.

Findings

Cross-site comparisons

The following section draws together data from the two research sites of Camden and Tucson, as well as the three additional open data sites—Detroit, New Orleans, and Seattle. Later sections of this chapter will examine the sites individually.

1. What is the volume/rate (per capita) of 911 calls received, and how does this vary by incident type (e.g., nuisance complaint, crime in progress, medical emergency, domestic violence incidents, or officer involved shootings), time of day, and geographic location?

Figure 5.1.6: Volume and variation of 911 calls for service

Research question/ topic		**CCPD (2016, 2017)**	**TPD (2016, 2017)**	**DPD (2017, 2018)**	**NOLA (2016, 2017)**	**SPD (2016, 2017)**
RQ1: volume of 911 calls	Total across both years	137,426 calls of 508,902 CAD entries	601,072 calls of 833,145 CAD entries	609,099 calls of 1,409,443 CAD entries	639,657 calls of 848,176 CAD entries	290,701 calls of 833,344 CAD entries
RQ1: 911 call volume variation; the most common of each call type	Priority type	Priority 2 Calls Non-emergency	Priority 3 & 4 Calls Non-emergency	Priority 2 & 3 Calls Non-emergency	Priority 1 Calls Non-emergency	Priority 3 Calls Non-emergency
	Incident type	Disturbance of the peace	911 hang up; welfare check	Disturbance	Complaint / other	Premise check
	Day of the week	Friday	Friday	Saturday & Sunday	Tuesday	___________

[207] For priority definitions, see Section 5.3.
[208] Public safety communication professionals advised Vera researchers about these discrepancies, raising serious concerns about the accuracy and reliability of open data.

	Time of day	1:00 p.m. – 7:00 p.m.	Noon – 8:00 p.m.	3:00 p.m. – 10:00 p.m.	Noon – 8:00 p.m.	2:00 p.m. – 10:00 p.m.

To answer this question, Vera examined 911 calls for service in Camden, Tucson, Detroit, New Orleans, and Seattle. In all five sites, the most frequent incident type was noncriminal in nature. In four of the five, the most frequent incident type was some variation of complaint or request for an officer to perform a welfare check. These findings are in line with Vera's hypothesis that most calls for service consist of trivial non-crime related complaints and not crimes in progress. Across all sites, the most common priority types were nonemergency, which further supports this hypothesis. In three of the five cities, the highest number of calls were placed on Fridays, a finding that challenges Vera's hypothesis that most calls for service occur on weekends. In each city, the peak call window was between noon and 10:00 p.m. This wide window fails to support the hypothesis that most calls are placed at night.

2. How promptly are calls responded to—by a call-taker, dispatcher, and an officer on-scene—and how does this vary by call volume, incident type, time of day, and geographic location?

Figure 5.1.7: Dispatcher and officer response times to CAD events

Research question/topic		**CCPD (2016, 2017)**	**TPD (2016, 2017)**	**DPD (2017, 2018)**	**NOPD (2016, 2017)**	**SPD (2016, 2017)**
RQ2: How promptly are calls responded to by dispatchers?	Overall	2016: 7.5 min 2017: 23 min	________	2017: 40 min 2018: 35 min	2016: 63 min 2017: 74 min	________
	Priority level	1	1	________	________	________
	Incident type	Health and behavioral health	Medical emergency, officer needs help, 911 hang up	Traffic stop, towing, special attention	Traffic calls	________
	Day of week	Negligible variation	Sunday	Wednesday	Negligible variation	________
	Time of day	10:00 p.m. – 5:00 a.m.	Midnight – 5:00 a.m.	Midnight – 5:00 a.m.	Midnight – 5:00 a.m.	________
RQ2: How promptly are calls responded to by police officers?	Overall	Both years: 7.6 min	________	2016: 8.4 min 2017: 8.2 min	2016: 8.1 min 2017: 7.3 min	2016: 34 min 2017: 33 min
	Priority level	1 & 2	1	________	________	________
	Incident type	Alarms, health	Medical emergency, officer needs help	Traffic stops	Traffic stops, area checks	Domestic violence – no arrest, assault/other

	Day of week	Sunday	Sunday	Negligible variation	Negligible variation	Saturday & Sunday
	Time of day	10:00 p.m. – 5:00 a.m.	10:00 p.m. – 5:00 a.m.	10:00 p.m. – 5:00 a.m.	10:00 p.m. – 5:00 a.m.	Midnight – 5:00 a.m.

This section examines not only 911 calls for service, but all CAD events, which include officer-initiated activity. Vera researchers focused on non-911 incidents to more richly understand how officers spend their time, as well as the current breakdown of police resources. The five sites have a wide range of dispatcher and officer response times, a finding that warrants further discussion. However, the two sites (New Orleans and Detroit) that provided response time by priority level data show that response times are shorter in emergency incidents. This supports the hypothesis that officers respond fastest to the scene when an incident involves a serious crime in progress. Among the fastest response times for dispatchers and officers were health incidents, medical emergencies, traffic stops, officer requests for help, area checks, and alarms. Such findings might support the hypothesis and existing research that demonstrates response times are a flawed metric of success.[209] Prompt response time is crucial mainly in cases of emergency, and in other cases, dispatchers and officers may take the requisite time to ensure that the call for service is met with the proper response. The data revealed no clear correlation between day of the week and response time, but across cities, both dispatchers and officers responded with the greatest speed between the hours of 10:00 p.m. and 5:00 a.m. Because the greatest call volumes generally occurred between noon and 10:00 p.m., the hypothesis that both call-takers and officers respond slower when call volumes are high is supported.

3. What proportion of police activity—especially enforcement—is proactive (i.e., officer initiated, such as traffic stops and directed patrols) versus reactive (i.e., in response to 911 calls/reported incidents)?

Figure 5.1.8: Comparing proactive and reactive policing

Research question/topic		**CCPD (2016, 2017)**	**TPD (2016, 2017)**	**DPD (2017, 2018)**	**NOLA (2016, 2017)**	**SPD (2016, 2017)**
RQ3: What proportion of police activity is proactive versus reactive?	% of CAD entries that are calls for service	2016: 25% 2017: 29%	2016: 71% 2017: 73%	2017: 54% 2018: 40%	2016: 78% 2017: 73%	2016: 54% 2017: 52%
	% of CAD entries that are self-initiated	2016: 75% 2017: 71%	2016: 29% 2017: 27%	2017: 46% 2018: 60%	2016: 22% 2017: 27%	—

This section compares the proportions of CAD events that are 911 calls for service with those that are officer-initiated activities. In Tucson and New Orleans, 911 calls for service made up most CAD entries across both years, which aligns with Vera's hypothesis that the majority of

[209] See, for example, Spelman and Brown, "Calling the Police," 1984.

police activity and enforcement is reactive rather than proactive. However, across both years in both Camden and Seattle, officer-initiated events accounted for the majority of CAD entries. In Detroit, the proportions of CAD entries switched from being mostly 911 responses in 2017 to mostly officer-initiated events in 2018. Overall, these findings neither support nor dispute the hypothesis of reactive policing as the norm.

Conclusion

Vera's descriptive analysis of CAD data from Camden, Tucson, Detroit, New Orleans, and Seattle provides some preliminary answers to the central questions related to call volume, proactive and reactive policing call proportions, and call intake and processing times. Importantly, the descriptive tables in this section use a different subsample from that used in the outcomes analysis. The subsamples differed for multiple reasons. Vera and the involved departments discussed the presence of unusual values and created a plan for how to approach these values. Specific values that were discussed included abnormally short travel and dispatch times, as well as negative values. It was agreed that these values should be removed, along with abnormally large or missing values. This removal, coupled with the difference in the variables of interest, lend itself to a different subsample, which illuminates information better suited to respond to the different research questions being investigated. The findings from all departments indicate that officers spend a substantial amount of their time responding to calls for service, most of which are not related to a serious crime in progress. The analyses support the need for additional research on these resource-intensive, but noncriminal calls for service, giving particular consideration to their underlying needs, causes, and consequences, as well as alternative responses. For more detailed information on the research sites, see Chapter 5, Section 2.

The following sections of this chapter examine additional areas beyond the specific research questions explored in this section. The next chapter presents findings from an outcome analysis performed on the Camden and Tucson data.

Chapter 5, Section 2: Site-Specific Analysis

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Camden County data

What is the volume/rate (per capita) of 911 calls received, and how does this vary by incident type (e.g., nuisance complaint, crime in progress, medical emergency, domestic violence incidents, or officer involved shootings), time of day, and geographic location?

To answer this question, researchers examined 911 calls for service entered into the CAD system.

Figure 5.2.1A: Camden County 911 call volumes, broken down by priority level[1]

	2016		2017	
Priority level	Frequency	Percentage	Frequency	Percentage
Priority 1	13,251	18.8%	11,676	17.4%
Priority 2	20,945	29.8%	21,566	32.1%
Priority 3	6,122	8.7%	5,852	8.7%
Priority 4	19,824	28.2%	20,583	30.7%
Priority 5-9	10,049	14.2%	7,298	10.8%
Missing	129	0.2%	131	0.2%

[1]Priority 1 refers to in-progress, life-threatening incidents that pose a potential for serious physical injury or where serious injuries are believed to exist; Priority 2 refers to a crime or incident, either in progress or having just occurred, where there is no known serious injury or threat to life; Priority 3 refers to a past crime or incident where there is no known serious injury or threat to life, but a unit response is necessary to secure contraband or evidence of a crime; and Priority 4 refers to incidents not involving an imminent threat to life or serious injury, not in progress and where emergency police response is not necessary to secure contraband or evidence of a crime. No definitions below priority level 4 were provided.

Figure 5.2.1A reveals that, in both 2016 and 2017, the majority of CCPD's calls were classified as Priority 2 (a crime or incident either in progress or having just occurred where there is no known serious injury or threat to life) and Priority 4 (incidents not involving serious injury or an imminent threat to life, not in progress, and where emergency police response is not necessary to secure contraband or evidence of a crime). This finding is partially consistent with the hypothesis that most 911 calls are unrelated to a crime in progress, though the researchers are again hampered by the inability to determine the proportion of Priority 2 calls regarding incidents in progress versus those that have recently occurred.

Figure 5.2.1B: Camden County 911 call volumes broken down by incident type

	2016		2017	
Incident type	Frequency	Percent	Frequency	Percent
Total crime	19,067	27.2%	17,958	26.7%
Alarms	5,425	7.7%	5,086	7.6%
Violent crimes	1,091	1.6%	967	1.4%
Domestic violence	4,711	6.7%	4,447	6.6%
Property crimes	2,316	3.3%	2,206	3.3%
Other crimes[1]	5,524	7.9%	5,252	7.8%
Behavioral health	1,522	2.2%	1,603	2.4%
Complaints/Environmental conditions[2]	16,088	22.9%	16,628	24.8%
Emergency call for help from police officer[3]	2	0.0%	N/A	N/A
Hang-ups and deferred calls[4]	N/A	N/A	578	0.9%
Health	2,862	4.1%	3,063	4.6%
Missing persons	605	0.9%	479	0.7%
Proactive[5]	732	1.0%	980	1.5%
Property check	767	1.1%	726	1.1%
Reports	1,008	1.4%	985	1.5%
Service assignments/Statuses	21,139	30.1%	18,262	27.2%
Suspicion	2,612	3.7%	2,398	3.6%
Traffic-related	2,576	3.7%	2,563	3.8%
Missing	1,340	1.9%	883	1.3%

[1] This category includes incidents such as criminal mischief and drug complaints.
[2] This category includes incidents such as animal complaints, open hydrants, and disturbance of the peace.
[3] The category for emergency calls for help from a police officer did not appear in 2017 data.
[4] The category for hang-ups and deferred calls does not appear in 2016 data. Deferred calls typically refer to calls that did not receive a response because the caller was directed to self-report the issue (e.g., accidents with no injuries).
[5] Although proactive incidents generally should not show up in 911 call for service data, CCPD reported numerous proactive incidents (e.g., pedestrian and traffic stops) as 911 calls for service. For example, in 2016, there were 732 incidents (572 pedestrian stops and 160 traffic stops) related to a 911 call and not classified as self-initiated. As such, the category for proactive incidents appears in this figure, as well as others, where analyses were restricted to 911 calls exclusively.

Figure 5.2.1B demonstrates that, for both years, CCPD received a substantial number of calls related to complaints regarding environmental conditions (e.g., hazardous material incidents and open hydrants), as well as service assignments or statuses. These findings provide partial support for the hypothesis that most 911 calls are nuisance complaints.

Figure 5.2.1C: Camden County 911 call volumes, broken down by day of week

	2016		2017	
Day	Frequency	Percentage	Frequency	Percentage
Sunday	9,296	13.2%	9,183	13.7%
Monday	9,953	14.2%	9,576	14.3%
Tuesday	10,212	14.5%	9,678	14.4%
Wednesday	10,137	14.4%	9,639	14.4%
Thursday	10,009	14.2%	9,382	14.0%
Friday	10,490	14.9%	9,930	14.8%
Saturday	10,223	14.5%	9,718	14.5%

Figure 5.2.1C demonstrates that, in both 2016 and 2017, CCPD most often received 911 calls on Fridays and Saturdays, and least often on Sundays. However, the variation in call volume by day of the week is so small that these findings neither support nor dispute Vera's hypothesis that 911 call volumes are highest during weekends.

Figure 5.2.1D: Camden County 911 call volumes, broken down by hour of day

	2016		2017	
Hour of day	Frequency	Percentage	Frequency	Percentage
0	2,615	3.7%	2,334	3.5%
1	2,064	2.9%	1,981	3.0%
2	1,579	2.2%	1,490	2.2%
3	1,408	2.0%	1,312	2.0%
4	994	1.4%	1,085	1.6%
5	928	1.3%	1,022	1.5%
6	1,789	2.5%	1,842	2.7%
7	2,787	4.0%	2,689	4.0%
8	2,884	4.1%	2,868	4.3%
9	2,702	3.8%	2,766	4.1%
10	3,231	4.6%	2,969	4.4%
11	3,362	4.8%	3,154	4.7%
12	3,371	4.8%	3,112	4.6%
13	3,669	5.2%	3,326	5.0%
14	3,623	5.2%	3,354	5.0%
15	3,982	5.7%	3,773	5.6%
16	3,984	5.7%	3,887	5.8%
17	3,980	5.7%	3,844	5.7%
18	4,130	5.9%	3,800	5.7%
19	3,746	5.3%	3,524	5.3%
20	3,602	5.1%	3,362	5.0%
21	3,541	5.0%	3,362	5.0%
22	3,389	4.8%	3,322	5.0%
23	2,960	4.2%	2,928	4.4%

Figure 5.2.1D shows that, in 2016 and 2017, CCPD most often received 911 calls during the 3:00 p.m., 4:00 p.m., 5:00 p.m., and 6:00 p.m. hours (Hours 15, 16, 17, and 18, respectively). These findings are inconsistent with the hypothesis that 911 call volume is concentrated in the late evening and night hours.

1. How promptly are calls responded to—by a dispatcher and an officer on-scene—and how does this vary by call volume, incident type, time of day, and geographic location?

To answer this question, Vera examined dispatcher and officer response times to all CAD entries, which include both 911 calls for service and officer-initiated activity.

Figure 5.2.2A: Camden County dispatcher response time in minutes, broken down by call type

	2016					
Call type	Mean	N	SD	Min	Max	Median
Phone	7.5	63,870	16.4	0	358	2
Police-initiated	0.0	85,218	0.3	0	60	0

Motor vehicle stop	0.0	20,720	0.2	0	31	0
Station call	2.4	21	2.5	0	8	2
2017						
Call type	Mean	N	SD	Min	Max	Median
Phone	23.1	59,549	1,777.9	0	355,981	2
Police-initiated	0.0	49,068	0.0	0	5	0
Motor vehicle stop	1.2	19,007	63.6	0	8,514	0
Station call	3.8	25	5.2	0	20	2
Info call	5.4	61	10.3	0	45	1
Susp. persons stop[1]	2.7	6,886	88.7	0	6,999	0
Other[2]	1.4	34,122	61.9	0	10,619	0

[1] The categories for suspicious persons stop and other do not appear in 2016 data.
[2] After reviewing several incidents classified as "other" in the 2017 data, researchers were unable to isolate one distinguishing feature of incidents labeled "other." Some of these incidents were walk-ups (e.g., a pedestrian walking up to an officer to ask a question), whereas others were labeled "knock and talk" (e.g., an officer conducting a check on a property).

Dispatcher response time was calculated by subtracting the time the call-taker answered from the time the call was dispatched. Figure 5.2.2A shows that the average dispatcher response time for 911 phone calls increased substantially between 2016 (7.46 minutes) to 2017 (23.11 minutes). This increase in response time came despite a decrease in overall call volume from 280,202 calls in 2016 to 228,700 calls in 2017 (see Figure 5.2.1A).

Figure 5.2.2B: Camden County officer response time in minutes, broken down by call type

2016						
Call type	Mean	N	SD	Min	Max	Median
Phone	7.6	58,707	17.4	0	1,243	5
Self-initiated	0.0	176,849	0.0	0	17	0
Motor vehicle stop	0.0	32,432	0.0	0	0	0
Station call	3.2	14	4.3	0	14	1
2017						
Call type	Mean	N	SD	Min	Max	Median
Phone	7.6	54,095	20.0	0	950	4
Self-initiated	0.0	94,730	0.0	0	3	0
Motor vehicle stop	0.0	23,957	0.8	0	103	0
Station call	6.5	17	7.4	0	29	4
Info call	4.3	46	5.0	0	23	2.5
Susp. persons stop[1]	0.1	6,853	1.9	0	104	0
Other[2]	0.1	33,983	2.1	0	294	0

[1] The categories for suspicious persons stop and other do not appear in 2016 data.
[2] After reviewing several incidents classified as "other" in the 2017 data, researchers were unable to isolate one distinguishing feature of incidents labeled "other". Some of these incidents were walk-ups (e.g., a pedestrian walking up to an officer to ask a question), whereas others were labeled "knock and talk" (e.g., an officer conducting a check on a property).

Officer response time was calculated by subtracting the time the call was dispatched from the time the officer arrived. Figure 5.2.2B shows that, for 2016 and 2017, officer response time remained consistent for 911 calls for service, despite a reduction in call volume.

Figure 5.2.2C: Camden County dispatcher response time in minutes, broken down by priority level[1]

2016						
Priority level	Mean	N	SD	Min	Max	Median
Priority 1	1.0	11,866	3.7	0	154	0
Priority 2	6.3	19,852	12.3	0	314	2
Priority 3	14.2	4,242	21.3	0	307	6
Priority 4	12.6	18,098	21.7	0	358	4
Priority 5-9	5.4	9,689	15.5	0	330	1
2017[2]						
Priority level	Mean	N	SD	Min	Max	Median
Priority 1	4.3	10,186	28.3	0	1348	1
Priority 2	9.2	19,004	64.4	0	8414	2
Priority 3	17.3	4,414	31.3	0	785	7
Priority 4	15.1	18,275	37.0	0	3060	4
Priority 5-9	8.2	6,506	27.0	0	690	1

[1] Priority 1 refers to in-progress, life-threatening incidents that pose a potential for serious physical injury or where serious injuries are believed to exist; Priority 2 refers to a crime or incident either in progress or having just occurred, where there is no known serious injury or threat to life; Priority 3 refers to a past crime or incident where there is no known serious injury or threat to life, but a unit response is necessary to secure contraband or evidence of a crime; and Priority 4 refers to incidents not involving an imminent threat to life or serious injury, not in progress and where emergency police response is not necessary to secure contraband or evidence of a crime. No definitions below Priority Level 4 were provided.
[2] Six outliers were removed for analyses of dispatcher response time broken down by priority level, incident type, day of week, time of day, hour of day, and geographic sector. These outliers were for response times greater than 10,000 minutes.

Figure 5.2.2C reveals that, for dispatchers, response time was quickest for Priority 1 calls (in-progress, life-threatening incidents that pose a potential for serious physical injury or where serious injuries are believed to exist), with higher response times for calls labeled Priority 3, Priority 4, Priority 5, Priority 7, and Priority 9.[210] This finding provides support for the hypothesis that 911 personnel respond fastest when an incident involves a serious crime in progress.

Figure 5.2.2D: Camden County officer response time in minutes broken down by priority level[1]

2016						
Priority level	Mean	N	SD	Min	Max	Median
Priority 1	5.7	10,895	6.3	0	119	4
Priority 2	5.7	18,612	6.6	0	184	4
Priority 3	6.1	3,939	7.8	0	307	4
Priority 4	7.6	16,426	9.9	0	168	5
Priority 5-9	14.7	8,716	40.3	0	1,243	7
2017						
Priority level	Mean	N	SD	Min	Max	Median

[210] No Priority Level 6 or 8 calls exist in the data provided to Vera. Priority levels 5, 7, and 9 are separate specifications that hold no relative sequential meaning according to urgency of event.

Priority 1	5.5	9,375	7.8	0	178	4
Priority 2	5.5	17,652	6.9	0	148	4
Priority 3	5.7	4,000	6.7	0	128	4
Priority 4	7.3	16,015	11.3	0	552	5
Priority 5-9	19.2	6,003	52.9	0	950	6.5

[1]Priority 1 refers to in-progress, life-threatening incidents that pose a potential for serious physical injury or where serious injuries are believed to exist; Priority 2 refers to a crime or incident, either in progress or having just occurred, where there is no known serious injury or threat to life; Priority 3 refers to a past crime or incident where there is no known serious injury or threat to life, but a unit response is necessary to secure contraband or evidence of a crime; and Priority 4 refers to incidents not involving an imminent threat to life or serious injury, not in progress, and where emergency police response is not necessary to secure contraband or evidence of a crime. No definitions below Priority Level 4 were provided.

Figure 5.2.2D demonstrates that, in both years, officers were quickest to respond to Priority 1 and 2 calls, a finding that supports the hypothesis that officers respond fastest when an incident involves a serious crime in progress. The slowest response time was for Priority 6 calls.

Figure 5.2.2E: Camden County dispatcher response time in minutes, broken down by incident type

2016						
Incident type	Mean	N	SD	Min	Max	Median
Alarms	13.8	3,614	21.5	0	307	6
Behavioral health	1.7	1,497	5.8	0	128	0
Complaints/ Environmental conditions[1]	6.8	14,822	13.0	0	309	2
Domestic violence	3.1	4,568	9.6	0	314	0
Emergency call for help from police officer[2]	0.0	1	0.0	0	0	0
Medical	1.6	2,697	3.2	0	45	1
Missing persons	1.6	589	7.2	0	154	0
Other crimes[3]	18.7	5,257	29.1	0	358	7
Proactive	6.3	709	15.6	0	155	1
Property check	14.8	709	25.6	0	246	5
Property crimes	9.1	2,213	15.3	0	149	3
Reports	4.9	948	8.8	0	136	2
Service assignments/ Statuses	6.0	20,139	14.7	0	330	1
Suspicion	11.0	2,499	18.9	0	199	4
Traffic- related	4.7	2,344	8.6	0	106	2
Violent crimes	5.3	1,024	10.4	0	128	2
2017						
Incident type	Mean	N	SD	Min	Max	Median
Alarms	16.1	3,753	27.6	0	435	6
Behavioral health	2.8	1,495	13.0	0	334	1
Complaints/ environmental conditions	9.5	14,822	71.6	0	8,414	2

Domestic violence	6.8	4,084	25.4	0	773	1
Hang-ups and deferred calls[4]	14.5	101	19.3	0	130	6
Medical	3.0	2,169	7.2	0	152	1
Missing persons	9.4	448	69.6	0	1,348	1
Other crimes	20.1	4,814	56.2	0	3,060	7
Proactive	7.5	923	46.0	0	155	2
Property check	16.3	657	29.6	0	307	5
Property crimes	15.3	2,035	31.8	0	428	4
Reports	9.2	879	34.5	0	785	2
Service assignments/ Statuses	9.3	16,746	26.1	0	690	2
Suspicion	15.4	2,219	28.0	0	269	5
Traffic-related	8.3	2,246	23.7	0	495	2
Violent crimes	16.8	867	65.2	0	837	3

[1] This category includes incidents such as animal complaints, open hydrants, and disturbance of the peace.
[2] The category for emergency calls for help from a police officer did not appear in 2017 data.
[3] This category includes incidents such as criminal mischief and drug complaints.
[4] The category for hang-ups and deferred calls does not appear in 2016 data. Deferred calls typically refer to calls that did not receive a response because the caller was directed to self-report the issue (e.g., accidents with no injuries).

Figure 5.2.2E demonstrates that, in both years, dispatchers were quickest to respond to calls involving medical and behavioral health incidents, though in keeping with the overall trend, dispatcher response times increased from 2016 to 2017.[211] In 2016, dispatchers took an average of 1.56 minutes to respond to calls regarding medical incidents and 1.65 minutes for behavioral health calls. In 2017, dispatchers responded in an average 3.02 minutes to medical calls and 2.79 minutes to behavioral health calls.

Additionally, dispatchers took the longest to respond to calls related to property checks (14.79 minutes in 2016 and 16.28 minutes in 2017), as well as those for crimes classified as “other” (18.65 minutes in 2016 and 20.14 minutes in 2017).

Figure 5.2.2F: Camden County officer response time in minutes broken down by incident type

2016						
Incident type	Mean	N	SD	Min	Max	Median
Alarms	4.9	3,299	7.0	0	307	4
Behavioral health	5.1	1,390	5.6	0	108	4
Complaints/ environmental conditions[1]	5.8	13,428	6.9	0	184	4
Domestic violence	6.8	4,319	6.8	0	94	5
Medical	5.0	2,473	6.2	0	111	3
Missing persons	9.6	575	9.6	0	119	7

[211] Except for a single emergency call from a police officer in 2016.

Other crimes[2]	6.4	4,767	8.9	0	159	4
Proactive	5.1	663	7.1	0	81	3
Property check	5.5	663	6.3	0	81	4
Property crimes	8.2	2,117	9.6	0	131	6
Reports	8.0	911	7.1	0	47	6
Service assignments/statuses	10.6	18,376	28.8	0	1243	5
Suspicion	6.2	2,328	8.5	0	142	4
Traffic-related	8.2	2,218	10.3	0	132	5
Violent crimes	6.7	962	7.8	0	92	4
2017						
Incident type	Mean	N	SD	Min	Max	Median
Alarms	4.4	3,355	3.9	0	65	4
Behavioral health	4.8	1,402	5.3	0	66	3
Complaints/ environmental conditions	5.5	13,003	6.5	0	269	4
Domestic violence	7.0	3,832	8.7	0	148	5
Hang -ups and deferred calls[3]	3.9	88	3.2	0	21	3
Medical	4.6	1,963	5.9	0	117	3
Missing persons	10.0	436	12.6	0	109	6
Other crimes	6.0	4,212	9.4	0	381	4
Proactive	5.5	879	8.4	0	143	4
Property check	5.3	608	6.9	0	109	4
Property crimes	8.2	1,916	16.0	0	552	6
Reports	8.1	844	10.3	0	128	5
Service assignments/ Statuses	11.5	15,474	34.4	0	950	5
Suspicion	6.3	2,024	10.5	0	362	4
Traffic-related	8.1	2,099	11.6	0	194	5
Violent crimes	7.1	817	11.5	0	126	4

[1] This category includes incidents such as animal complaints, open hydrants, and disturbance of the peace.
[2] This category includes incidents such as criminal mischief and drug complaints
[3] The category for hang-ups and deferred calls does not appear in 2016 data. Deferred calls typically refer to calls that did not receive a response because the caller was directed to self-report the issue (e.g., accidents with no injuries).

Figure 5.2.2F demonstrates that, in 2016, officers were quickest to respond to alarms and health calls. In 2017, officers were quickest to respond to calls involving the newly added category of hang-ups and deferred calls. However, they responded to alarm and medical calls with the second and third greatest speeds, respectively. Additionally, in both years, officers took the longest to respond to calls related to missing persons.

Figure 5.2.2G: Camden County dispatcher response time in minutes broken down by hour of day

2016						
Hour of day	Mean	N	SD	Min	Max	Median
0	4.9	2,420	13.0	0	358	1
1	4.1	1,892	11.2	0	151	1
2	4.5	1,479	10.4	0	183	1
3	5.1	1,307	13.7	0	292	1
4	4.3	895	11.6	0	159	1
5	9.4	802	18.3	0	154	2
6	7.7	1,555	17.5	0	225	2
7	7.1	2,550	18.2	0	239	2
8	10.7	2,573	23.1	0	238	2
9	13.6	2,385	23.5	0	320	3
10	8.6	2,901	17.8	0	348	2
11	8.2	3,028	17.4	0	273	2
12	8.2	3,087	19.0	0	339	2
13	7.9	3,344	17.0	0	230	2
14	7.1	3,318	15.4	0	244	2
15	7.2	3,659	16.9	0	314	2
16	7.6	3,651	16.6	0	178	2
17	12.9	3,546	21.5	0	144	2
18	7.6	3,734	13.6	0	270	2
19	5.8	3,405	11.6	0	146	2
20	6.1	3,307	13.0	0	235	2
21	5.7	3,232	12.3	0	184	1
22	5.5	3,099	11.9	0	175	1
23	5.2	2,701	12.3	0	162	1
2017						
Hour of day	Mean	N	SD	Min	Max	Median
0	6.5	2,081	24.4	0	757	2
1	6.2	1,750	20.9	0	435	1
2	13.8	1,289	236.0	0	8414	2
3	8.7	1,168	38.5	0	837	2
4	8.6	942	31.6	0	400	2
5	16.5	871	45.1	0	526	2
6	13.9	1,601	37.6	0	602	2
7	13.7	2,327	34.5	0	690	2
8	16.0	2,460	32.5	0	440	3
9	17.2	2,381	31.8	0	495	5
10	12.0	2,539	24.0	0	269	3
11	10.9	2,753	27.8	0	605	3
12	9.4	2,745	20.8	0	439	2
13	10.2	2,919	24.0	0	357	2
14	9.8	2,973	23.3	0	436	2
15	10.2	3,321	23.7	0	409	2
16	13.2	3,389	26.6	0	315	3
17	19.4	3,265	67.6	0	3060	5
18	9.7	3,225	23.2	0	741	3
19	6.2	3,080	15.3	0	318	2

20	6.4	2,929	14.7	0	328	2
21	7.2	2,976	18.6	0	284	2
22	6.7	2,929	19.4	0	510	2
23	7.0	2,588	17.8	0	386	2

Figure 5.2.2G demonstrates that, in terms of time of day, dispatchers responded fastest during the 1:00 a.m. hour in both years and took the longest to respond during the 9:00 a.m. hour (Hour 9) in 2016 and during the 5:00 p.m. hour (Hour 17) in 2017, this could be due to shift changes. These findings generally fail to support the hypothesis that response time is slowest at night.

Figure 5.2.2H: Camden County officer response time in minutes, broken down by hour of day

2016						
Hour of day	Mean	N	SD	Min	Max	Median
0	5.7	2,236	6.5	0	74	4
1	5.3	1,773	5.5	0	62	4
2	5.3	1,368	5.8	0	65	4
3	5.1	1,224	5.5	0	65	4
4	4.6	846	5.3	0	73	3
5	6.4	761	10.5	0	175	4
6	9	1,492	25.7	0	490	4
7	10.7	2,428	36.0	0	658	4
8	9.2	2,434	29.0	0	611	4
9	8.0	2,190	16.8	0	527	5
10	8.0	2,626	15.6	0	346	5
11	7.9	2,759	12.9	0	331	5
12	9.5	2,773	17.2	0	356	6
13	8.3	3,015	14.1	0	312	5
14	8.7	2,976	15.9	0	276	5
15	8.4	3,310	13.9	0	357	5
16	8.6	3,307	15.5	0	367	5
17	8.7	3,158	16.3	0	319	5
18	9.0	3,438	32.5	0	1243	5
19	5.5	3,181	5.6	0	131	4
20	6.5	3,062	13.7	0	383	4
21	5.8	2,969	6.3	0	119	4
22	5.9	2,876	11.4	0	378	4
23	5.8	2,505	9.0	0	257	4
2017						
Hour of day	Mean	N	SD	Min	Max	Median
0	5.3	1,925	10.6	0	293	3
1	5.0	1,625	6.8	0	131	3
2	5.2	1,199	6.4	0	74	3
3	4.9	1,091	7.7	0	117	3
4	4.5	876	5.2	0	54	3
5	5.4	825	7.4	0	99	4
6	9.0	1,529	20.7	0	301	4
7	10.3	2,184	26.6	0	624	5

8	9.5	2,272	31.7	0	728	5
9	8.9	2,150	27.6	0	668	5
10	7.8	2,265	17.1	0	476	5
11	8.5	2,481	27.9	0	950	5
12	8.3	2,417	17.5	0	485	5
13	8.9	2,582	18.9	0	324	5
14	8.6	2,606	16.3	0	264	5
15	10.7	2,964	30.0	0	845	5
16	10.3	3,031	27.1	0	825	5
17	8.9	2,880	20.3	0	583	5
18	6.9	2,962	17.0	0	473	4
19	6.1	2,829	22.3	0	646	4
20	5.8	2,678	12.7	0	552	4
21	5.6	2,726	9.2	0	269	4
22	5.8	2,681	13.3	0	371	4
23	5.4	2,379	8.5	0	176	4

Figure 5.2.2H demonstrates that, in both years, officers responded to calls fastest during the 4:00 a.m. hour (Hour 4), a time that Figure 5.2.1G shows to have the second lowest number of CAD entries for both years. In 2016, officers were slowest to respond to calls during the 7:00 a.m. hour (Hour 7), and in 2017, officers were slowest to respond during the 3:00 p.m. hour (Hour 15). These findings generally fail to support the hypothesis that response time is slowest at night. Such results may be explained by traffic patterns or staffing differences, though future exploration of these potential explanations is necessary.

2. What proportion of police activity—especially enforcement—is proactive (i.e., officer initiated, such as traffic stops and directed patrols) versus reactive (i.e., in response to 911 calls/reported incidents)?

Figure 5.2.3A: Camden County total volume of 911 calls received and other CAD entries

	2016			2017		
	Frequency	Percentage	Rate per capita[4]	Frequency	Percentage	Rate per capita
Info call	1	0.0%	1.34	84	0.0%	112.7
Station call	27	0.0%	36.24	34	0.0%	45.6
Motor vehicle stop	32,518	11.6%	43,640.71	24,261	10.6%	3,2551.1
Self-initiated	177,336	63.3%	237,993.40	94,910	41.5%	127,341.3
Phone (911 CFS)	70,320	25.1%	94,372.79	67,106	29.3%	90,036.5
Phone[1]				65,915	28.8%	88,438.5
911				1,050	0.5%	1,408.8
911-A				73	0.0%	97.9
911-B		N/A[1]		68	0.0%	91.2
Suspicious persons stop[2]				7,709	3.1%	10,343.2
Other[3]				35,226	15.4%	47,262.9
Total	280,202		376,044.4	228,700		306,848.1

[1] The categories for "911", '911-A" and "911-B" only appear in the new CAD system, which was deployed in 2017. These categories still refer to a 911 call for service made to different call stations (e.g., "911-A" refers to a call made to Call Station A).
[2] The categories for suspicious persons stop and other do not appear in 2016 data.

3 After reviewing several incidents classified as "other" in the 2017 data, researchers were unable to isolate one distinguishing feature of incidents labeled "other". Some of these incidents were walk-ups (e.g., a pedestrian walking up to an officer to ask a question), whereas others were labeled "knock and talk" (e.g., an officer conducting a check on a property).

4 This refers to the rate of CAD entry per 100,000 residents.

Figure 5.2.3A reveals that CCPD officers spent most of their time in 2016 and 2017 responding to self-initiated calls. This finding does not support Vera's hypothesis that most police activity is reactive rather than proactive. However, CCPD may have a large proportion of self-initiated activity because its CAD system records all officer statuses (e.g., bathroom breaks and gas stops) as self-initiated. As such, this finding may not be typical of CAD policing records nationally, but may represent a more nuanced view of how officers spend their time and agency resources overall. Additionally, self-initiated calls decreased by approximately 82,000 between 2016 and 2017, raising questions around what kind(s) of changes in CCPD officers' workload may have prompted this reduction in self-initiated activity.

Figure 5.2.3B: Camden County top 10 volumes for 911 calls for service and police-initiated activities

2016				2017			
Calls for service		Police-initiated		Calls for service		Police-initiated	
Incident	Frequency	Incident	Frequency	Incident	Frequency	Incident	Frequency
Disturbance of the peace	12,220	Crime condition check	49,217	Disturbance of the peace	12,399	Crime condition check	24,380
Meet complainant	6,516	Pedestrian stop	32,261	Meet complainant	6,799	Pedestrian stop	13,481
Burglar alarm (business)	3,526	Service assignment (other)	12,013	Burglar alarm (business)	3,179	30-minute break	8,554
Domestic involving two adults with injury or offender present	3,220	30-minute break	9,310	Vice complaint (drugs)	3,033	Service assignment (other)	5,616
Vice complaint (drugs)	3,217	Property check (business)	8,656	Domestic involving two adults with injury or offender present	2,963	Property check (business)	5,201
Secondary employment	2,881	Service assignment (paperwork)	4,404	Secondary employment	2,860	Service assignment (paperwork)	2,653
Crime (other)	1,842	Service assignment (meeting supervisor)	3,443	EMS call non-emergent (other)	2,171	Service assignment (meeting supervisor)	2,326
Person with a firearm	1,810	Suspicious person (adult)	2,702	Traffic complaint	1,940	Service assignment	1,309

						(vehicle deficiency)	
Traffic complaint	1,808	Traffic stop	2,283	Crime (other)	1,767	Secondary employment	1,029
Animal complaint	1,550	Service assignment (vehicle deficiency)	2,014	Person with a firearm	1,572	Traffic stop	996

Figure 5.2.3B demonstrates that, in both years, the highest frequency of calls for service CAD entries was related to disturbance of the peace calls, with over 12,000 calls placed each year. This finding is in line with the hypothesis that most calls are related to nuisance complaints, and it presents an opportunity to examine whether police officers should be responding to such calls.

Tucson data

1. What is the volume/rate (per capita) of 911 calls received, and how does this vary by incident type (e.g., nuisance complaint, crime in progress, medical emergency, domestic violence incidents, or officer involved shootings), time of day, and geographic location?

Figure 5.2.4A: Tucson call volumes, broken down by priority level[1]

	2016		2017	
Priority level	Frequency	Percentage	Frequency	Percentage
1	2,107	0.7%	2,327	0.7%
2	45,112	15.9%	44,901	14.1%
3	83,142	29.4%	85,156	26.8%
4	79,879	28.2%	84,435	26.6%
5	1,190	0.4%	1,680	0.5%
6	1	0%	1	0%
7	17,993	6.4%	22,055	6.9%
8	4,097	1.4%	9,128	2.9%
9	49,718	17.6%	68,142	21.4%
Missing	6	0%	2	0%

[1]Priority Level 1 refers to an incident posing an immediate threat to life where the threat is present and ongoing and/or an incident posing an immediate threat to life involving the actual use or threatened use of a weapon (e.g., someone being shot); Priority Level 2 refers to an incident involving a situation of imminent danger to life or a high potential for a threat to life to develop or escalate, and is either in progress or occurred within the past five minutes (e.g., a domestic violence dispute where physical violence has transpired); Priority Level 3 refers to crimes against persons or significant property crimes where a rapid response is needed and the incident is in progress, has occurred within the past five minutes, or is about to escalate to a more serious situation (e.g., a family fight is brewing); Priority Level 4 refers to other crimes or matters requiring police response, generally occurring more than 10 minutes prior to dispatch (e.g., a neighbor dispute); Priority Level 5 refers to onsite activity and 911 hang-ups transferred from Public Safety Answering Points (PSAPs) with information available; No definition for priority level 6 was provided; Priority Level 7 refers to unverified reports of alarms to public safety communication departments (PSCDs) and 911 hang-ups from pay phones; Priority Level 8 refers to onsite activity (e.g., a traffic stop) and internal TPD resource requests; and Priority Level 9 refers to callback/alternative response call (ARC) unit reports (e.g., nonpriority calls without any evidence, witnesses, or suspects).

Figure 5.2.4A reveals that, in both 2016 and 2017, most of TPD's calls were classified as Priority 3 (crimes against persons or significant property crimes where a rapid response is needed and the incident is in progress, has occurred within the past five minutes, or is about to escalate to a more serious situation) and Priority 4 (other crimes or matters requiring police response, generally occurring more than 10 minutes prior to dispatch). This finding is partially consistent with the hypothesis that most 911 calls are unrelated to a serious crime in progress, as Priority 3 calls include incidents that are in progress, but the most common calls in this priority level were unrelated to crime.

Figure 5.2.4B: Tucson call volumes, broken down by incident type

	2016		2017	
Incident type	Frequency	Percent age	Frequency	Percent age
Total crime	94,132	33.3%	101,378	31.9%
Alarms	13,837	4.9%	14,172	4.5%
Violent crimes	2,869	1%	4,159	1.3%
Domestic violence	20,552	7.3%	21,755	6.8%
Property crimes	23,496	8.3%	24,314	7.7%
Other crimes[1]	33,378	11.8%	36,978	11.6%
Accidents/Traffic-related	17,178	6.1%	14,794	4.7%
Assisting the public	25,688	9.1%	26,713	8.4%
Behavioral health	4,209	1.5%	4,311	1.4%
Callback	5,882	2.1%	6,937	2.2%
Call-related issues[2]	54,493	19.2%	78,473	24.7%
Complaints/environmental conditions[3]	28,752	10.2%	28,369	8.9%
Drugs	2,310	0.8%	2,304	0.7%
Fire	55	0%	54	0%
Liquor violations	287	0.1%	262	0.1%
Medical emergencies	13	0%	32	0%
Missing persons	4,036	1.4%	5,210	1.6%
Officer needs help	19	0%	5	0%
Officer status	25,837	9.1%	26,738	8.4%
Other (not crime)[4]	3,355	1.2%	2,955	0.9%
Sex offense	1,296	0.5%	1,799	0.6%
Status offense	2	0%	2	0%
Suspicion	15,162	5.4%	17,108	5.4%
Warrants	539	0.2%	483	0.2%

[1] This category includes incidents such as custodial interference, cruelty to animals, and disorderly conduct.
[2] This category includes incidents such as hang-ups and abandoned calls.
[3] This category includes incidents such as animal complaints, open hydrants, and disturbance of the peace.
[4] This category includes the following incidents: "other," "weapons/carrying concealed," "unknown trouble," and "task force."

Figure 5.2.4B demonstrates that, for both years, only about 30 percent of the 911 calls to which TPD responded were crime related. However, crimes were most often classified as "other" or property crimes, and these categories typically represent lower-priority calls. Beyond calls related to crimes, TPD received a substantial number of calls categorized as hang-ups and abandoned calls (19 percent and 25 percent in 2016 and 2017, respectively), as well as complaints related to environmental conditions (10 percent and 9 percent), such as reports of firecrackers, gas leaks, and loose animals. These findings support the hypothesis that most 911 calls are unrelated to a crime in progress.

Figure 5.2.4C: Tucson call volumes broken down by day of week

	2016		2017	
Day	Frequency	Percentage	Frequency	Percentage
Sunday	37,816	13.4%	42,993	13.5%
Monday	39,365	13.9%	45,413	14.3%
Tuesday	39,373	13.9%	44,778	14.1%
Wednesday	40,358	14.2%	45,339	14.3%
Thursday	40,501	14.3%	46,052	14.5%
Friday	43,784	15.5%	47,648	15%
Saturday	42,048	14.8%	45,604	14.3%

Figure 5.2.4C demonstrates that, in both 2016 and 2017, call volume was consistent across all days of the week, with TPD receiving marginally more 911 calls on Fridays. These findings are inconsistent with Vera's hypothesis that 911 call volumes are heaviest on weekends.

Figure 5.2.4D: Tucson call volumes broken down by hour of day

	2016		2017	
Hour	Frequency	Percentage	Frequency	Percentage
0	9,022	3.2%	9,866	3.1%
1	7,549	2.7%	8,147	2.6%
2	6,710	2.4%	7,232	2.3%
3	5,139	1.8%	5,779	1.8%
4	4,392	1.6%	4,718	1.5%
5	4,356	1.5%	4,837	1.5%
6	5,195	1.8%	6,123	1.9%
7	7,597	2.7%	9,296	2.9%
8	10,136	3.6%	12,040	3.8%
9	11,397	4%	13,922	4.4%
10	12,520	4.4%	14,844	4.7%
11	13,950	4.9%	16,027	5%
12	14,727	5.2%	16,430	5.2%
13	14,812	5.2%	16,667	5.2%
14	15,735	5.6%	17,753	5.6%
15	16,734	5.9%	19,241	6.1%
16	17,148	6.1%	19,332	6.1%

17	18,151	6.4%	19,980	6.3%
18	17,604	6.2%	19,305	6.1%
19	16,330	5.8%	18,501	5.8%
20	15,802	5.6%	17,187	5.4%
21	14,672	5.2%	15,356	4.8%
22	12,842	4.5%	13,720	4.3%
23	10,725	3.8%	11,524	3.6%

Figure 5.2.4D shows that, in 2016 and 2017, TPD most often received 911 calls between the hours of 4:00 p.m. and 6:00 p.m. (Hours 16 and 18, respectively), with both years peaking at the 5:00 p.m. hour (Hour 17). These findings are inconsistent with Vera's hypothesis that 911 call volumes concentrate in the early evening and night hours.

2. How promptly are calls responded to—by a call-taker, dispatcher, and an officer on-scene—and how does this vary by call volume, incident type, time of day, and geographic location?

To answer this question, Vera examined dispatcher and officer response times to all CAD entries, which include both 911 calls for service and officer-initiated activity.

Figure 5.2.5A: Tucson dispatcher response time in minutes broken down by-priority level[1]

2016						
Priority level	Mean	N	SD	Min	Max	Median
Priority 1	2.2	2,021	15.0	0	608	1
Priority 2	10.4	39,816	72.1	0	5,478	2
Priority 3	33.7	72,775	185.5	0	20,093	8
Priority 4	184.8	63,457	509.9	0	11,574	70
Priority 5	14.2	42	47.9	0	303	1
Priority 6	1.2	4	1.1	0	3	1
Priority 7	27.0	2,079	41.2	0	660	15
Priority 8	14.4	84	33.3	0	182	3
Priority 9	466.1	248	1279.3	0	7,166	4
2017						
Priority level	Mean	N	SD	Min	Max	Median
Priority 1	2.59	2,240	14.94	0	482	1
Priority 2	18.04	39,805	166.87	0	11,447	3
Priority 3	65.76	73,013	461.54	0	19,547	14
Priority 4	324.09	66,631	1076.11	0	20,564	109
Priority 5	197.76	56	1447.87	0	10,839	0
Priority 6	0.76	3	0.33	0	1	1
Priority 8	42.86	1,507	86.57	0	920	19
Priority 9	12.16	101	22.9	0	141	3

[1] Priority Level 1 refers to an incident posing an immediate threat to life where the threat is present and on-going; and/or an incident posing an immediate threat to life involving the actual use or threatened use of a weapon (e.g., someone being shot); Priority Level 2 refers to an incident involving a situation of imminent danger to life or a high potential for a threat to life to develop or escalate, and is either in progress or occurred within the past five minutes (e.g., a domestic violence dispute where physical violence has transpired); Priority Level 3 refers to crimes against persons or significant property crimes where a rapid response is needed and the incident is in progress, has occurred within the past five minutes or is about to escalate to a more serious situation (e.g., a family fight is brewing); Priority Level 4 refers to other crimes or matters requiring police response, generally occurring more than 10 minutes prior to dispatch (e.g., a neighbor dispute); Priority Level 5 refers to onsite activity and 911 hang-ups transferred from PSAP with information available; No definition for priority level 6 was provided; Priority Level 7 refers to unverified reports of alarms and 911 hang-ups from pay phones; Priority Level 8 refers to onsite activity (e.g., a traffic stop) and internal TPD resource requests; and Priority Level 9 refers to callback/alternative response call (ARC) unit reports (e.g., nonpriority calls without any evidence, witnesses, or suspects).

Figure 5.2.5A shows that, in both years, dispatchers were quickest to respond to Priority 1 calls (except for Priority 6 calls, which are undefined and for which N=7 across both years), a finding that supports the hypothesis that 911 personnel respond fastest when an incident involves a serious crime in progress.

Figure 5.2.5B: Tucson officer response time in minutes broken down by priority level[1]

2016						
Priority level	Mean	N	SD	Min	Max	Median
Priority 1	5.3	2,021	14.8	0	618	4
Priority 2	17.7	39,816	72.5	0	5,478	10
Priority 3	41.6	72,775	185.5	0	20,094	17
Priority 4	192.9	63,457	509.3	0	11,574	78
Priority 5	16.4	42	48.0	0	303	2
Priority 6	1.3	4	1.2	0	3	1
Priority 7	31.9	2,079	41.9	0	666	20
Priority 8	20.3	84	34.7	0	182	8
Priority 9	463.2	248	1259.4	0	7,166	16
2017						
Priority level	Mean	N	SD	Min	Max	Median
Priority 1	6.5	2,240	18.1	0	482	4
Priority 2	26.0	39,805	167.0	0	11,447	11
Priority 3	74.2	73,013	461.5	0	19,547	23
Priority 4	331.7	66,631	1074.1	0	20,564	117
Priority 5	200.5	56	1447.5	0	10,839	2
Priority 6	0.8	3	0.3	0	1	1
Priority 8	47.8	1,507	87.0	0	934	24
Priority 9	17.6	101	24.0	0	141	8

[1]Priority Level 1 refers to an incident posing an immediate threat to life where the threat is present and on-going; and/or an incident posing an immediate threat to life involving the actual use or threatened use of a weapon (e.g., someone being shot); Priority Level 2 refers to an incident involving a situation of imminent danger to life or a high potential for a threat to life to develop or escalate, and is either in progress or occurred within the past five minutes (e.g., a domestic violence dispute where physical violence has transpired); Priority Level 3 refers to crimes against persons or significant

property crimes where a rapid response is needed and the incident is in progress, has occurred within the past five minutes or is about to escalate to a more serious situation (e.g., a family fight is brewing); Priority Level 4 refers to other crimes or matters requiring police response, generally occurring more than 10 minutes prior to dispatch (e.g., a neighbor dispute); Priority Level 5 refers to onsite activity and 911 hang-ups transferred from PSAP with information available; No definition for priority Level 6 was provided; Priority Level 7 refers to unverified reports of alarms and 911 hang-ups from pay phones; Priority Level 8 refers to onsite activity (e.g., a traffic stop) and internal TPD resource requests; and Priority Level 9 refers to callback/alternative response call (ARC) unit reports (e.g., nonpriority calls without any evidence, witnesses, or suspects).

Figure 5.2.5B demonstrates that, for both 2016 and 2017, officers were quickest to respond to Priority 1 calls, which supports the hypothesis that officers respond fastest when the incident involves a serious crime in progress. Officers responded least quickly to Priority 4 calls in both years. This finding highlights the question of whether calls classified as Priority 4 may be better handled without a sworn response, given that it took officers an average of three hours in 2016 and 5.5 hours in 2017 to respond to those calls.

Figure 5.2.5C: Tucson dispatcher response time in minutes, broken down by incident type

2016						
Incident type	Mean	N	SD	Min	Max	Median
Alarms	37.3	6,141	72.2	0	799	10
Assisting the public	20.5	22,479	49.7	0	3,722	6
Behavioral health	6.9	4,220	15.0	0	401	2
Callback	2,772.2	1,199	2,125.2	0	11,574	2,516
Call-related issues[1]	6.09	2,364	12.5	0	278	2
Complaints/ environmental conditions[2]	80.2	23,478	167.7	0	8,100	32
Domestic violence	33.1	20,230	116.7	0	9,135	5
Drugs	124.4	2,065	267.9	0	5,209	49
Fire	2.6	43	3.1	0	14	1
Liquor violations	63.9	235	72.2	0	407	35
Medical emergencies	3.5	11	4.4	1	15	2
Missing persons	131.9	2,966	170.7	0	3,407	66
Officer needs help	1.3	10	0.9	0	3	1
Officer status	91.9	15,123	219.7	0	11,087	28
Other crimes[3]	68.8	27,591	216.7	0	8,385	13
Other (not crime)[4]	11.2	3,395	60.3	0	1,494	2
Property crimes	158.6	19,683	312.7	0	7,182	65
Sex offense	141.6	1,170	633.9	0	20,093	41
Suspicion	27.6	13,445	90.9	0	6,611	7
Traffic-related	34.3	11,275	163.1	0	5,630	5
Violent crimes	34.2	2,808	199.4	0	8,428	2
Warrants	57.9	588	101.5	0	753	15

2017						
Incident Type	Mean	N	SD	Min	Max	Median
Alarms	60.2	4,663	112.3	0	1,256	14
Assisting the public	38.4	22,968	117.9	0	10,980	10
Behavioral health	12.3	3,932	36.3	0	946	3
Callback	7187.3	1,036	4389.6	0	20,564	6,939
Call-related issues	9.1	2,144	27.1	0	544	3
Complaints/ environmental conditions	125.5	22,668	320.0	0	12,917	49
Domestic violence	60.4	19,174	191.9	0	10,584	10
Drugs	173.3	1,869	348.5	0	8,150	64
Fire	17.5	45	36.9	0	209	3
Liquor violations	91.6	214	87.7	1	505	66
Medical emergencies	2.1	23	2.6	1	13	1
Missing persons	254.5	3,353	481.7	0	15,797	132
Officer needs help	0.9	1	N/A	1	1	1
Officer status	150.2	13,706	285.3	0	9,319	46
Other crimes	128.1	29,797	474.9	0	15,760	26
Other (not crime)	14.8	2,710	66.9	0	1,202	2
Property crimes	247.4	19,547	641.1	0	17,200	99
Sex offense	213.0	1,468	449.0	0	6,607	63
Status offense	70.2	1	N/A	70	70	70
Suspicion	49.1	14,360	287.3	0	15,850	11
Traffic-related	51.7	9,875	390.0	0	15,614	5
Violent crimes	85.3	3,610	438.4	0	15,602	3
Warrants	87.1	466	146.9	0	946	25

[1] This category includes incidents such as hang-ups and abandoned calls.
[2] This category includes incidents such as animal complaints, open hydrants, and disturbances of the peace.
[3] This category includes incidents such as custodial interference, cruelty to animals, and disorderly conduct.
[4] This category includes the following incidents: "other," "weapons/carrying concealed," "unknown trouble," and "task force."

Figure 5.2.5C demonstrates that, in both years, dispatchers were quickest to respond to calls involving medical emergencies, fires, and officers needing help, though the frequency of those calls was low. Beyond those call types, dispatchers responded fastest to calls related to behavioral health and call-related issues (e.g., 911 hang-ups in which the call-taker either suspected trouble or could not get in contact with the caller after multiple attempts and a call location was available). Additionally, dispatchers took the longest to respond to calls related to callbacks, property crimes, missing persons, and sex offenses. Overall, response times increased from 2016 to 2017, which may be partly due to the increase in calls for service between the two years.

Figure 5.2.5D: Tucson officer response time in minutes, broken down by incident type

2016						
Incident type	Mean	N	SD	Min	Max	Median
Alarms	43.1	6,141	73.2	0	799	17
Assisting the public	28.3	22,479	51.2	0	3,726	14
Behavioral health	15.1	4,220	16.7	0	401	11
Callback	2,771.9	1,199	2,127.7	0	11,574	2,506
Call-related issues[1]	13.4	2,364	13.7	0	278	10
Complaints/ environmental conditions[2]	86.8	23,478	168.3	0	8,100	38
Domestic violence	41.7	20,230	117.3	0	9,135	15
Drugs	131.6	2,065	268.5	0	5,209	57
Fire	7.9	43	4.8	0	17	7
Liquor violations	67.7	235	72.2	0	407	38
Medical emergencies	10.9	11	4.8	3	21	9
Missing persons	141.4	2,966	172.1	0	3,407	76
Officer needs help	2.4	10	0.9	1	5	2
Other crimes[3]	75.7	27,591	214	0	8,385	21
Other (not crime)[4]	16.9	3,395	60.6	0	1,494	8
Property crimes	168.4	19,683	312.5	0	7,182	76
Sex offense	154.2	1,170	634.0	0	20,094	56
Statuses	101.4	15,123	220.2	0	11,087	39
Suspicion	34.5	13,445	90.3	0	6,611	14
Traffic-related	41.6	11,275	162.7	0	5,630	13
Violent crimes	39.5	2,808	200.0	0	8,428	6
Warrants	66.6	588	102.8	0	754	26
2017						
Incident type	Mean	N	SD	Min	Max	Median
Alarms	66.1	4,663	113.0	0	1,261	21
Assisting the public	46.6	22,968	118.5	0	10,980	19
Behavioral health	21.7	3,932	37.8	0	964	13
Callback	7,187.7	1,036	4,389.2	0	20,564	6,939
Call-related issues	16.6	2,144	27.8	0	544	11
Complaints/ environmental conditions	131.9	22,668	319.7	0	12,931	56
Domestic violence	69.7	19,174	192.4	0	10,584	20

Drugs	181.4	1,869	350.1	0	8,150	73
Fire	25.4	45	39.6	1	222	11
Liquor violations	95.3	214	87.4	1	506	69
Medical emergencies	7.7	23	6.3	1	29	5
Missing persons	260.4	3,353	457.0	0	15,797	139
Officer needs help	2.7	1	N/A	3	3	3
Other crimes	135.1	29,797	470.5	0	15,760	34
Other (not crime)	21.0	2,710	67.6	0	1,209	9
Property crimes	258.0	19,547	641.0	0	17,200	111
Sex offense	224.2	1,468	450.0	0	6,658	77
Status offense	74.6	1	N/A	75	75	75
Statuses	159.4	13,706	285.5	0	9,324	56
Suspicion	56.3	14,360	287.4	0	15,850	19
Traffic-related	59.2	9,875	387.7	0	15,614	14
Violent crimes	91.0	3,610	439.1	0	15,602	8
Warrants	96.1	466	148.9	0	947	36

[1] This category includes incidents such as hang-ups and abandoned calls.
[2] This category includes incidents such as animal complaints, open hydrants, and disturbances of the peace.
[3] This category includes incidents such as custodial interference, cruelty to animals, and disorderly conduct.
[4] This category includes the following incidents: "other," "weapons/carrying concealed," "unknown trouble," and "task force."

Figure 5.2.5D shows that, in both 2016 and 2017, officers were quickest to respond to calls involving medical emergencies and officers needing help, though the frequency of those calls was low. Beyond those call types, in 2016, officers responded most quickly to calls related to behavioral health and call-related issues (e.g., 911 hang-ups in which the dispatcher either suspected trouble or could not get in contact with the caller after multiple attempts and a call location was available). In 2017, officers responded most quickly to calls classified as other (noncriminal in nature) and call-related issues. Additionally, for both years, officers took the longest to respond to calls related to callbacks, missing persons and property crimes. These findings are partially consistent with the hypothesis that officers respond most quickly to emergencies and crimes in progress, though the finding that they responded most slowly to calls about missing persons and property crimes stands directly in contrast to that hypothesis.

Figure 5.2.5E: Tucson dispatcher response time in minutes, broken down by hour of day

2016						
Hour of day	Mean	N	SD	Min	Max	Median
0	57.5	6,400	205.2	0	6,260	6
1	49.5	5,302	170.5	0	6,257	7
2	51.0	4,654	195.3	0	6,130	7
3	53.5	3,620	210.7	0	6,085	7
4	46.3	3,015	167.6	0	4,997	6
5	45.9	2,884	98.8	0	3,118	13

6	42.5	3,441	152.7	0	5,889	15
7	46.7	4,951	201.0	0	4,639	8
8	48.4	6,637	179.8	0	5,931	9
9	64.1	7,495	307.8	0	8,721	9
10	72.9	7,973	306.1	0	7,366	9
11	87.3	8,771	368.3	0	8,456	11
12	94.2	9,163	390.4	0	8,570	13
13	89.6	9,226	345.0	0	8,388	15
14	89.9	9,589	371.9	0	8,351	14
15	115.0	9,956	495.3	0	20,093	14
16	115.7	10,350	410.1	0	6,997	20
17	122.2	10,662	489.9	0	11,574	19
18	105.5	10,690	411.0	0	8,330	16
19	95.0	10,193	350.4	0	8,221	15
20	87.3	9,844	316.3	0	9,477	17
21	77.9	9,457	308.8	0	8,100	12
22	66.7	8,736	266.4	0	9,422	7
23	59.0	7,517	251.5	0	9,135	7
2017						
Hour of day	Mean	N	SD	Min	Max	Median
0	97.7	6,450	400.3	0	15,079	12
1	86.0	5,505	312.8	0	10,584	11
2	75.4	4,701	317.2	0	11,840	10
3	82.1	3,810	454.5	0	13,372	11
4	85.9	3,048	548.1	0	16,288	11
5	79.7	2,995	261.0	0	8,860	33
6	90.4	3,746	550.1	0	14,478	21
7	101.9	5,498	596.8	0	15,886	12
8	109.1	7,181	567.1	0	14,509	15
9	123.3	8,313	671.2	0	20,564	14
10	130.1	8,562	674.1	0	18,631	15
11	149.8	9,028	697.2	0	16,002	18
12	163.9	9,062	817.5	0	18,641	21
13	174.1	9,084	873.2	0	17,200	26
14	156.0	9,288	721.1	0	16,967	20
15	194.1	9,980	903.5	0	17,200	25
16	203.1	10,440	913.1	0	18,391	33
17	225.7	10,531	993.7	0	18,171	33
18	218.9	10,499	1008.7	0	19,547	27
19	188.9	10,423	852.8	0	18,305	30
20	167.6	9,929	796.2	0	19,442	35
21	128.1	9,353	551.0	0	16,625	21
22	130.4	8,683	627.5	0	17,934	14
23	105.2	7,477	481.9	0	13,727	12

Figure 5.2.5E demonstrates that, in 2016, dispatchers responded to calls most quickly during the 6:00 a.m. hour (Hour 6), whereas in 2017, they responded fastest during the 2:00 a.m. hour (Hour 2). In both years, dispatchers were slowest to respond during the 5:00 p.m. hour (Hour 17). These findings generally fail to support the hypothesis that response time is slowest at night. However, as noted above, the lower call volume at night may facilitate faster response times.

Figure 5.2.5F: Tucson officer response time in minutes, broken down by hour of day

2016						
Hour of day	Mean	N	SD	Min	Max	Median
0	63.0	6,400	205.6	0	6,260	13
1	55.0	5,302	171.1	0	6,257	13
2	56.6	4,654	195.7	0	6,131	13
3	59.6	3,620	211.2	0	6,085	14
4	52.6	3,015	168.1	0	4,998	14
5	53.4	2,884	100.3	0	3,118	20
6	51.8	3,441	152.4	0	5,889	26
7	55.5	4,951	194.7	0	4,639	18
8	57.3	6,637	180.0	0	5,931	19
9	72.7	7,495	307.7	0	8,721	18
10	81.5	7,973	306.1	0	7,366	19
11	95.3	8,771	365.3	0	8,456	21
12	102.4	9,163	390.8	0	8,630	22
13	98.2	9,226	344.8	0	8,388	24
14	98.4	9,589	370.8	0	8,351	24
15	123.5	9,956	494.9	0	20,094	25
16	124.6	10,350	409.3	0	6,997	31
17	130.6	10,662	489.3	0	11,574	30
18	113.3	10,690	410.7	0	8,330	25
19	102.4	10,193	350.3	0	8,222	23
20	94.5	9,844	316.0	0	9,477	26
21	85.0	9,457	309.0	0	8,100	20
22	73.0	8,736	266.9	0	9,422	15
23	64.9	7,517	251.8	0	9,135	14
2017						
Hour of day	Mean	N	SD	Min	Max	Median
0	103.7	6,450	400.6	0	15,079	19
1	92.0	5,505	313.8	0	10,584	18
2	81.2	4,701	317.5	0	11,840	17
3	88.4	3,810	454.5	0	13,372	18
4	92.6	3,048	548.0	0	16,288	18
5	88.0	2,995	260.8	0	8,860	40
6	100.2	3,746	549.7	0	14,478	32
7	111.6	5,498	596.5	0	15,886	24
8	118.9	7,181	567.4	0	14,509	25

9	132.4	8,313	671.0	0	20,564	24
10	138.9	8,562	673.7	0	18,631	25
11	158.2	9,028	694.1	0	16,002	29
12	172.6	9,062	816.9	0	18,641	31
13	182.7	9,084	872.4	0	17,200	37
14	164.9	9,288	720.9	0	16,967	31
15	201.2	9,980	894.2	0	17,114	35
16	212.0	10,440	912.8	0	18,392	43
17	233.8	10,531	991.4	0	18,171	42
18	227.0	10,499	1008.1	0	19,547	37
19	196.8	10,423	852.5	0	18,305	38
20	175.1	9,929	795.9	0	19,442	44
21	135.5	9,353	551.1	0	16,623	30
22	137.0	8,683	627.6	0	17,934	21
23	111.5	7,477	482.1	0	13,727	19

Figure 5.2.5F demonstrates that, judging by the median, officers were fastest to respond between the hours of midnight and 4:00 a.m. (Hours 0 to 4) in both years. Given the large range, the median is a more appropriate metric for assessing response time here. These findings generally fail to support Vera's hypothesis that response time is slowest at night, though again, the results may be related to the lower volume of calls that come in at night.

3. What proportion of police activity—especially enforcement—is proactive (i.e., officer initiated, such as traffic stops and directed patrols) versus reactive (i.e., in response to 911 calls/reported incidents)?

Figure 5.2.6A: Tucson total volume of 911 calls received and other CAD entries

	2016			2017		
	N	Percent	Rate per capita[4]	N	Percent	Rate per capita
Phone (911 CFS)[1]	283,245	71.1%	53,686	317,827	73.2%	60,242
Self-initiated[2]	114,696	28.8%	21,740	115,369	26.5%	21,867
Walk-in[3]	714	0.2%	135	877	0.2%	166
Missing	8	0%		407	0.1%	
Total	**398,663**	100%	75,564	**434,482**	100	82,353

[1] Phone (911 CFS) refers to 911 calls for service placed by members of the community.
[2] Self-initiated refers to activities that officers proactively initiated on their own and were not related to a 911 call for service.
[3] Walk-ins refer to when a civilian reports an incident at a police station and a CAD entry is created from it.
[4] Rate per capita reports the rate per 100,000 people in Tucson and was calculated using Tucson's 2016 ACS reported population of 527,586.

Figure 5.2.6A reveals that TPD officers spent most of their time in 2016 and 2017 responding to 911 calls for service. This finding supports Vera's hypothesis that most police activity is reactive rather than proactive. There were also approximately 35,000 more 911 calls in 2017 compared to 2016, which may have implications for how TPD responded to calls for service.

Figure 5.2.6B: Tucson top 10 incidents for 911 calls for service and police-initiated activities

2016				2017			
Calls for service		Police-initiated		Calls for service		Police-initiated	
Incident	Frequency	Incident	Frequency	Incident	Frequency	Incident	Frequency
911 Hang-up from PSAP[212]	50,764	Traffic stop	63,103	911 Hang-up from PSAP	75,234	Traffic stop	55,998
Check welfare	21,479	Other[1]	14,294	Check welfare	22,307	Other	11,444
Family fight/domestic violence	11,935	10-80 field interview/subject in vehicle	8,227	Family fight/domestic violence	10,807	Community engagement/special check activity	6,706
Larceny	10,477	Bicycle traffic	3,334	Larceny	10,330	10-80 field interview/ subject in vehicle	5,660
Non-verified alarm	8,273	Flag down	3,172	Non-verified alarm	7,927	Bicycle traffic	3,227
Suspicious person	6,307	10-81 field interview	2,032	Suspicious activity	7,658	Flag down	2,993
Fight brewing	6,228	Mental health unit	1,884	Suspicious person	6,182	Community engagement/targeted enforcement	2,234
Suspicious activity	6,000	Stalled vehicle	1,574	Family fight/domestic violence brewing	5,933	Mental health unit	2,049
Family fight/domestic Violence brewing	5,928	Larceny	1,265	Fight brewing	5,894	Miscellaneous /officer	1,724
Accident w/ injuries	5,555	Transport unit event	1,179	Unwanted person	5,831	Pedestrian traffic	1,485

[1] Police-Initiated Activities listed as "other" include events that an officer cannot immediately categorize (e.g., a community member frantically pointing at a place or vehicle), events where the officer lacks sufficient time to describe it over the radio (e.g., an officer sees a hazardous situation that requires immediate attention), and events that defy categorization (e.g., a collision occurs in the presence of the officer and immediate action is necessary to preserve life). Most frequently, "other" refers to the former two events, not the latter.

Figure 5.2.6B shows that, in both years, the highest frequency of calls for service (CFS) CAD entries were 911 hang-ups from PSAPs, and the highest number of self-initiated CAD entries were traffic stops. Further analysis revealed that more than 75 percent of the hang-ups from PSAPs were classified as callbacks. Thus, although a substantial portion of the call volume was driven by hang-ups that may not have resulted in officers being dispatched to the scene, 911 hang-ups still present a serious drain on the Tucson Communications Center's resources—communications procedures require that every 911 hang-up receive an immediate callback to attempt contact with the caller. If the call-taker is unsuccessful in contacting someone associated with the number

[212] According to officials in Tucson, before department consolidation of the fire/EMS and police call centers, fire call-takers received all initial calls. Therefore, calls that required police assistance had to be transferred, and during this process, most callers were put on hold, which resulted in a large number of hang-ups. The high volume of hang-ups has been attributed to this original system and is expected to improve post-communication department consolidation.

involved in the hang-up to confirm that the call does not present an emergency, a call for service is then generated, provided that the original call was made from a landline.

Detroit data

1. What is the volume/rate (per capita) of 911 calls received, and how does this vary by incident type (e.g., nuisance complaint, crime in progress, medical emergency, domestic violence incidents, or officer involved shootings), time of day, and geographic location?

Figure 5.2.7A: Detroit 911 call volumes, broken down by priority level

	2017		2018	
Priority level	Frequency	Percentage	Frequency	Percentage
1	61,876	18.8%	73,848	23.0%
2	128,038	38.9%	119,910	37.3%
3	125,738	38.2%	116,651	36.3%
4	10,313	3.1%	8,197	2.6%
5	2,587	0.8%	2,500	0.8%
9	1	0.0%	0	0.0%
Missing	424	0.1%	322	0.1%

Figure 5.2.7A reveals that, in both 2017 and 2018, the majority of DPD's calls were classified as Priority 2 and 3.

Figure 5.2.7B: Detroit 911 call volumes, broken down by incident type

2017			2018		
Incident type	Frequency	Percentage	Incident type	Frequency	Percentage
Disturbance	51,158	15.6%	Disturbance	50,902	15.8%
Assault and battery	29,089	8.8%	Unknown problem	25,138	7.8%
Unknown problem	22,174	6.7%	Assault and battery	24,251	7.5%
Investigate person	17,874	5.4%	Investigate person	15,430	4.8%
Felonious assault I/P	15,111	4.6%	Felonious assault I/P	15,145	4.7%
One down or over wheel	10,138	3.1%	Auto unknown impaired	9,813	3.1%
Auto unknown impaired	10,128	3.1%	Verified alarm	8,544	2.7%
Person with weapon	8,824	2.7%	Burglary occupied residence I/P	7,766	2.4%
Verified alarm	7,854	2.4%	Person with weapon	7,669	2.4%
Burglary occupied residence I/P	7,220	2.2%	Shots fired I/P	6,753	2.1%

Shots fired /IP	7,021	2.1%	Remarks	6,583	2.0%
Malicious destruction I/P	5,519	1.7%	One down or over wheel	5,410	1.7%

Figure 5.2.7B demonstrates that most calls DPD officers responded to were classified as disturbance incidents in both 2017 and 2018. In 2017 assault and battery calls were second most frequent call type followed by calls categorized as unknown problem. While in 2018 unknown problem calls were second most frequent followed by assault and battery calls.

The ambiguous call types like disturbance and unknown problems coupled with physically violent crimes is something not seen in many cities, while simultaneously supporting and opposing the hypothesis that most calls are for nonviolent and non-emergency based situations.

Figure 5.2.7C: Detroit 911 call volumes, broken down by day of week

	2017		2018	
Day	Frequency	Percentage	Frequency	Percentage
Sunday	49,665	15.1%	47,508	14.8%
Monday	45,463	13.8%	44,996	14.0%
Tuesday	45,324	13.8%	43,952	13.7%
Wednesday	46,140	14.0%	44,463	13.8%
Thursday	45,064	13.7%	44,789	13.9%
Friday	47,275	14.4%	46,204	14.4%
Saturday	50,046	15.2%	49,516	15.4%

Figure 5.2.7C demonstrates that, in 2017 and 2018, the DPD received 911 calls most often on Saturdays and Sundays. These findings are consistent with Vera's hypothesis that 911 call volumes concentrate on weekends.

Figure 5.2.7D: Detroit 911 call volumes, broken down by hour of day

	2017		2018	
Hour	Frequency	Percentage	Frequency	Percentage
0	14,749	4.5%	13,673	4.3%
1	12,345	3.8%	10,733	3.3%
2	10,224	3.1%	10,273	3.2%
3	8,955	2.7%	9,998	3.1%
4	7,915	2.4%	8,362	2.6%
5	6,739	2.0%	6,815	2.1%
6	6,709	2.0%	6,413	2.0%
7	8,129	2.5%	8,329	2.6%
8	9,875	3.0%	9,860	3.1%
9	11,459	3.5%	11,064	3.4%
10	13,098	4.0%	12,599	3.9%

11	14,009	4.3%	14,048	4.4%
12	15,048	4.6%	14,470	4.5%
13	15,344	4.7%	15,219	4.7%
14	15,207	4.6%	15,341	4.8%
15	16,589	5.0%	17,132	5.3%
16	18,412	5.6%	18,114	5.6%
17	18,905	5.7%	18,098	5.6%
18	18,393	5.6%	17,793	5.5%
19	17,497	5.3%	16,546	5.1%
20	17,607	5.4%	16,684	5.2%
21	17,586	5.3%	17,382	5.4%
22	17,425	5.3%	16,571	5.2%
23	16,758	5.1%	15,911	5.0%

Figure 5.2.7D shows that, in 2017, DPD most often received 911 calls during the 5:00 p.m. and 6:00 p.m. hours (Hours 17 and 18, respectively), whereas in 2017, calls most frequently came in during the 4:00 p.m. and 5:00 p.m. hours (Hours 16 and 17). These findings are inconsistent with the hypothesis that 911 call volumes concentrate at night.

2. How promptly are calls responded to—by a call-taker, dispatcher, and an officer on-scene—and how does this vary by call volume, incident type, time of day, and geographic location?

Figure 5.2.8A: Detroit dispatcher response time in minutes, broken down by call type

2017						
Call type	Mean	N	SD	Min	Max	Median
Phone	40.1	265,659	73.4	0	2,237.7	9.1
Officer-initiated	0.0	279,473	0.9	0	419.6	0.0
2018						
Call type	Mean	N	SD	Min	Max	Median
Phone	35.0	267,276	64.5	0	1,368.8	7.8
Officer-initiated	0.0	478,038	1.1	0	414.0	0.0

Figure 5.2.8A shows that dispatcher response time for phone calls decreased by approximately five minutes from 2017 to 2018.

Figure 5.2.8B: Detroit officer response time, broken down by call type

2017						
Call type	Mean	N	SD	Min	Max	Median
Phone	8.4	268,700	14.6	0	894.6	6.3
Officer-initiated	0.0	279,420	0.8	0	154.5	0.0

Total	4.1	548,120	11.1	0	894.6	0.0
2018						
Call type	Mean	N	SD	Min	Max	Median
Phone	8.2	271,417	14.5	0	1,307.1	5.8
Officer-initiated	0.0	477,894	1.0	0	286.4	0.0
Total	3.0	749,311	9.6	0	1,307.1	0.0

Figure 5.2.8B demonstrates that officer response time was consistent between 2017 and 2018 and was much quicker when responding to officer-initiated events. This finding is not surprising, as officer-initiated events involve an officer on-scene; thus, little to no time lapses between the "call" and the officer's arrival.

Figure 5.2.8C: Detroit dispatcher response time, broken down by incident type

2017						
Incident type	Mean	N	SD	Min	Max	Median
Disturbance	44.5	38,950	65.9	0	1,165.0	18.6
Assault and battery	58.5	25,489	80.3	0	942.3	28.0
Unknown problem	45.3	19,412	64.7	0	820.2	20.4
Investigate person	36.3	14,289	59.4	0	692.0	11.1
Felonious assault IP	4.1	12,477	11.6	0	479.5	1.8
One down or over wheel	19	8,080	37.4	0	633.6	6.1
Auto unknown impaired	41	8,643	65.6	0	694.7	13.6
Person with weapon	44.7	7,964	69.6	0	842.6	17.0
Verified alarm	40.2	7,193	68.1	0	934.4	13.3
Burglary occupied residence IP	3.8	6,068	13.6	0	728.1	1.6
Shots fired IP	6	6,141	19.7	0	411.7	1.7
Malicious destruction IP	65.8	3,861	89.6	0	865.6	31.3
2018						
Incident type	Mean	N	SD	Min	Max	Median
Disturbance	40.2	41,098	60.7	0	1,020.5	15.7
Unknown problem	38.8	22,229	57.3	0	783.0	16.5
Assault and battery	60.4	21,776	83.9	0	1,017.4	27.8
Investigate person	31.4	13,078	52.2	0	840.8	9.8
Felonious assault IP	5.1	12,228	11.5	0	270.0	2.1
Auto unknown impaired	37.2	8,597	58.9	0	622.2	13.8

Verified alarm	29.5	7,868	50.9	0	628.7	9.2
Burglary occupied residence IP	5.1	6,420	13.1	0	270.8	2.1
Person with weapon	44.5	7,072	69.4	0	830.2	15.9
Shots fired IP	5.6	5,801	18.1	0	444.1	1.8
Remarks	18.7	4,403	41.6	0	712.2	4.0
One down or over wheel	16.4	4,417	30.9	0.1	774.8	5.4

Figure 5.2.8C demonstrates that, among the 10 most frequent call types in 2017 and 2018, dispatcher response time was slowest for assault and battery incidents.

Figure 5.2.8D: Detroit officer response time, broken down by incident type

2017						
Incident type	Mean	N	SD	Min	Max	Median
Disturbance	8.1	38,637	13.6	0	454.9	6.2
Assault and battery	8.9	25,618	15.1	0	439.7	6.7
Unknown problem	8.6	19,070	14.4	0	424.7	6.5
Investigate person	7.0	14,385	13.4	0	874.7	5.2
Felonious assault IP	7.1	14,397	6.4	0	183.7	5.9
One down or over the wheel	7.0	7,665	8.7	0	295.8	5.7
Auto unknown impaired	8.5	8,591	12.8	0	377.4	6.5
Person with weapon	7.5	8,046	13.8	0	491.0	5.8
Verified alarm	8.6	7,048	15.7	0	751.5	6.7
Burglary occupied residence	6.8	6,928	6.2	0	121.6	5.6
Shots fired IP	5.6	6,650	5.7	0	182.2	4.6
Malicious destruction IP	9.1	3,826	18.6	0	579.8	6.7
2018						
Incident type	Mean	N	SD	Min	Max	Median
Disturbance	8.1	40,613	13.5	0	464.3	6.0
Unknown problem	8.2	21,748	13.7	0	554.3	6.1
Assault and battery	8.6	21,835	16.3	0	589.6	6.2
Investigate person	6.7	12,956	11.2	0	416.2	4.9
Felonious assault IP	6.4	14,242	6.2	0	230.0	5.2
Auto unknown impaired	8.5	8,529	13.1	0	468.0	6.3
Verified alarm	8.5	7,765	14.2	0	364.9	6.3
Burglary occupied residence	6.1	7,397	5.5	0	85.7	4.9
Person with weapon	7.2	7,121	12.3	0	352.4	5.3
Shots fired IP	5.1	6,395	5.0	0	118.8	4.1
Remark	24.9	3,813	25.7	0	433.9	22.5
One down or over the wheel	6.8	4,151	8.0	0	180.1	5.3

Figure 5.2.8D demonstrates, that in 2017 and 2018, DPD officers took the longest to respond to calls coded as remarks and malicious destruction.

Figure 5.2.8E: Detroit dispatcher response time, broken down by hour of day

2017						
Hour	Mean	N	SD	Min	Max	Median
0	33.2	11,742	68.1	0	1322.9	7.5
1	30.4	9,825	63.2	0	673.0	6.4
2	31.3	8,121	68.8	0	775.7	5.2
3	38.0	7,156	73.7	0	842.6	6.6
4	41.8	6,398	76.1	0	881.9	7.2
5	42.2	5,551	72.1	0	865.6	7.4
6	55.3	5,516	90.7	0	764.0	24.0
7	36.0	6,787	70.5	0	1564.5	11.3
8	23.4	8,116	50.6	0	751.8	5.2
9	25.8	9,408	58.4	0	1267.6	4.7
10	29.3	10,708	61.4	0	821.0	5.5
11	34.8	11,387	68.7	0	887.9	6.7
12	42.0	12,172	74.2	0	1098.9	9.2
13	46.0	12,466	78.6	0	1034.7	10.5
14	54.7	12,406	82.4	0	1301.8	24.9
15	45.4	13,873	76.9	0	1045.7	16.8
16	36.2	15,342	75.2	0	1165.0	8.5
17	37.5	15,658	75.8	0	1114.6	8.2
18	39.1	15,101	74.7	0	918.4	8.5
19	42.1	14,143	77.4	0	847.9	8.8
20	44.1	13,996	76.9	0	858.5	10.7
21	44.9	13,726	76.4	0	935.9	9.5
22	55.5	13,236	79.6	0	2237.7	22.3
23	44.1	12,825	68.9	0	1030.9	16.4

2018						
Hour	Mean	N	SD	Min	Max	Median
0	29.1	11,540	60.2	0	767.4	6.8
1	30.3	9,062	69.8	0	962.4	5.6
2	34.9	8,627	72.5	0	720.6	5.7
3	40.8	8,535	77.6	0	866.1	7.2
4	40.4	7,091	75.1	0	748.2	6.6
5	40.8	5,831	71.4	0	715.4	6.9
6	46.5	5,399	66.6	0	713.7	18.7
7	33.6	7,133	53.8	0	560.6	11.4
8	22.9	8,304	48.7	0	775.4	4.8
9	25.7	9,131	56.7	0	1008.7	4.8
10	28.9	10,235	59.7	0	823.6	5.4
11	33.6	11,469	64.4	0	647.8	6.2
12	39.0	11,736	66.9	0	743.1	8.3
13	41.2	12,554	67.3	0	783.3	9.3
14	46.9	12,505	64.7	0	1020.5	21.5
15	36.5	14,258	60.6	0	1368.8	13.4
16	27.1	15,164	53.9	0	956.7	7.1
17	27.7	15,097	55.3	0	863.2	6.3
18	30.4	14,851	60.8	0	880.5	6.7
19	32.8	13,838	64.1	0	923.4	7.3
20	34.1	13,980	65.4	0	797.4	7.7
21	36.4	14,358	70.1	0	842.5	7.1
22	46.5	13,500	71.1	0	1077.9	14.4
23	40.4	13,078	66.5	0	1012.1	13.9

For both years, dispatcher response time was shortest in the 8:00 a.m. hour (Hour 8) and longest during the 6:00 a.m. and 10:00 p.m. hours (Hours 6 and 22, respectively). This finding is partially consistent with the hypothesis that response times are longest at night.

Figure 5.2.8F: Detroit officer response time, broken down by hour of day

2017						
Hour	Mean	N	SD	Min	Max	Median
0	7.0	11,826.0	14.4	0.0	874.7	5.3
1	6.9	9,978.0	12.7	0.0	480.8	5.1
2	7.0	8,209.0	11.5	0.0	326.6	5.3
3	7.4	7,217.0	12.7	0.0	329.8	5.6
4	7.9	6,493.0	12.8	0.0	454.9	6.0
5	8.5	5,585.0	14.7	0.0	438.3	6.4
6	9.8	5,479.0	17.0	0.0	529.4	7.2
7	9.6	6,804.0	13.9	0.0	489.1	7.7
8	9.1	8,361.0	14.5	0.0	464.4	7.2
9	9.0	9,737.0	12.0	0.0	384.5	7.3
10	9.2	10,996.0	15.9	0.0	579.8	7.1
11	9.4	11,611.0	15.5	0.0	385.8	7.1
12	9.5	12,305.0	15.6	0.0	596.4	7.2
13	9.4	12,628.0	16.2	0.0	639.9	7.1
14	9.2	12,395.0	14.3	0.0	449.6	6.8
15	8.8	13,838.0	15.5	0.0	491.0	6.5
16	8.8	15,588.0	17.5	0.0	751.5	6.2
17	8.7	15,871.0	15.7	0.0	452.4	6.2
18	8.2	15,290.0	13.2	0.0	403.2	6.0
19	8.3	14,378.0	14.6	0.0	509.6	6.0
20	8.1	14,218.0	14.4	0.0	418.2	5.9
21	8.2	13,842.0	15.9	0.0	894.6	5.9
22	7.6	13,232.0	12.9	0.0	382.2	5.6
23	7.4	12,819.0	12.0	0.0	413.5	5.6
2018						
Hour	Mean	N	SD	Min	Max	Median
0	6.6	11,598	13.1	0	464.3	4.9
1	6.7	9,140	14.9	0	426.1	4.6
2	6.9	8,737	13.5	0	361.0	4.9
3	7.2	8,640	12.6	0	373.3	5.1
4	7.2	7,147	12.1	0	326.5	5.2
5	7.8	5,863	14.4	0	433.9	5.6
6	8.1	5,359	11.2	0	391.8	6.1
7	8.5	7,136	12.9	0	396.9	6.7
8	8.5	8,579	12.1	0	416.2	6.8
9	8.7	9,493	17.8	0	1,307.1	6.7
10	8.8	10,622	12.8	0	341.6	6.7

11	8.7	11,822	12.8	0	421.8	6.6
12	9.1	11,956	13.6	0	518.2	6.9
13	9.1	12,734	14.0	0	276.3	6.7
14	9.1	12,458	18.0	0	836.6	6.5
15	8.6	14,295	14.1	0	452.2	6.1
16	8.9	15,576	15.9	0	492.0	5.9
17	8.5	15,532	15.2	0	829.4	5.8
18	8.4	15,204	15.1	0	774.1	5.8
19	8.2	14,125	13.7	0	665.1	5.6
20	8.3	14,160	18.1	0	846.7	5.5
21	7.7	14,589	15.0	0	589.6	5.3
22	7.7	13,613	15.5	0	535.9	5.2
23	6.8	13,039	11.8	0	536.7	5.1

In 2017, officer response time was longest at the 6:00 a.m. and 7:00a.m. hours (Hours 6 and 7, respectively), but longest at noon, 1:00 p.m., and 2:00 p.m. in 2018 (Hours 12, 13, and 14). For both years, officer response time was shortest between the hours of midnight and 2:00a.m. (Hours 0 and 2, respectively). These findings are inconsistent with the hypothesis that response time is highest at night.

3. What proportion of police activity—especially enforcement—is proactive (i.e., officer initiated, such as traffic stops and directed patrols) versus reactive (i.e., in response to 911 calls/reported incidents)?

Figure 5.2.9A: Detroit total volume of 911 calls received and other CAD entries

	2017			2018		
	Frequency	Percentage	Rate per capita[1]	Frequency	Percentage	Rate per capita
Self-initiated	280,122	46.0%	41,616.45	478,916	59.8%	Unavailable
Phone (911 CFS)	328,977	54.0%	48,874.62	321,428	40.2%	Unavailable
Total	609,099			800,344		

[1] Rate per capita reports the rate per 100,000 people in Detroit, and was calculated using Detroit's [ACS reported population](#) of 672,662.[213]

Figure 5.2.9A reveals that, in 2017, officers spent more time responding to calls for service than self-initiated activity. In 2018, more of officers' time was spent responding to self-initiated calls.

Figure 5.2.9B: Detroit top 10 volumes for 911 calls for service and self-initiated activities

2017				2018			
Calls for service		Officer-initiated		Calls for service		Officer-initiated	
Incident type	Frequency	Incident type	Frequency	Incident type	Frequency	Incident type	Frequency
Disturbance	51,158	Special attention	79,945	Disturbance	50,902	Traffic stop	128,195

[213] Population per 2018 Census Bureau's Population Estimates Program.

Assault and battery	29,089	Traffic stop	66,899	Unknown problem	25,138	Special attention	117,307
Unknown problem	22,174	Towing detail	24,656	Assault and battery	24,251	Start of shift information	58,104
Investigate person	17,874	Bus boarding	13,095	Investigate person	15,430	Remarks	43,121
Felonious assault IP	15,111	Larceny report	11,054	Felonious Assault IP	15,145	Towing detail	23,689
One down or over wheel	10,138	Investigate person	11,009	Auto unknown impaired	9,813	Investigate person	15,666
Auto unknown impaired	10,128	UDAA report	7,594	Verified alarm	8,544	Larceny report	11,649
Person with weapon	8,842	Remarks	6,975	Burglary occupied residence IP	7,766	Bus boarding	8,152
Verified alarm	7,854	Fraud report	5,112	Person with weapon	7,669	UDAA report	6,663
Burglary occupied residence IP	7,220	Threats report	4,625	Shots fired IP	6,753	Building check	5,283
Shots fired IP	7,021	Malicious destruction RPT	3,775	Remarks	6,543	Fraud report	5,227
Malicious destruction IP	5,519	Building check	3,560	One down or over wheel	5,410	Threats report	5,194

Figure 5.2.9B demonstrates that, across both years, most call for service CAD entries were related to disturbances. In 2017, officer-initiated calls were categorized as special attention, and in 2018, officer-initiated calls were most frequently categorized as traffic stops. It should also be noted that the significant increase in start of shift information incidents between the two years might be the result of a new policy that altered how officers record their time.

New Orleans data

1. What is the volume/rate (per capita) of 911 calls received, and how does this vary by incident type (e.g., nuisance complaint, crime in progress, medical emergency, domestic violence incident, or officer involved shooting), time of day, and geographic location?

Figure 5.2.10A: New Orleans 911 call volumes, broken down by priority level[1]

2016			2017		
Priority level	Frequency	Percentage	Priority level	Frequency	Percentage
0	21,227	5.3%	0	19,057	5.9%
1	263,317	65.2%	1	209,467	64.4%
2	119,465	29.6%	2	96,757	29.7%
3	56	0.0%	3	107	0.0%

[1] Code 3 is considered the highest priority and is reserved for officer needs assistance. Code 2 are considered "emergency" calls for service. Code 1 are considered "non-emergency" calls for service. Code 0 calls do not require a police presence.

Figure 5.2.10A demonstrates that, in both years, the majority of NOPD's calls were classified as Priority 1. This finding is consistent with Vera's hypothesis that most 911 calls are unrelated to a crime in progress.

Figure 5.2.10B: New Orleans 911 call volumes, broken down by incident type

Incident type	2016		2017	
	Frequency	Percentage	Frequency	Percentage
Complaint other	66,859	21.3%	64,230	19.7%
Burglar alarm	44,312	14.1%	34,807	10.7%
Disturbance (other)	28,317	9.0%	26,457	8.1%
Auto accident	16,193	5.2%	15,806	4.9%
Traffic incident	15,390	4.9%	17,815	5.5%
Suspicious person	13,778	4.4%	13,738	4.2%
Domestic disturbance	10,335	3.3%	11,269	3.5%
Hit and run	7,904	2.5%	8,042	2.5%
Mental Health	5,049	1.6%	5,083	1.6%
Warrant stop with release	5,005	1.6%	6,934	2.1%
Medical	5,001	1.6%	5,350	1.6%
Auto accident with injury	4,802	1.5%	4,901	1.5%
Theft	4,772	1.5%	5,005	1.5%
Silent 911 call	4,194	1.3%	3,119	1.0%
Return for additional info	4,160	1.3%	5,387	1.7%
Simple battery domestic	4,123	1.3%	4,508	1.4%
Simple criminal damage	4,122	1.3%	3,659	1.1%
Noise complaint	4,025	1.3%	4,541	1.4%

Figure 5.2.10B demonstrates that, in both 2016 and 2017, complaint/other incidents were logged with the highest frequency (21.3 percent in 2016, 19.7 percent in 2017). These findings are consistent with our hypothesis that nuisance-based calls make up a majority of calls, as nuisance calls would fall in the complaint and other category.

Figure 5.2.10C: New Orleans 911 call volumes, broken down by day of week

Day	2016		2017	
	Frequency	Percentage	Frequency	Percentage
Sunday	18,102	14.6%	18,421	14.4%
Monday	16,172	13.0%	16,376	12.8%
Tuesday	19,925	16.0%	21,076	16.4%
Wednesday	16,191	13.0%	16,340	12.7%

Thursday	18,152	14.6%	18,884	14.7%
Friday	18,253	14.9 %	18,553	14.5%
Saturday	17,363	14.0%	18,594	14.5%

Figure 5.2.10C demonstrates that, for both years, the highest number of calls were received on Tuesdays, while the lowest number of calls were received on Mondays and Wednesdays. These findings are inconsistent with the hypothesis that 911 call volumes are highest on weekends.

Figure 5.2.10D: New Orleans 911 call volumes, broken down by hour of day

	2016		2017	
Hour of day	Frequency	Percentage	Frequency	Percentag e
0	11,613	3.7%	12,304	3.8%
1	9,742	3.1%	10,225	3.1%
2	8,216	2.6%	8,423	2.6%
3	6,855	2.2%	7,375	2.3%
4	6,591	2.1%	6,398	2.0%
5	6,069	1.9%	6,389	2.0%
6	7,386	2.4%	7,259	2.2%
7	10,283	3.3%	10,074	3.1%
8	13,088	4.2%	13,446	4.1%
9	14,105	4.5%	14,600	4.5%
10	14,743	4.7%	15,171	4.7%
11	15,298	4.9%	15,964	4.9%
12	15,918	5.1%	16,708	5.1%
13	15,964	5.1%	16,328	5.0%
14	15,876	5.1%	15,846	4.9%
15	17,119	5.4%	17,549	5.4%
16	18,151	5.8%	18,642	5.7%
17	17,960	5.7%	18,445	5.7%
18	16,838	5.4%	17,373	5.3%
19	15,570	5.0%	17,250	5.3%
20	15,385	4.9%	16,770	5.2%
21	15,105	4.8%	15,692	4.8%
22	13,933	4.4%	13,862	4.3%
23	12,460	4.0%	13,296	4.1%

Figure 5.2.10D shows that, in both years, the highest frequency of CAD entries took place at the 4:00 p.m. and 5:00 p.m. hours (Hours 16 and 17, respectively). This is inconsistent with the

hypothesis that 911 call volumes are highest during the night. In both years, the lowest frequency of calls was made during the 4:00 a.m. and 5:00 a.m. hours (Hours 4 and 5).

2. How promptly are calls responded to—by a call-taker, dispatcher, and an officer on-scene—and how does this vary by call volume, incident type, time of day, and geographic location?

Figure 5.2.11A: New Orleans dispatcher response time, broken down by call type

2016						
Call type	Mean	N	SD	Min	Max	Median
Phone	62.9	280,093	158.0	0	4,964	3.7
Self-initiated	16.1	16,198	49.2	0	1,524	1.8
Call type	Mean	N	SD	Min	Max	Median
Phone	73.7	285,904	223.1	0	6,627	3.8
Self-initiated	20.1	20,316	71.9	0	5,771	2.0

Figure 5.2.11A shows that the average dispatcher response time for 911 calls increased substantially, from 62.9 minutes in 2016 to 73.7 minutes in 2017. This increase in response time was accompanied by a relatively small increase in overall call volume, from 314,268 calls in 2016 to 325,389 calls in 2017.

Figure 5.2.11B: New Orleans officer response time, broken down by call type

2016						
Call type	Mean	N	SD	Min	Max	Median
Phone	8.1	216,622	11.6	0	772	5.9
Self-initiated	0.1	142	0.3	0	3	0.1
Call type	Mean	N	SD	Min	Max	Median
Phone	7.3	232,990	10.5	0	1,345	5.3
Self-initiated	14.4	21	12.3	1	51	9.6

Figure 5.2.11B shows that, between 2016 and 2017, officer response time decreased from 8.1 minutes to 7.3 minutes.

Figure 5.2.11C: New Orleans dispatcher response time, broken down by incident type

2016						
Incident type	Mean	N	SD	Min	Max	Median
Complaint other	69.9	60,012	166.3	0	4,019	4.0
Disturbance (other)	49.0	25,727	110.8	0	2,129	6.0
Traffic incident	5.0	14,152	28.4	0	623	0.0

Auto accident	53.5	13,142	77.8	0	1,291	23.8
Suspicious person	19.5	13,137	65.9	0	2,014	2.1
Domestic disturbance	78.4	10,037	195.7	0	3,715	4.8
Hit and run	124.4	7,086	186.7	0	2,625	55.2
Mental Health	45.1	4,758	157.1	0	4,912	3.6
Medical	6.3	4,693	31.3	0	1,527	1.5
Theft	190.4	4,526	255.4	0	3,341	106.1
Warr stop with release	0.3	4,321	1.6	0	33	0.0
Auto accident with injury	17.1	4,068	41.8	0	799	3.2
Return for additional info	79.0	3,989	231.5	0	4,140	0.0
Simple battery domestic	81.4	3,962	214.1	0	2,961	4.3
Simple criminal damage	189.3	3,798	270.8	0	3,360	86.6
Noise complaint	76.0	3,731	91.1	0	771	44.7
Fight	12.0	3,541	55.2	0	1,532	1.9
Lost property	168.1	3,466	226.3	0	2,806	89.2
2017						
Incident type	Mean	N	SD	Min	Max	Median
Complaint other	91.9	56,144	266.1	0	6,627	6.5
Disturbance (other)	68.9	23,364	164.3	0	3,264	9.7
Traffic incident	8.2	16,107	44.4	0	1,354	0.0
Suspicious person	28.9	12,999	97.2	0	2,956	2.2
Auto accident	54.5	12,839	91.7	0	3,627	22.6
Domestic disturbance	118.1	10,908	324.5	0	4,240	5.2
Hit and run	137.1	7,148	256.6	0	3,755	52.9
Area check	0.2	6,653	2.9	0	155	0.0
Warr stop with release	0.5	5,404	7.8	0	393	0.0
Return for additional info	100.0	5,192	355.4	0	5,082	0.0
Medical	8.8	4,960	57.2	0	2,074	1.7
Mental Health	56.4	4,748	210.3	0	5,029	3.6
Theft	180.1	4,680	301.4	0	3,520	80.0
Simple battery domestic	105.5	4,318	309.2	0	3,431	4.2
Noise complaint	87.3	4,131	114.3	0	1,456	49.3
Business check	0.1	4,065	0.7	0	21	0.0
Auto accident with injury	22.7	4,007	59.0	0	956	3.5
Simple burglary vehicle	240.4	3,802	423.4	0	3,901	91.2

Figure 5.2.11C demonstrates that, in 2017, dispatchers were quickest to respond to calls in the newly created categories of area check and business check (0.2 and 0.1 minutes, respectively). In 2016, they were quickest to respond to warrant stop with release (0.3 minutes). In 2016, officers were slowest in responding to calls concerning simple criminal damage (189.3 minutes), whereas

in 2017, they were slowest in responding to simple burglary vehicle calls (240.4 minutes). It is worth noting that each of these categories existed only in the one year that they had the longest response time, suggesting that they might be used to code the same type of calls.

Figure 5.2.11D: New Orleans officer response time, broken down by incident type

2016						
Incident type	Mean	N	SD	Min	Max	Median
Complaint other	7.4	43,055	10.3	0	371	5.1
Burglar alarm, silent	6.9	29,257	5.5	0	244	5.9
Disturbance (other)	7.1	21,663	10.3	0	772	5.6
Suspicious person	6.1	11,371	5.6	0	186	5.1
Traffic incident	3.0	11,190	6.2	0	128	0.5
Auto accident	12.9	10,918	14.6	0	252	9.0
Domestic disturbance	9.1	9,146	9.2	0	195	7.3
Hit and run	12.7	5,886	17.0	0	772	9.1
Mental Health	7.3	4,340	6.2	0	144	6.2
Medical	6.4	4,006	7.6	0	261	5.0
Auto accident with injury	12.2	3,631	15.1	0	218	7.9
Simple battery domestic	10.3	3,609	14.6	0	380	7.5
Theft	11.4	3,516	14.9	0	304	8.1
Simple criminal damage	11.5	3,232	19.1	0	687	8.5
Fight	6.3	3,151	5.3	0	71	5.2
Simple burglary vehicle	13.2	3,071	15.3	0	201	9.3
Return for additional info	9.7	2,817	25.6	0	627	1.7
Simple battery	9.4	2,712	13.7	0	476	6.9
2017						
Incident Type	Mean	N	SD	Min	Max	Median
Complaint other	7.1	44,013	10.4	0	646	5.0
Burglar alarm, silent	7.1	23,017	6.4	0	362	6.0
Disturbance (other)	7.1	20,395	7.8	0	281	5.6
Traffic incident	2.6	13,526	5.8	0	117	0.3
Auto accident	12.0	11,462	12.3	0	399	8.8
Suspicious person	5.9	11,326	5.6	0	149	4.9
Domestic disturbance	8.7	10,178	9.9	0	376	7.0
Hit and run	12.1	6,410	15.0	0	362	9.0
Area check	2.6	5,938	9.5	0	225	0.2
Mental Health	7.3	4,426	7.0	0	262	6.1

Medical	6.0	4,295	6.9	0	183	4.6
Simple battery domestic	8.9	4,008	9.9	0	239	7.0
Theft	8.2	3,943	24.6	0	1345	4.2
Return for additional info	7.1	3,876	15.5	0	314	0.7
Auto accident with injury	11.2	3,668	12.4	0	156	7.8
Business check	1.9	3,511	6.5	0	172	0.2
Simple burglary vehicle	11.3	3,478	11.6	0	200	8.7
Noise complaint	7.9	3,096	8.0	0	133	6.4

Figure 5.2.11D demonstrates that, in 2016, officers were quickest to respond to traffic calls. In 2017, officers were quickest to respond to calls involving the newly added categories of business check and area check. However, they responded to traffic calls with the second greatest speed that year. Additionally, in both years, officers took the longest to respond to calls related to hit and runs and auto accidents.

Figure 5.2.11E: New Orleans dispatcher response time, broken down by hour of day

2016						
Hour of day	Mean	N	SD	Min	Max	Median
0	31.7	10,513	120.9	0	3,289	1.7
1	27.1	8,815	101.2	0	2,308	1.5
2	27.4	7,392	114.9	0	3,346	1.5
3	32.8	6,199	124.6	0	2,808	1.6
4	27.5	5,950	94.0	0	2,117	1.5
5	37.7	5,464	112.6	0	1,828	1.7
6	56.0	6,403	148.2	0	3,208	5.9
7	52.5	9,142	140.3	0	3,715	4.6
8	62.3	11,725	160.7	0	4,019	4.4
9	68.4	12,642	164.2	0	2,356	6.0
10	73.0	13,249	168.9	0	2,740	67.0
11	76.7	13,715	173.0	0	2,826	6.2
12	81.2	14,113	173.8	0	4,140	6.2
13	87.9	14,074	174.9	0	2,839	8.3
14	94.2	13,882	182.6	0	2,921	25.5
15	73.9	15,185	161.2	0	2,480	7.9
16	78.4	16,038	183.4	0	3,785	5.8
17	74.4	15,770	171.0	0	3,750	5.9
18	77.3	14,868	181.6	0	4,964	6.4

19	64.2	13,930	162.7	0	2,675	3.4
20	57.3	13,906	162.4	0	3,884	2.4
21	51.4	13,523	137.6	0	3,480	2.2
22	51.9	12,412	140.9	0	4,912	3.3
23	34.9	11,183	109.6	0	2,125	2.3
2017						
Hour of day	Mean	N	SD	Min	Max	Median
0	40.6	10,802	172.3	0	6,187	1.6
1	37.5	8,994	162.9	0	3,913	1.4
2	40.3	7,328	192.8	0	4,263	1.5
3	37.7	6,537	189.0	0	4,072	1.5
4	39.6	5,580	182.6	0	4,553	1.4
5	46.8	5,574	195.8	0	5,029	1.5
6	76.1	6,255	234.1	0	5,463	6.5
7	64.3	8,859	215.3	0	5,543	7.4
8	73.1	11,975	257.7	0	6,627	4.4
9	80.0	12,952	242.5	0	4,899	5.8
10	86.6	13,455	251.5	0	5,083	6.6
11	83.3	14,105	230.4	0	4,727	5.8
12	93.2	14,698	241.5	0	5,082	6.8
13	98.6	14,310	231.2	0	4,236	9.5
14	106.0	13,715	231.8	0	3,619	33.1
15	83.5	15,545	240.7	0	4,940	8.0
16	79.0	16,346	220.4	0	3,968	5.9
17	84.6	16,243	250.9	0	5,752	5.5
18	83.2	15,405	228.3	0	4,398	5.6
19	71.3	15,125	219.3	0	5,996	3.3
20	73.9	14,709	230.0	0	5,538	2.8
21	70.0	13,639	202.2	0	3,520	2.4
22	70.4	12,059	206.1	0	3,966	4.1
23	45.1	11,694	161.7	0	3,413	2.1

Figure 5.2.11E demonstrates that dispatchers responded to calls most quickly during the 1:00 a.m. hour (Hour 1) in both years (27.11 minutes in 2016, 37.54 minutes in 2017). Across both years, the shortest response times fell between the 11:00 p.m. and 5:00 a.m. hours (Hours 23 and 5, respectively). Dispatchers took the longest to respond during the 2:00 p.m. hour (Hour 14) in both years (94.19 minutes in 2016, 105.97 minutes in 2017). These findings generally fail to support the hypothesis that response time is slowest at night.

Figure 5.2.11F: New Orleans officer response time, broken down by hour of day

2016						
Hour of day	Mean	N	SD	Min	Max	Median
0	6.4	8,147	8.9	0	145	4.6
1	6.3	6,898	12.8	0	772	4.4
2	6.4	5,843	9.3	0	205	4.5
3	6.5	4,878	9.5	0	177	4.6
4	6.3	4,620	7.7	0	93	4.7
5	6.8	4,278	10.5	0	389	4.9
6	8.6	4,897	10.1	0	184	6.4
7	9.7	7408	12.6	0	476	7.2
8	9.1	9,368	12.2	0	355	6.7
9	8.8	10,075	11.7	0	283	6.4
10	8.9	10,414	12.0	0	295	6.4
11	9.1	10,644	12.9	0	539	6.5
12	8.7	10,947	11.5	0	371	6.4
13	8.9	10,705	15.0	0	687	6.4
14	8.9	10,430	10.6	0	201	6.8
15	9.2	11,536	12.9	0	627	6.8
16	8.8	12,189	11.9	0	348	6.4
17	8.6	11,977	11.3	0	275	6.4
18	8.2	11,392	10.5	0	231	6.1
19	7.8	10,801	10.1	0	181	5.8
20	7.3	10,724	14.7	0	772	5.3
21	7.1	10,339	10.6	0	380	5.1
22	7.3	9,474	10.1	0	256	5.4
23	7.1	8,780	8.9	0	173	5.3
2017						
Hour of day	Mean	N	SD	Min	Max	Median
0	6.0	8,647	9.0	0.0	225	4.2
1	5.9	7,154	9.4	0.0	262	3.9
2	5.9	5,948	10.6	0.0	362	3.9
3	5.6	5,340	8.3	0.0	143	3.9
4	6.0	4,531	9.2	0.0	135	4.0
5	6.0	4,580	8.6	0.0	151	4.1
6	8.0	4,932	9.4	0.0	199	5.9
7	8.9	7,708	10.2	0.0	279	6.8
8	8.0	10,092	10.6	0.0	371	5.9

9	7.9	10,887	11.5	0.0	647	5.7
10	8.0	11,240	11.3	0.0	362	5.8
11	7.7	11,745	9.9	0.0	352	5.7
12	7.6	12,142	9.9	0.0	230	5.7
13	7.6	11,744	9.0	0.0	189	5.8
14	8.3	11,156	16.2	0.0	1,345	6.3
15	8.2	12,961	10.6	0.0	320	6.2
16	7.7	13,362	10.5	0.0	337	5.6
17	7.6	13,153	10.3	0.0	399	5.6
18	7.3	12,408	10.5	0.0	471	5.3
19	7.0	11,992	9.7	0.0	264	5.1
20	6.8	11,606	9.3	0.0	239	4.9
21	6.5	10,738	9.3	0.0	313	4.7
22	6.9	9,469	11.5	0.0	424	5.0
23	6.9	9,476	11.2	0.0	314	4.6

Figure 5.2.11F demonstrates that, in 2016, officers were quickest to respond to calls during the 1:00 a.m. and 4:00 a.m. hours, and in 2017, officers were quickest to respond during the 3:00 a.m. hour. Response time was shortest in the early morning hours (midnight to 5:00 a.m.; Hours 0 to 5) for both years. Across years, the longest response time was at 7:00 a.m. (Hour 7). These findings generally fail to support the hypothesis that response time is slowest at night. These findings may be explained by traffic patterns or staffing differences, though future exploration of these potential explanations is necessary.

3. What proportion of police activity—especially enforcement—is proactive (i.e., officer initiated, such as traffic stops and directed patrols) versus reactive (i.e., in response to 911 calls/reported incidents)?

Figure 5.2.12A: New Orleans total 911 call volumes and CAD entries for 2016 and 2017

	2016			2017		
	Frequency	Percentage	Rate per capita	Frequency	Percentage	Rate per capita
Self-initiated	89,797	28.6%	22847.89	118,722	36.5%	36486.18
911	314,268	82.4%		325,389	74.5%	
Total	TOTAL = 404,065			TOTAL = 444,111		

Figure 5.2.12A reveals that the majority of the NOPD officers' time in 2016 and 2017 was spent responding to 911 calls. This finding supports Vera's hypothesis that most police activity is reactive rather than proactive. However, between 2016 and 2017, the percentage of CAD entries reflecting self-initiated activity grew by 7.9 percent, an increase of nearly 30,000 entries, whereas the number of call for service entries increased by roughly 11,000. This raises questions about what kind(s) of changes in NOPD and the New Orleans community might result in a relative increase in proactive police activity.

Figure 5.2.12B: New Orleans top 10 volumes for 911 calls for service and self-initiated activities

2016 TOTAL = 404,065				2017 TOTAL = 444,111			
Calls for service		Self-initiated		Calls for service		Self-initiated	
Incident	Frequency	Incident	Frequency	Incident	Frequency	Incident	Frequency
Complaint other	66,859	Complaint other	32,143	Complaint other	64,230	Traffic incident	26,567
Burglar alarm (silent)	44,312	Traffic incident	22,741	Burglar alarm	34,807	Complaint other	23,648
Disturbance (other)	28,317	WARR stop with release	7,704	Disturbance (other)	26,457	Area check	12,710
Auto accident	16,193	Return for additional info	4,828	Traffic incident	17,815	WARR stop with release	11,868
Traffic incident	15,390	Municipal attachment	3,115	Auto accident	15,806	Business check	8,458
Suspicious person	13,778	Fugitive attachment	2,308	Suspicious person	13,738	Return for additional info	7,761
Domestic disturbance	10,335	Suspicious person	2,307	Domestic disturbance	11,269	Municipal attachment	4,236
Hit and run	7,904	Disturbance (other)	1,615	Hit and run	8,042	Directed patrol	2,908
Mental Health	5,049	Medical	1,342	WARR stop with release	6,934	Fugitive attachment	2,844
Complaint other	66,859	Drug violations	1,335	Complaint other	64,230	Suspicious person	2,274

Figure 5.2.12B demonstrates that, for both years, the highest number of calls for service CAD entries were categorized as complaint/other. Although researchers were unable to ascertain the exact number of calls in this category that were true nuisance complaints versus other types, the findings appear to support the hypothesis that most calls for service are related to nuisance complaints.

Seattle data

In reviewing Seattle's open data with the department's local administrators, Vera researchers learned that the data available publicly includes all events entered in CAD, not just those events based on telephone call volume. As a result of these categorizations, Seattle's internal CAD and 911 call volumes may differ from those figures available through the open data sources. This consideration may apply to open data sources in general, not only the data and figures here in the presentation of Seattle's 911 calls.

- What is the volume/rate (per capita) of 911 calls received, and how does this vary by incident type (e.g., nuisance complaint, crime in progress, medical emergency, domestic violence incidents, or officer involved shootings), time of day, and geographic location?

Figure 5.2.13A: Seattle CAD volumes, broken down by priority level

	2016		2017	
Priority level	Frequency	Percentage	Frequency	Percentage
1	49,587	12.10%	50,664	11.90%
2	95,221	23.30%	97,955	23.00%
3	142,512	34.90%	139,604	32.80%
4	10,941	2.70%	10,678	2.50%
5	9,568	2.30%	8,950	2.10%
6	2,282	0.60%	1,458	0.30%
7	72,090	17.70%	89,878	21.10%
8	0	0.00%	1	0.00%
9	25,962	6.40%	25,993	6.10%

Figure 5.2.13A above demonstrates that more than 60 percent of Seattle's call volume is driven by priority levels 3 or below, supporting the hypothesis that CAD volume is largely unrelated to serious crimes or crimes in progress.

Figure 5.2.13B: Seattle CAD volumes broken, down by incident type

2016			2017		
Incident type	Frequency	Percentage	Incident type	Frequency	Percentage
Premise check	37,059	9.10%	Premise check	40,274	9.50%
Disturbance-other	32,897	8.10%	Disturbance-other	32,924	7.70%
Suspicious person	31,709	7.80%	Suspicious person	29,895	7.00%
Traffic parking lot violation	22,432	5.50%	Traffic moving violation	21,796	5.10%
Auto collision	19,686	4.80%	Traffic parking lot violation	21,214	5.00%
Traffic moving violation	19,159	4.70%	Auto collision	18,398	4.30%
Assist public-other	17,066	4.20%	Assist public-other	17,687	4.20%
Off-duty employment	15,369	3.80%	Off-duty employment	15,104	3.60%
Trespassing	11,284	2.80%	Trespassing	13,638	3.20%
Crisis complaint	10,042	2.50%	Crisis complaint	10,238	2.40%

When examining the CAD entries by incident type, researchers found that premise checks, disturbances, and suspicious persons drive the CAD volume.

Figure 5.2.13C: Seattle CAD volumes, broken down by day of week

	2016		2017	
Day of the week	Frequency	Percentage	Frequency	Percentage
Sunday	48,740	11.90%	52,959	12.50%
Monday	57,393	14.10%	59,315	14.00%
Tuesday	60,812	14.90%	62,216	14.60%
Wednesday	60,417	14.80%	63,441	14.90%
Thursday	60,515	14.80%	63,353	14.90%
Friday	63,193	15.50%	65,522	15.40%
Saturday	57,093	14.00%	58,375	13.70%

As demonstrated in Figure5.2.13C, CAD volume in Seattle was evenly distributed throughout the week, with the largest volume of calls occurring on Fridays and the lowest on Sundays. This finding fails to fully support Vera's hypothesis that call volume is highest on weekends.

Figure 5.2.13D: Seattle CAD volumes, broken down by hour of day

	2016		2017	
Hour	Frequency	Percentage	Frequency	Percentage
0	13,275	3.30%	14,229	3.30%
1	11,928	2.90%	12,839	3.00%
2	9,902	2.40%	10,358	2.40%
3	7,164	1.80%	7,136	1.70%
4	9,336	2.30%	10,028	2.40%
5	7,694	1.90%	8,524	2.00%
6	9,877	2.40%	9,894	2.30%
7	16,985	4.20%	16,787	3.90%
8	17,224	4.20%	17,704	4.20%
9	19,447	4.80%	19,842	4.70%
10	19,932	4.90%	20,036	4.70%
11	20,862	5.10%	21,485	5.10%
12	24,557	6.00%	26,069	6.10%
13	23,991	5.90%	25,548	6.00%
14	22,009	5.40%	23,140	5.40%
15	23,783	5.80%	24,573	5.80%
16	25,425	6.20%	25,326	6.00%
17	20,796	5.10%	20,865	4.90%
18	18,454	4.50%	19,065	4.50%
19	16,306	4.00%	17,828	4.20%
20	18,638	4.60%	20,109	4.70%
21	17,920	4.40%	19,058	4.50%
22	17,300	4.20%	18,602	4.40%
23	15,358	3.80%	16,136	3.80%

The largest CAD volume in Seattle was generated in the late afternoon hours, noon to 4:00 p.m. (Hours 12 to 16), which fails to support the hypothesis that volume is highest at night.

- How promptly are calls responded to—by a call-taker, dispatcher, and an officer on-scene—and how does this vary by call volume, incident type, time of day, and geographic location?

Figure 5.2.14A: Seattle officer response time, broken down by call type

2016						
Call type	Mean	N	SD	Min	Max	Median
911 calls	33.6	134,646	107	0	33,118.4	11.7
2017						
Call type	Mean	N	SD	Min	Max	Median
911 calls	32.6	135,496	55.3	0	2,863.6	11.8

As demonstrated in Figure 5.2.14A, the mean of 911 call response time was faster by one minute in 2017 compared to 2016. The number of incoming calls increased only slightly, whereas the standard deviation decreased substantially, suggesting that less variation exists in call times in 2017.

Figure 5.2.14B: Seattle dispatcher response time, broken down by incident type

2016						
Incident type	Mean	N	SD	Min	Max	Median
Disturbance- other	29.3	22,887	50.6	0	821.7	10.6
Suspicious person	39.3	18,834	60.9	0	693.5	14.9
Auto collision	28.8	10,734	45.7	0.1	699.3	11.9
Crisis complaint- general	23.3	6,824	43.4	0	634.9	9.2
Assist public- other	33.8	6,194	57.8	0.1	677.6	12
Trespassing	32.2	5,670	50.3	0.2	821.4	13.6
Assault- other	20	3,763	44.5	0.1	649.6	6.9
Suspicious vehicle	46.4	3,551	67.5	0.1	992.2	20.4
Mischief/nuisance	50.1	3,308	76.1	0.2	783.1	20.3
Domestic violence- argument	20.7	3,510	40.1	0.2	716.4	9.3
2017						
Incident type	Mean	N	SD	Min	Max	Median
Disturbance- other	30.7	23,345	48.7	0.1	669.1	11.6
Suspicious person	38.9	17,658	60.4	0.4	2,863.60	15.2
Auto collision	27.6	10,281	41.9	0.2	461.1	12.1
Assist public- other	31.9	6,831	55.4	0.1	693	11.5
Trespassing	31	6,960	47.4	0.3	690.8	13
Crisis complaint- general	24.2	7,124	53.1	0.1	1,961.90	9.3
Assault- other	22.3	3,870	45.8	0.1	528.2	7.1
Theft- shoplifting	34.9	3,663	45.7	0.3	360.1	16.2
Domestic violence- argument	21.1	3,586	37.7	0.4	491.5	9.4

Suspicious vehicle	45.6	3,345	63	0.5	848.1	20

Figure 5.2.14B illustrates that the longest response times occurred for suspicious person and suspicious vehicle incidents in each 2016 and 2017. Assault and domestic violence events had the fastest response times for both years, which supports Vera's hypothesis that serious crimes in progress result in the fastest response.

Figure 5.2.14C: Seattle dispatcher response time broken down by day of week

2016						
Day of the week	Mean	N	SD	Min	Max	Median
Sunday	29.8	18,334	50.6	0	640.8	10.6
Monday	35.6	18,787	61.4	0.1	1,271.20	12.1
Wednesday	33.8	18,782	56.8	0.1	887.9	12.2
Tuesday	33.9	18,859	59	0	992.2	12
Thursday	37.1	19,277	245.8	0.1	33,118.40	12.3
Friday	34	20,568	58.6	0	1,450.30	12
Saturday	30.9	20,039	54.9	0	1,264.80	11
2017						
Day of the week	Mean	N	SD	Min	Max	Median
Sunday	30	18,674	54	0	2,863.60	10.6
Monday	33.2	18,851	57.1	0.1	1,961.90	11.8
Tuesday	33	18,962	56	0.1	1,053.60	11.9
Wednesday	34	19,367	56	0.1	917.1	12.5
Thursday	33.8	19,559	55.3	0.2	1,432.40	12.3
Friday	33.1	20,303	55.7	0.1	1,134.10	12.1
Saturday	31.4	19,780	52.7	0.1	905.4	11.2

Figure 5.2.13D demonstrates that, in both years, the slowest response times occurred on Wednesdays and Thursdays, whereas the fastest average response times occurred on Sundays. These findings are contrary to the hypothesis that response time is slowest during weekends.

Figure 5.2.14D: Seattle dispatcher response time, broken down by hour of day

2016						
Hour of day	Mean	N	SD	Min	Max	Median
0	24.1	5,512	46.0	0.0	716.0	8.1
1	20.7	4,793	40.2	0.0	589.3	7.2
2	23.4	4,505	40.6	0.1	773.9	7.0
3	24.7	3,209	34.1	0.2	546.2	12.2
4	14.5	2,678	26.5	0.1	560.1	7.0
5	16.1	2,602	34.2	0.3	551.2	7.6
6	22.1	3,095	43.4	0.1	571.4	9.6
7	28.1	3,952	62.6	0.0	1,271.2	10.6
8	41.6	4,933	475.5	0.0	33,118.4	12.1

9	43.4	5,195	70.0	0.1	705.1	14.1
10	52.4	5,396	72.0	0.1	1,264.8	17.6
11	41.8	5,821	56.7	0.1	893.1	24.0
12	31.8	6,277	58.7	0.1	622.2	12.1
13	31.9	6,423	58.4	0.1	783.1	11.8
14	37.5	6,720	66.2	0.0	735.4	12.9
15	38.4	6,924	66.5	0.1	821.4	13.8
16	38.2	7,219	63.8	0.1	772.4	13.6
17	42.7	7,507	69.5	0.0	853.0	13.6
18	47.5	7,305	66.7	0.1	1,450.3	15.2
19	40.1	7,169	52.1	0.0	677.6	22.7
20	26.4	7,044	46.3	0.1	684.9	10.5
21	28.0	7,141	51.8	0.1	649.6	9.8
22	27.4	6,958	49.1	0.1	622.1	9.7
23	25.3	6,268	44.0	0.1	491.1	9.2
2017						
Hour of day	Mean	N	SD	Min	Max	Median
0	23.5	5,426	43.0	0.2	413.7	8.2
1	21.5	4,764	41.2	0.2	655.5	7.2
2	25.7	4,189	46.5	0.2	1,053.6	7.2
3	27.6	3,149	34.6	0.2	463.6	14.2
4	16.5	2,738	31.6	0.2	446.9	7.4
5	18.6	2,662	39.7	0.2	875.2	7.7
6	23.7	3,212	49.7	0.3	912.2	9.8
7	27.6	3,990	55.3	0.0	947.0	11.1
8	34.8	4,945	60.6	0.1	708.2	12.7
9	43.2	5,290	67.8	0.2	748.5	14.2
10	52.2	5,488	65.0	0.2	635.4	19.1
11	41.0	5,904	54.1	0.2	610.1	23.6
12	29.2	6,643	55.4	0.2	929.3	11.9
13	31.8	6,617	54.5	0.2	820.4	12.5
14	34.7	6,782	65.9	0.1	1,961.9	12.9
15	36.0	7,158	68.1	0.1	2,863.6	13.4
16	38.4	7,564	62.7	0.2	640.5	14.0
17	39.6	7,592	62.1	0.2	692.9	13.5
18	46.1	7,228	60.3	0.2	1,257.1	16.0
19	38.5	7,237	51.7	0.1	1,224.6	21.1
20	24.5	7,225	43.2	0.2	848.1	10.0
21	26.3	6,820	47.3	0.0	688.3	9.5
22	25.5	6,656	46.5	0.2	1,134.1	9.0
23	25.9	6,217	45.2	0.1	544.7	9.0

Figure 5.2.14D demonstrates that, in 2016, dispatcher response time was fastest during the hours of 2:00 a.m. and 4:00 a.m. (Hours 2 and 4, respectively), while in 2017 dispatcher response time was fastest during 1:00 a.m. and 1:00 a.m. (Hours 1 and 2). Whereas, in both 2016 and 2017the slowest dispatcher times occurred during the hours of 11:00 a.m. and 7:00 p.m. (Hours 11 and 19). These findings do not correspond with the hypothesis that response times are longest during nighttime hours.

Conclusion

Vera's analysis of CAD data from police departments in Camden (CCPD), Tucson (TPD), Detroit (DPD), New Orleans (NOPD), and Seattle (SPD) provides some preliminary answers to questions regarding call volume and response time, at different times periods and across varying incident types. The findings from all departments indicate that officers spend a substantial amount of their time responding to calls for service, most of which are not related to a serious crime in progress. The analyses support the need for additional consideration of the underlying needs, causes, and consequences of these resource-intensive calls for service that do not involve a crime.

Chapter 5, Section 3: A Further Descriptive Exploration

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Section 5.3 explores 911 call volumes in greater detail. This section includes descriptive analysis of call volume and frequency by priority levels, times of day, day of week, and incident types for each of the five study sites.

Camden County data

Part 1: CAD events

Part 1 examines all CAD events, including both 911 calls for service and officer-initiated events.

Figure 5.3.1A: Camden CAD entries, broken down by priority level[1]

	2016		2017	
Priority level	Frequency	Percentage	Frequency	Percentage
1	14,527	5.2%	12,504	5.5%
2	144,249	51.5%	116,241	50.8%
3	8,357	3.0%	8,114	3.5%
4	26,391	9.4%	26,528	11.6%
5-9	86,540	28.3%	35,180	28.5%
Missing	138	0.1%	133	0.1%

[1] Priority Level 1 refers to in-progress, life-threatening incidents that pose a potential for serious physical injury or where serious injuries are believed to exist; Priority Level 2 refers to a crime or incident that is either in progress or having just occurred where there is no known serious injury or threat to life; Priority Level 3 refers to a past crime or incident where there is no known serious injury or threat to life, but a unit response is necessary to secure contraband or evidence of a crime; and Priority Level 4 refers to incidents not involving an imminent threat to life or serious injury, not in progress and where emergency police response is not necessary to secure contraband or evidence of a crime. No definitions for Priority Levels 5-9 were provided.

Figure 5.3.1A shows that the most frequently occurring priority levels across all CAD activities for both years were Priority 2 (a crime or incident that is either in progress or having just occurred where there is no known threat to life or serious injury) and Priority 5 (no definition provided). Because Priority 2 encompasses both crimes in progress and crimes that have recently concluded, this finding is unable to speak to the hypothesis that most calls would be unrelated to a crime in progress. Approximately 60 percent of the Priority 2 calls were related to complaints or environmental conditions (e.g., complaints about an animal or disturbance of the peace), whereas the Priority 5 calls were primarily related to officers' service assignments (e.g., completing paperwork).

Figure 5.3.1B: Camden CAD entries, broken down by incident type

	2016		2017	
Incident type	Frequency	Percentage	Frequency	Percentage
Total crime	21,472	7.8%	19,589	8.5%
Alarms	5,481	2.0%	5,122	2.2%
Violent crimes	1,268	0.5%	1,090	.5%
Domestic violence	4,907	1.8%	4,614	2.0%
Property crimes	2,911	1.0%	2,666	1.2%
Other crimes[1]	6,905	2.5%	6,097	2.7%
Behavioral health	1,809	0.6%	1,874	0.8%
Complaints/ environmental conditions[2]	19,507	7.0%	19,511	8.5%
Emergency call for help from police officer[3]	2	0.0%	N/A	N/A
Hang-ups and deferred calls[4]	N/A	N/A	578	0.3%
Health	3,822	1.4%	4,337	1.9%
Missing persons	642	0.2%	505	0.2%
Proactive	67,441	24.1%	48,737	21.3%
Property check	11,233	4.0%	11,299	4.9%
Reports	1,089	0.4%	1,060	0.5%
Service assignments/statuses	138,339	49.4%	110,797	48.4%
Suspicion	8,781	3.1%	5,251	2.3%
Traffic-related	3,208	1.1%	3,427	1.5%
Missing	2,857	1.0%	1,735	0.8%

[1] This category includes incidents such as criminal mischief and drug complaints.
[2] This category includes incidents such as animal complaints, open hydrants, and disturbances of the peace.
[3] The category for emergency calls for help from a police officer did not appear in 2017 data.
[4] The category for hang-ups and deferred calls does not appear in 2016 data. Deferred calls typically refer to calls that were not responded to because the caller was directed to self-report their issue (e.g., accidents with no injuries).

Figure 5.3.1B shows that, in 2016, a mere 7.8 percent of the overall CAD entries were related to crime, and in 2017, this number rose slightly to 8.5 percent. This finding is consistent with the hypothesis that most calls for service are unrelated to crimes in progress. Beyond crimes (which may or may not have been in progress), CCPD officers most often engaged in activities that were related to service assignments/statuses, spending nearly half of their time on such incidents (49.4 percent in 2016 and 48.4 percent in 2017).

Figure 5.3.1C: Camden CAD entries, broken down by day of week

	2016		2017	
Day	Frequency	Percent age	Frequency	Percentage
Sunday	35,376	12.6%	28,398	12.4%
Monday	38,979	13.9%	31,655	13.8%
Tuesday	42,538	15.2%	34,438	15.1%
Wednesday	43,048	15.4%	35,289	15.4%
Thursday	42,748	15.3%	34,551	15.1%
Friday	41,067	14.7%	35,457	15.5%
Saturday	36,446	13.0%	28,912	12.6%

Figure 5.3.1C shows that, in 2016, the highest number of CAD entries were logged on Wednesdays and Thursdays. In 2017, the highest number of CAD entries were logged on Wednesdays and Fridays. In both years, the lowest number of CAD entries were logged on Sundays. These results are mostly inconsistent with the hypothesis that 911 call volume concentrates during weekends.

Figure 5.3.1D: Camden CAD entries, broken down by time of day

2016						
	Early morning[1]	Late morning	Afternoon	Early evening	Night	Total
Info call	0	0	1	0	0	1
Motor vehicle stop	2,043	1,796	6,689	13,458	8,532	32,518
Phone	11,090	6,593	18,629	18,999	15,009	70,320
Self-initiated	16,560	14,364	46,022	50,723	49,667	177,336
Station call	2	1	12	9	3	27
Total	29,695	22,754	71,353	83,189	73,211	280,202
2017						
	Early morning	Late morning	Afternoon	Early evening	Night	Total
Info call	16	9	13	28	18	84
Motor vehicle stop	1,869	2,490	6,049	9,133	4,720	24,261
Phone	11,187	6,123	17,452	17,892	14,452	67,106
Self-initiated	11,771	11,211	29,148	21,518	21,262	94,910
Station call	11	4	4	9	6	34
Suspicious persons stop	448	891	2,200	2,490	1,050	7,079
Other[2]	4,593	4,440	11,560	8,393	6,240	35,226
Total	29,895	25,168	66,426	59,463	47,748	228,700

[1]Time of day is defined as follows:

- Early morning: 5:00 a.m.–9:59 a.m.
- Late morning: 10:00 a.m.–11:59 a.m.
- Afternoon: noon–4:59 p.m.
- Early evening: 5:00 p.m.–9:59 p.m.
- Night: 10:00 p.m.–4:59 a.m.

[2] After reviewing several incidents classified as "other" in the 2017 data, researchers were unable to isolate one distinguishing feature of incidents labeled "other." Some of these incidents were walk-ups (e.g., a pedestrian walking up to an officer to ask a question), whereas others were labeled "knock and talk" (e.g., an officer conducting a check on a property).

Figure 5.3.1D demonstrates that, for both years, the highest number of CAD entries were logged during the afternoon and early evening, which is partially consistent with Vera's hypothesis that 911 call volume is heavier at night. However, the second highest number of CAD entries in 2016 and the highest number of CAD entries in 2017 took place during the afternoon, a finding that is inconsistent with the hypothesis. In both years, the lowest number of CAD entries took place in the late morning.

Figure 5.3.1E: Camden CAD entries, broken down by hour of day

	2016		2017	
Hour of day	Frequency	Percentage	Frequency	Percentage
0	13,059	4.7%	8,410	3.7%
1	11,303	4.0%	7,090	3.1%
2	9,319	3.3%	5,460	2.4%
3	6,507	2.3%	3,574	1.6%
4	3,528	1.3%	2,422	1.1%
5	2,214	0.8%	1,846	0.8%
6	4,046	1.4%	3,922	1.7%
7	6,591	2.4%	6,604	2.9%
8	8,351	3.0%	8,061	3.5%
9	8,493	3.0%	9,462	4.1%
10	10,587	3.8%	11,910	5.2%
11	12,167	4.3%	13,258	5.8%
12	13,034	4.7%	13,972	6.1%
13	14,148	5.0%	14,509	6.3%
14	14,668	5.2%	13,589	5.9%
15	15,165	5.4%	13,186	5.8%
16	14,338	5.1%	11,170	4.9%
17	13,332	4.8%	9,640	4.2%
18	15,505	5.5%	11,839	5.2%
19	19,136	6.8%	12,732	5.6%
20	18,191	6.5%	12,961	5.7%
21	17,025	6.1%	12,291	5.4%
22	14,808	5.3%	10,819	4.7%
23	14,687	5.2%	9,973	4.4%

Figure 5.3.1E shows that, in 2016, the highest frequency of CAD entries occurred during the 7:00 p.m. and 8:00 p.m. hours (Hours 15 and 16, respectively). This result is consistent with the hypothesis that 911 call volumes are highest during the night. However, in 2017, the highest frequency of CAD entries took place during the noon and 1:00 p.m. hours (Hours 12 and 1), which is inconsistent with the hypothesis. In both years, the lowest frequency of entries took place in the 5:00 a.m. hour.

Part 2: Further analyses of priority levels

The following section provides a more in-depth look at how call volumes across different contexts (e.g., hour of day, day of week, and incident type) are parsed out by priority levels. See Figure 5.3.3A below for an explanation of the different priority levels.

Figure 5.3.2A: Camden priority levels and their definitions

Priority level	Definition
1	In-progress, life-threatening incidents that pose a potential for serious physical injury or where serious injuries are believed to exist
2	A crime or incident that is either in progress or having just occurred where there is no known serious injury or threat to life
3	A past crime or incident where there is no known serious injury or threat to life, but a unit response is necessary to secure contraband or evidence of a crime
4	Incidents not involving an imminent threat to life or serious injury, not in progress, and where emergency police response is not necessary to secure contraband or evidence of a crime
5-9	Miscellaneous

Priority 7 has been removed due to the occurrence of only a single call at that level. Levels 6 and 8 are also not included in this section, as there were no calls of these levels present in the CAD data.

Figure 5.3.2B: Camden call types, broken down by priority level

2016							
Call type	Priority level	1	2	3	4	5-9	Total[1]
	Total count	**14,527**	**144,249**	**8,357**	**26,391**	**86,539**	**280,058**
Phone (CFS)	Count	13,251	20,945	6,122	19,824	10,049	70,191
	% within call type	18.9%	29.8%	8.7%	28.2%	14%	
	% within priority	91.2%	14.5%	73.3%	75.1%	12%	
Self-initiated	Count	1,270	90,962	2,145	6,531	76,418	177,326
	% within call type	0.7%	51.3%	1.2%	3.7%	43%	
	% within priority	8.7%	63.1%	25.7%	24.7%	88%	
Motor vehicle stop	Count	3	32,329	90	32	64	32,518
	% within call type	0.0%	99.4%	0.3%	0.1%	0%	
	% within priority	0.0%	22.4%	1.1%	0.1%	0%	
Station call	Count	2	13	0	4	8	27
	% within call type	7.4%	48.1%	0.0%	14.8%	30%	
	% within priority	0.0%	0.0%	0.0%	0.0%	0%	
Info call	Count	1	0	0	0	0	1
	% within call type	100.0%	0.0%	0.0%	0.0%	0%	
	% within priority	0.0%	0.0%	0.0%	0.0%	0%	
2017							
Call type	Priority level	1	2	3	4	5-9	Total
	Total	**12,504**	**116,241**	**8,114**	**26,528**	**65,180**	**228,567**
Phone (CFS)	Count	11,676	21,566	5,852	20,583	7,298	66,975
	% within call type	17.4%	32.2%	8.7%	30.7%	11%	
	% within priority	93.4%	18.6%	72.1%	77.6%	11%	
Self-initiated	Count	498	41,066	1,212	3,306	48,827	94,909
	% within call type	0.5%	43.3%	1.3%	3.5%	52%	
	% within priority	4.0%	35.3%	14.9%	12.5%	75%	
Motor vehicle stop	Count	11	23,818	156	142	134	24,261
	% within call type	0.0%	98.2%	0.6%	0.6%	1%	

	% within priority	0.1%	20.5%	1.9%	0.5%	0%	
Station call	Count	1	20	1	2	10	34
	% within call type	2.9%	58.8%	2.9%	5.9%	29%	
	% within priority	0.0%	0.0%	0.0%	0.0%	0%	
Info call	Count	1	20	1	2	10	34
	% within call type	2.9%	58.8%	2.9%	5.9%	29%	
	% within priority	0.0%	0.0%	0.0%	0.0%	0%	
Suspicious persons stop	Count	18	6,826	24	80	131	7,079
	% within call type	0.3%	96.4%	0.3%	1.1%	2%	
	% within priority	0.1%	5.9%	0.3%	0.3%	0%	
Other[2]	Count	291	22,909	860	2,394	8,771	35,225
	% within call type	0.8%	65.0%	2.4%	6.8%	25%	
	% within priority	2.3%	19.7%	10.6%	9.0%	13%	

[1] Different procedures are used to examine each research question, so totals may not match up exactly across tables.
[2] After reviewing several incidents classified as "other" in the 2017 data, researchers were unable to isolate one distinguishing feature of incidents labeled "other." Some of these incidents were walk-ups (e.g., a pedestrian walking up to an officer to ask a question), whereas others were labeled "knock and talk" (e.g., an officer conducting a check on a property).

Figure 5.3.2B shows that, though most 911 calls for service were classified as Priority 2 or 4, the majority of self-initiated activity was classified as Priority 2 or 5, providing partial support for the hypothesis that most calls are unrelated to an emergency or serious crime in progress. Additionally, overall call volume decreased between 2016 and 2017, as did the number of high priority calls. These results highlight the need to better understand priority levels, particularly those classified as Priority 4 and above.

Figure 5.3.2C: Camden incident types broken down by priority level for 911 calls for service[1]

2016							
Incident type	Priority level	1	2	3	4	5-9	Total
	Total	12,175	20,945	5,861	19,824	10,049	68,854
Alarms	Count	813	3	4,603	2	0	5,421
	% within incident type	15.0%	0.1%	84.9%	0.0%	0.0%	
	% within priority	6.7%	0.0%	78.5%	0.0%	0.0%	
Behavioral health	Count	1,257	260	0	0	0	1,517
	% within incident type	82.9%	17.1%	0.0%	0.0%	0.0%	
	% within priority	10.3%	1.2%	0.0%	0.0%	0.0%	
Complaints/ environmenta l conditions	Count	519	12,195	2	3,360	0	16,076
	% within incident type	3.2%	75.9%	0.0%	20.9%	0.0%	
	% within priority	4.3%	58.2%	0.0%	16.9%	0.0%	
Domestic violence	Count	3,415	1,286	0	0	0	4,701
	% within incident type	72.6%	27.4%	0.0%	0.0%	0.0%	

	% within priority	28.0%	6.1%	0.0%	0.0%	0.0%	
Emergency call for help from officer	Count	2	0	0	0	0	2
	% within incident type	100.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	
Health	Count	1,345	1,513	0	0	0	2,858
	% within incident type	47.1%	52.9%	0.0%	0.0%	0.0%	
	% within priority	11.0%	7.2%	0.0%	0.0%	0.0%	
Missing persons	Count	559	0	0	0	0	559
	% within incident type	100.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	4.6%	0.0%	0.0%	0.0%	0.0%	
Other crimes[1]	Count	9	293	0	5,215	0	5,517
	% within incident type	0.2%	5.3%	0.0%	94.5%	0.0%	
	% within priority	0.1%	1.4%	0.0%	26.3%	0.0%	
Proactive	Count	0	732	0	0	0	732
	% within incident type	0.0%	100.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	3.5%	0.0%	0.0%	0.0%	
Property crimes	Count	344	778	0	1,193	0	2,315
	% within incident type	14.9%	33.6%	0.0%	51.5%	0.0%	
	% within priority	2.8%	3.7%	0.0%	6.0%	0.0%	
Property check	Count	5	0	0	0	762	767
	% within incident type	0.7%	0.0%	0.0%	0.0%	99.3%	
	% within priority	0.0%	0.0%	0.0%	0.0%	7.58%	
Service assignments/ statuses	Count	2,849	1,279	219	7,483	9,280	21,110
	% within incident type	13.5%	6.1%	1.0%	35.4%	44.0%	
	% within priority	23.4%	6.1%	3.7%	37.7%	92.3%	
Reports	Count	215	87	706	0	0	1,008
	% within incident type	21.3%	8.6%	70.0%	0.0%	0.0%	
	% within priority	1.8%	0.4%	12.0%	0.0%	0.0%	
Suspicion	Count	5	1,635	324	645	0	2,609
	% within incident type	0.2%	62.7%	12.4%	24.7%	0.0%	
	% within priority	0.0%	7.8%	5.5%	3.3%	0.0%	
Traffic-related	Count	634	2	7	1,926	7	2,576
	% within incident type	24.6%	0.1%	0.3%	74.8%	0.3%	
	% within priority	5.2%	0.0%	0.1%	9.7%	0.1%	
Violent crimes	Count	204	882	0	0	0	1,086
	% within incident type	18.8%	81.2%	0.0%	0.0%	0.0%	
	% within priority	1.7%	4.2%	0.0%	0.0%	0.0%	
2017							
Incident type	Priority level	1	2	3	4	5 & 9	Total
	Total	11,059	21,565	5,587	20,583	7,298	66,092
Alarms	Count	704	9	4,370	0	0	5,083

	% within incident type	13.9%	0.2%	86.0%	0.0%	0.0%	
	% within priority	6.4%	0.0%	78.2%	0.0%	0.0%	
Behavioral health	Count	1,387	210	0	0	0	1,597
	% within incident type	86.9%	13.1%	0.0%	0.0%	0.0%	
	% within priority	12.5%	1.0%	0.0%	0.0%	0.0%	
Complaints/ environmenta l conditions	Count	393	12,665	2	3,550	0	16,610
	% within incident type	2.4%	76.2%	0.0%	21.4%	0.0%	
	% within priority	3.6%	58.7%	0.0%	17.2%	0.0%	
Domestic violence	Count	3,243	1,200	0	0	0	4,443
	% within incident type	73.0%	27.0%	0.0%	0.0%	0.0%	
	% within priority	29.3%	5.6%	0.0%	0.0%	0.0%	
Hang-ups and deferred calls	Count	0	153	0	0	424	577
	% within incident type	0.0%	26.5%	0.0%	0.0%	73.5%	
	% within priority	0.0%	0.7%	0.0%	0.0%	5.81%	
Health	Count	861	2,201	0	0	0	3,062
	% within incident type	28.1%	71.9%	0.0%	0.0%	0.0%	
	% within priority	7.8%	10.2%	0.0%	0.0%	0.0%	
Missing persons	Count	459	0	0	0	0	459
	% within incident type	100.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	4.2%	0.0%	0.0%	0.0%	0.0%	
Other crimes	Count	6	266	2	4,962	0	5,236
	% within incident type	0.1%	5.1%	0.0%	94.8%	0.0%	
	% within priority	0.1%	1.2%	0.0%	24.1%	0.0%	
Proactive	Count	0	977	0	0	0	977
	% within incident type	0.0%	100.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	4.5%	0.0%	0.0%	0.0%	
Property check	Count	2	3	1	1	717	724
	% within incident type	0.3%	0.4%	0.1%	0.1%	99.0%	
	% within priority	0.0%	0.0%	0.0%	0.0%	9.82%	
Property crimes	Count	238	735	1	1,232	0	2,206
	% within incident type	10.8%	33.3%	0.0%	55.8%	0.0%	
	% within priority	2.2%	3.4%	0.0%	6.0%	0.0%	
Reports	Count	226	88	671	0	0	985
	% within incident type	22.9%	8.9%	68.1%	0.0%	0.0%	
	% within priority	2.0%	0.4%	12.0%	0.0%	0.0%	
Service assignments/ statuses	Count	2,628	956	221	8,265	6,145	18,215
	% within incident type	14.4%	5.2%	1.2%	45.4%	33.7%	
	% within priority	23.8%	4.4%	4.0%	40.2%	84.2%	
Suspicion	Count	4	1,425	289	673	0	2,391
	% within incident type	0.2%	59.6%	12.1%	28.1%	0.0%	
	% within priority	0.0%	6.6%	5.2%	3.3%	0.0%	
Traffic-related	Count	616	4	30	1,900	12	2,562

	% within incident type	24.0%	0.2%	1.2%	74.2%	0.5%	
	% within priority	5.6%	0.0%	0.5%	9.2%	0.2%	
Violent crimes	Count	292	673	0	0	0	965
	% within incident type	30.3%	69.7%	0.0%	0.0%	0.0%	
	% within priority	2.6%	3.1%	0.0%	0.0%	0.0%	

[1] Priority Level 7 calls were omitted from this figure and the ones following because there was only one call in 2016 and none in 2017. Additionally, the data provided to Vera did not contain any Level 6 or Level 8 calls. As such, this section includes only levels 5 and 9.

Figure 5.3.2C demonstrates that the highest volume of calls classified as Priority 1 was related to domestic violence (more than 25 percent in both 2016 and 2017); most calls classified as Priority 2 were related to complaints/environmental conditions (more than 52 percent in both years); the highest number of calls classified as Priority 3 were related to alarms (approximately 78 percent in both years); and the highest volume of calls classified as Priority 4 and Priority 5 were related to service assignments/statuses (Priority 4 over 37 percent in both years; Priority 5 over 80 percent both years). One hundred percent of Priority 6, Priority 8, and Priority 9 calls were related to service assignments/statuses in both years. Though these findings do not speak directly to the research questions, they provide contextual information that is useful to understanding the landscape of calls for service.

Figure 5.3.2D: Camden call volumes at different times of the day, broken down by priority level

2016							
Hour of day	Priority level	1	2	3	4	5-9	Total
	Total	13,251	20,945	6,122	19,824	10,049	70,191
Early morning	Count	1,426	2,247	1,763	2,989	2,652	11,077
	% within time of day[1]	12.9%	20.3%	15.9%	27.0%	23.9%	
	% within priority	10.8%	10.7%	28.8%	15.1%	26.4%	
Late morning	Count	1,037	1,667	547	2,490	838	6,579
	% within time of day	15.8%	25.3%	8.3%	37.8%	12.7%	
	% within priority	7.8%	8.0%	8.9%	12.6%	8.3%	
Afternoon	Count	3,079	5,138	1,296	6,308	2,774	18,595
	% within time of day	16.6%	27.6%	7.0%	33.9%	14.9%	
	% within priority	23.2%	24.5%	21.2%	31.8%	27.6%	
Early evening	Count	4,041	6,167	1,401	5,328	2,022	18,959
	% within time of day	21.3%	32.5%	7.4%	28.1%	10.7%	
	% within priority	30.5%	29.4%	22.9%	26.9%	20.1%	
Night	Count	3,668	5,726	1,115	2,709	1,763	14,981
	% within time of day	24.5%	38.2%	7.4%	18.1%	11.8%	
	% within priority	27.7%	27.3%	18.2%	13.7%	17.5%	
2017							
Hour of day	Priority level	1	2	3	4	5-9	Total

	Total	11,676	21,566	5,852	20,583	7,298	66,975
Early morning	Count	1,488	2,654	1,646	3,081	2293	11,162
	% within time of day	13.3%	23.8%	14.7%	27.6%	20.5%	
	% within priority	12.7%	12.3%	28.1%	15.0%	31.4%	
Late morning	Count	867	1,728	519	2,401	599	6,114
	% within time of day	14.2%	28.3%	8.5%	39.3%	9.9%	
	% within priority	7.4%	8.0%	8.9%	11.7%	8.2%	
Afternoon	Count	2,714	4,965	1,312	6,440	1,985	17,416
	% within time of day	15.6%	28.5%	7.5%	37.0%	11.4%	
	% within priority	23.2%	23.0%	22.4%	31.3%	27.2%	
Early evening	Count	3,465	6,160	1,315	5,556	1362	17,858
	% within time of day	19.4%	34.5%	7.4%	31.1%	7.6%	
	% within priority	29.7%	28.6%	22.5%	27.0%	18.7%	
Night	Count	3,142	6,059	1,060	3,105	1059	14,425
	% within time of day	21.8%	42.0%	7.3%	21.5%	7.3%	
	% within priority	26.9%	28.1%	18.1%	15.1%	14.5%	

[1]Time of day is defined as follows:

- Early morning: 5:00 a.m.–9:59 a.m.
- Late morning: 10:00 a.m.–11:59 a.m.
- Afternoon: noon–4:59 p.m.
- Early evening: 5:00 p.m.–9:59 p.m.
- Night: 10:00 p.m.–4:59 a.m.

Figure 5.3.2D demonstrates that, for both years, the largest number of Priority 1 and Priority 2 calls were received during the early evening. This is consistent with the hypothesis that 911 call volumes concentrate during the night. Additionally, the number of Priority 1 calls received at night decreased from 2016 to 2017, whereas the number of Priority 2 calls received at night increased between the two years.

Figure 5.3.2E: Camden 911 call volumes at different hours of the day, broken down by priority level

2016							
Hour of day	Priority level	1	2	3	4	5-9	Total
	Total	13,251	20,945	6,122	19,824	10,049	70,191
0	Count	712	1,016	180	422	277	2,607
	% within hour of day	27.3%	39.0%	6.9%	16.2%	10.6%	
	% within priority	5.4%	4.9%	2.9%	2.1%	2.8%	
1	Count	531	778	152	334	265	2,060
	% within hour of day	25.8%	37.8%	7.4%	16.2%	12.9%	
	% within priority	4.0%	3.7%	2.5%	1.7%	2.6%	
2	Count	362	616	123	259	218	1,578
	% within hour of day	22.9%	39.0%	7.8%	16.4%	13.9%	
	% within priority	2.7%	2.9%	2.0%	1.3%	2.2%	
3	Count	309	496	135	222	246	1,408

	% within hour of day	21.9%	35.2%	9.6%	15.8%	17.5%	
	% within priority	2.3%	2.4%	2.2%	1.1%	2.4%	
4	Count	206	354	118	163	150	991
	% within hour of day	20.8%	35.7%	11.9%	16.4%	15.1%	
	% within priority	1.6%	1.7%	1.9%	0.8%	1.5%	
5	Count	176	255	213	179	103	926
	% within hour of day	19.0%	27.5%	23.0%	19.3%	11.1%	
	% within priority	1.3%	1.2%	3.5%	0.9%	1.0%	
6	Count	185	330	373	299	602	1,789
	% within hour of day	10.3%	18.4%	20.8%	16.7%	33.7%	
	% within priority	1.4%	1.6%	6.1%	1.5%	6.0%	
7	Count	315	476	391	585	1,018	2,785
	% within hour of day	11.3%	17.1%	14.0%	21.0%	36.6%	
	% within priority	2.4%	2.3%	6.4%	3.0%	10.1%	
8	Count	344	553	449	884	652	2,882
	% within hour of day	11.9%	19.2%	15.6%	30.7%	22.7%	
	% within priority	2.6%	2.6%	7.3%	4.5%	6.5%	
9	Count	406	633	337	1,042	277	2,695
	% within hour of day	15.1%	23.5%	12.5%	38.7%	10.2%	
	% within priority	3.1%	3.0%	5.5%	5.3%	2.8%	
10	Count	506	750	275	1,254	439	3,224
	% within hour of day	15.7%	23.3%	8.5%	38.9%	13.6%	
	% within priority	3.8%	3.6%	4.5%	6.3%	4.4%	
11	Count	531	917	272	1,236	399	3,355
	% within hour of day	15.8%	27.3%	8.1%	36.8%	11.8%	
	% within priority	4.0%	4.4%	4.4%	6.2%	4.0%	
12	Count	539	936	263	1,199	427	3,364
	% within hour of day	16.0%	27.8%	7.8%	35.6%	12.7%	
	% within priority	4.1%	4.5%	4.3%	6.0%	4.2%	
13	Count	573	974	302	1,274	538	3,661
	% within hour of day	15.7%	26.6%	8.2%	34.8%	14.7%	
	% within priority	4.3%	4.7%	4.9%	6.4%	5.4%	
14	Count	609	980	235	1,219	578	3,621
	% within hour of day	16.8%	27.1%	6.5%	33.7%	15.9%	
	% within priority	4.6%	4.7%	3.8%	6.1%	5.8%	
15	Count	668	1,110	251	1,285	658	3,972
	% within hour of day	16.8%	27.9%	6.3%	32.4%	16.6%	
	% within priority	5.0%	5.3%	4.1%	6.5%	6.5%	
16	Count	690	1,138	245	1,331	573	3,977
	% within hour of day	17.3%	28.6%	6.2%	33.5%	14.4%	
	% within priority	5.2%	5.4%	4.0%	6.7%	5.7%	
17	Count	798	1,207	291	1,247	429	3,972

	% within hour of day	20.1%	30.4%	7.3%	31.4%	10.8%	
	% within priority	6.0%	5.8%	4.8%	6.3%	4.3%	
18	Count	774	1,211	355	1,209	577	4,126
	% within hour of day	18.8%	29.4%	8.6%	29.3%	14.0%	
	% within priority	5.8%	5.8%	5.8%	6.1%	5.7%	
19	Count	821	1,175	280	1,084	375	3,735
	% within hour of day	22.0%	31.5%	7.5%	29.0%	10.0%	
	% within priority	6.2%	5.6%	4.6%	5.5%	3.7%	
20	Count	780	1,279	262	944	329	3,594
	% within hour of day	21.7%	35.6%	7.3%	26.3%	9.2%	
	% within priority	5.9%	6.1%	4.3%	4.8%	3.3%	
21	Count	868	1,295	213	844	312	3,532
	% within hour of day	24.6%	36.7%	6.0%	23.9%	8.8%	
	% within priority	6.6%	6.2%	3.5%	4.3%	3.1%	
22	Count	781	1,322	217	752	311	3,383
	% within hour of day	23.1%	39.1%	6.4%	22.2%	9.2%	
	% within priority	5.9%	6.3%	3.5%	3.8%	3.1%	
23	Count	767	1,144	190	557	296	2,954
	% within hour of day	26.0%	38.7%	6.4%	18.9%	10.1%	
	% within priority	5.8%	5.5%	3.1%	2.8%	2.9%	

2017

Hour of day	Priority level	1	2	3	4	5	Total
	Total	11,676	21,566	5,852	20,583	7,298	66,975
0	Count	552	966	152	497	161	2,328
	% within hour of day	23.7%	41.5%	6.5%	21.3%	6.9%	
	% within priority	4.7%	4.5%	2.6%	2.4%	2.2%	
1	Count	434	862	123	400	157	1,976
	% within hour of day	22.0%	43.6%	6.2%	20.2%	7.9%	
	% within priority	3.7%	4.0%	2.1%	1.9%	2.2%	
2	Count	328	614	99	293	154	1,488
	% within hour of day	22.0%	41.3%	6.7%	19.7%	10.4%	
	% within priority	2.8%	2.8%	1.7%	1.4%	2.1%	
3	Count	295	526	121	258	110	1,310
	% within hour of day	22.5%	40.2%	9.2%	19.7%	8.4%	
	% within priority	2.5%	2.4%	2.1%	1.3%	1.5%	
4	Count	214	429	149	202	90	1,084
	% within hour of day	19.7%	39.6%	13.7%	18.6%	8.3%	
	% within priority	1.8%	2.0%	2.5%	1.0%	1.2%	
5	Count	199	345	192	205	78	1,019
	% within hour of day	19.5%	33.9%	18.8%	20.1%	7.7%	
	% within priority	1.7%	1.6%	3.3%	1.0%	1.1%	

6	Count	213	362	301	343	619	1,838
	% within hour of day	11.6%	19.7%	16.4%	18.7%	33.7%	
	% within priority	1.8%	1.7%	5.1%	1.7%	8.5%	
7	Count	298	541	423	598	825	2,685
	% within hour of day	11.1%	20.1%	15.8%	22.3%	30.8%	
	% within priority	2.6%	2.5%	7.2%	2.9%	11.3%	
8	Count	375	682	399	893	513	2,862
	% within hour of day	13.1%	23.8%	13.9%	31.2%	18.0%	
	% within priority	3.2%	3.2%	6.8%	4.3%	7.0%	
9	Count	403	724	331	1,042	258	2,758
	% within hour of day	14.6%	26.3%	12.0%	37.8%	9.3%	
	% within priority	3.5%	3.4%	5.7%	5.1%	3.5%	
10	Count	414	827	273	1,173	276	2,963
	% within hour of day	14.0%	27.9%	9.2%	39.6%	9.3%	
	% within priority	3.5%	3.8%	4.7%	5.7%	3.8%	
11	Count	453	901	246	1,228	323	3,151
	% within hour of day	14.4%	28.6%	7.8%	39.0%	10.2%	
	% within priority	3.9%	4.2%	4.2%	6.0%	4.4%	
12	Count	449	871	248	1,190	349	3,107
	% within hour of day	14.5%	28.0%	8.0%	38.3%	11.2%	
	% within priority	3.8%	4.0%	4.2%	5.8%	4.8%	
13	Count	506	986	258	1,268	300	3,318
	% within hour of day	15.3%	29.7%	7.8%	38.2%	9.1%	
	% within priority	4.3%	4.6%	4.4%	6.2%	4.1%	
14	Count	525	925	264	1,235	397	3,346
	% within hour of day	15.7%	27.6%	7.9%	36.9%	11.9%	
	% within priority	4.5%	4.3%	4.5%	6.0%	5.4%	
15	Count	612	1,037	254	1,342	522	3,767
	% within hour of day	16.2%	27.5%	6.7%	35.6%	13.8%	
	% within priority	5.2%	4.8%	4.3%	6.5%	7.2%	
16	Count	622	1,146	288	1,405	417	3,878
	% within hour of day	16.0%	29.6%	7.4%	36.2%	10.8%	
	% within priority	5.3%	5.3%	4.9%	6.8%	5.7%	
17	Count	643	1,131	305	1,375	379	3,833
	% within hour of day	16.8%	29.5%	8.0%	35.9%	10.0%	
	% within priority	5.5%	5.2%	5.2%	6.7%	5.2%	
18	Count	716	1,216	291	1,211	360	3,794
	% within hour of day	18.9%	32.1%	7.7%	31.9%	9.5%	
	% within priority	6.1%	5.6%	5.0%	5.9%	4.9%	
19	Count	705	1,214	262	1,116	224	3,521
	% within hour of day	20.0%	34.5%	7.4%	31.7%	6.5%	
	% within priority	6.0%	5.6%	4.5%	5.4%	3.1%	

20	Count	711	1,260	250	944	193	3,358
	% within hour of day	21.2%	37.5%	7.4%	28.1%	5.7%	
	% within priority	6.1%	5.8%	4.3%	4.6%	2.6%	
21	Count	690	1,339	207	910	206	3,352
	% within hour of day	20.6%	39.9%	6.2%	27.1%	6.1%	
	% within priority	5.9%	6.2%	3.5%	4.4%	2.8%	
22	Count	715	1,374	213	809	205	3,316
	% within hour of day	21.6%	41.4%	6.4%	24.4%	6.3%	
	% within priority	6.1%	6.4%	3.6%	3.9%	2.8%	
23	Count	604	1,288	203	646	182	2,923
	% within hour of day	20.7%	44.1%	6.9%	22.1%	6.3%	
	% within priority	5.2%	6.0%	3.5%	3.1%	2.5%	

Figure 5.3.2E shows that, in 2016, the highest number of Priority 1 calls were received during the 9:00 p.m. hour (6.6 percent of Priority 1 calls; Hour 21), whereas in 2017, most Priority 1 calls came in during the 6:00 p.m., 8:00 p.m., and 10:00 p.m. hours (6.1 percent of Priority 1 calls; Hours 18, 20, and 22, respectively). In both years, the highest number of Priority 2 calls were received during the 10:00 p.m. hour (Hour 22; 6.3 percent and 6.4 percent, respectively). The highest number of Priority 3 calls were received during the 8:00 a.m. hour in 2016 (7.3 percent; Hour 20) and the 7:00 a.m. hour in 2017 (7.2 percent; Hour 7). Lastly, in both years, the highest number of Priority 4 calls came in during the 4:00 p.m. hour (Hour 16; 6.7 percent in 2016 and 6.8 percent in 2017). These findings are partially consistent with the hypothesis that 911 call volume is highest at night.

Figure 5.3.2F: Camden call volumes on different days of the week, broken down by priority level

2016							
Day	Priority level	1	2	3	4	5-9	Total
	Total	13,251	20,945	6,122	19,824	10,049	70,191
Sunday	Count	1,968	3,102	798	2,405	1,005	9,278
	% within day of week	21.2%	33.4%	8.6%	25.9%	10.8%	
	% within priority	14.9%	14.8%	13.0%	12.1%	10.0%	
Monday	Count	1,830	2,903	854	2,858	1,494	9,939
	% within day of week	18.4%	29.2%	8.6%	28.8%	15.0%	
	% within priority	13.8%	13.9%	13.9%	14.4%	14.9%	
Tuesday	Count	1,755	2,888	902	2,974	1,678	10,197
	% within day of week	17.2%	28.3%	8.8%	29.2%	16.5%	
	% within priority	13.2%	13.8%	14.7%	15.0%	16.7%	
Wednesday	Count	1,828	2,819	864	2,969	1,641	10,121
	% within day of week	18.1%	27.9%	8.5%	29.3%	16.2%	
	% within priority	13.8%	13.5%	14.1%	15.0%	16.3%	
Thursday	Count	1,781	2,836	870	2,892	1,608	9,987
	% within day of week	17.8%	28.4%	8.7%	29.0%	16.1%	
	% within priority	13.4%	13.5%	14.2%	14.6%	16.0%	

Friday	Count	1,972	2,978	890	3,067	1,562	10,469
	% within day of week	18.8%	28.4%	8.5%	29.3%	14.9%	
	% within priority	14.9%	14.2%	14.5%	15.5%	15.5%	
Saturday	Count	2,117	3,419	944	2,659	1,061	10,200
	% within day of week	20.8%	33.5%	9.3%	26.1%	10.4%	
	% within priority	16.0%	16.3%	15.4%	13.4%	10.6%	
2017							
Day	Priority level	1	2	3	4	5	Total
	Total	**11,676**	**21,566**	**5,852**	**20,583**	**7,298**	**66,975**
Sunday	Count	1,856	3,350	771	2,613	581	9,171
	% within day of week	20.2%	36.5%	8.4%	28.5%	6.4%	
	% within priority	15.9%	15.5%	13.2%	12.7%	8.0%	
Monday	Count	1,639	2,904	833	3,103	1,082	9,561
	% within day of week	17.1%	30.4%	8.7%	32.5%	11.3%	
	% within priority	14.0%	13.5%	14.2%	15.1%	14.8%	
Tuesday	Count	1,614	2,884	863	2,982	1,315	9,658
	% within day of week	16.7%	29.9%	8.9%	30.9%	13.5%	
	% within priority	13.8%	13.4%	14.7%	14.5%	18.0%	
Wednesday	Count	1,544	2,911	838	3,070	1,249	9,612
	% within day of week	16.1%	30.3%	8.7%	31.9%	13.0%	
	% within priority	13.2%	13.5%	14.3%	14.9%	17.1%	
Thursday	Count	1,526	2,817	800	2,982	1,236	9,361
	% within day of week	16.3%	30.1%	8.5%	31.9%	13.2%	
	% within priority	13.1%	13.1%	13.7%	14.5%	16.9%	
Friday	Count	1,673	3,178	863	3,070	1,129	9,913
	% within day of week	16.9%	32.1%	8.7%	31.0%	11.3%	
	% within priority	14.3%	14.7%	14.7%	14.9%	15.5%	
Saturday	Count	1,824	3,522	884	2,763	706	9,699
	% within day of week	18.8%	36.3%	9.1%	28.5%	7.3%	
	% within priority	15.6%	16.3%	15.1%	13.4%	9.7%	

Figure 5.3.2F demonstrates that, in both years, high numbers of Priority 1, Priority 2, and Priority 3 calls were received on Saturdays. In both 2016 and 2017, the highest number of Priority 4 calls were received on Fridays. These findings are partially consistent with the hypothesis that 911 call volumes are highest on weekends.

Tucson data

Part 1: CAD events

Part 1 examines all CAD events, including both 911 calls for service and officer-initiated events.

Figure 5.3.3A: Tucson CAD entries broken down by priority level[1]

	2016		2017	
Priority level	Frequency	Percent age	Frequency	Percent age
1	2,125	0.5%	2,354	0.5%
2	45,879	11.5%	45,547	10.5%
3	87,036	21.8%	88,655	20.4%
4	107,018	26.8%	123,923	28.5%
5	8,119	2%	8,126	1.9%
6	444	0.1%	1,064	0.2%
7	17,996	4.5%	22,079	5.1%
8	69,193	17.4%	66,592	15.3%
9	60,847	15.3%	76,139	17.5%
Missing	6	0%	2	0%

[1]Priority Level 1 refers to an incident posing an immediate threat to life where the threat is present and on-going; and/or an incident posing an immediate threat to life involving the actual use or threatened use of a weapon (e.g., someone being shot); Priority Level 2 refers to an incident involving a situation of imminent danger to life or a high potential for a threat to life to develop or escalate, and is either in progress or occurred within the past five minutes (e.g., a domestic violence dispute where physical violence has transpired); Priority Level 3 refers to crimes against persons or significant property crimes where a rapid response is needed and the incident is in progress, has occurred within the past five minutes, or is about to escalate to a more serious situation (e.g., a family fight is brewing); Priority Level 4 refers to other crimes or matters requiring police response, generally occurring more than 10 minutes prior to dispatch (e.g., a neighbor dispute); Priority Level 5 refers to onsite activity and 911 hang-ups transferred from PSAP with information available; Priority Level 6 refers to training entries; Priority Level 7 refers to unverified reports of alarms by owner or location of the alarm and 911 hang-ups from pay phones; Priority Level 8 refers to onsite activity (e.g., a traffic stop) and internal TPD resource requests; and Priority Level 9 refers to callback/alternative response call (ARC) unit reports (i.e., nonpriority calls without any evidence, witnesses, or suspects).

Figure 5.3.3A demonstrates that the most frequently occurring priority levels across all CAD activities were Priority 3 and 4, a finding that provides mixed support for Vera's hypothesis that most calls are unrelated to a crime in progress—though Priority Level 3 includes crimes where the incident is in progress, the most common call types within this priority were not crime-related. In both 2016 and 2017, the most common call type within Priority 3 was activity related to assisting the public (e.g., checking someone's welfare or transporting people to warm locations when the weather is below freezing temperatures). Within Priority 4, the most common activities were related to complaints/environmental conditions (e.g., complaints about animals, illegal dumping, or loud parties) and property crimes (e.g., burglary or vandalism).

Figure 5.3.3B: Tucson breakdown of CAD entries by incident type

	2016		2017	
Incident type	Frequency	Percentage	Frequency	Percentage
Total crime	98,339	25.3%	106,462	24.5%
Alarms	13,854	3.5%	14,217	3.3%
Violent crimes	3,069	0.8%	4,355	1%
Domestic violence	20,856	5.2%	22,127	5.1%

Property crimes	25,524	6.4%	26,759	6.2%
Other crimes[1]	35,036	9.4%	39,004	9%
Accidents/traffic-related	83,033	20.8%	73,378	16.9%
Assisting the public	26,291	6.6%	27,422	6.3%
Behavioral health	6,123	1.5%	6,603	1.5%
Callback	6,383	1.6%	7,176	1.7%
Call-related issues[2]	54,493	13.7%	78,484	18.1%
Complaints/environmental conditions[3]	33,342	8.4%	33,026	7.6%
Drugs	3,079	0.8%	2,987	0.7%
Fire	101	0%	100	0%
Liquor violations	300	0.1%	279	0.1%
Medical emergencies	46	0%	57	0%
Missing persons	4,173	1%	5,332	1.2%
Officer needs help	23	0%	6	0%
Officer status	45,204	11.3%	55,443	12.8%
Other (not crime)[4]	18,332	4.6%	15,018	3.5%
Sex offense	1,454	0.4%	1,969	0.5%
Status offense	3	0%	14	0%
Suspicion	15,647	3.9%	17,765	4.1%
Training academy	443	0.1%	1,063	0.2%
Warrants	1,886	0.5%	1,918	0.4%

[1] This category includes incidents such as custodial interference, cruelty to animals, and disorderly conduct.
[2] This category includes incidents such as hang-ups and abandoned calls.
[3] This category includes incidents such as animal complaints, open hydrants, and disturbance of the peace.
[4] This category includes the following incidents: "other," "weapons/carrying concealed," "unknown trouble," and "task force."

Figure 5.3.3B shows that only a quarter of the overall CAD entries in each year was related to crime, which is consistent with the hypothesis that most calls for service are unrelated to crimes in progress. Beyond crimes (which may or may not have been in progress), TPD officers most often engaged in activities that were related to traffic or automobile accidents and call-related issues.

Figure 5.3.3C: Tucson breakdown of CAD entries by day of week

	2016		2017	
Day	Frequency	Percentage	Frequency	Percentage
Sunday	47,896	12.0%	53,596	12.3%
Monday	57,347	14.4%	63,501	14.6%
Tuesday	59,200	14.8%	64,722	14.9%
Wednesday	57,904	14.5%	64,255	14.8%
Thursday	60,154	15.1%	65,675	15.1%

Friday	61,650	15.5%	64,525	14.9%
Saturday	54,512	13.7%	58,208	13.4%

Figure 5.3.3C shows that, in both years, CAD-reported police activity was fairly consistent, regardless of the day of the week. The most noticeable discrepancy in volumes was between Sundays and the other days, with Sundays seeing the lowest number of CAD entries logged. This finding does not support the hypothesis that call volume concentrates on weekends.

Figure 5.3.3D: Tucson breakdown of CAD entries by time of day

2016						
	Early morning[4]	Late morning	Afternoon	Early evening	Night	Total
Phone (911 CFS)[1]	38,681	26,470	79,156	82,559	56,379	283,245
Self-initiated[2]	26,778	11,322	25,463	21,583	29,550	114,696
Walk-in[3]	107	183	406	18	0	714
Total	65,566	37,975	105,025	104,160	85,929	398,655
2017						
	Early morning	Late morning	Afternoon	Early evening	Night	Total
Phone (911 CFS)	46,218	30,871	89,423	90,329	60,986	317,827
Self-initiated	29,125	11,838	26,952	20,473	26,981	115,369
Radio	0	0	2	0	0	2
Walk-in	130	203	530	14	0	877
Total	75,473	42,912	116,907	110,816	87,967	434,075

1 Phone (911 CFS) refers to 911 calls for service placed by members of the community.
2 Police-initiated refers to activities that officers proactively initiated and were not related to a 911 call for service.
3 Walk-ins refer to when a civilian reports an incident at a police station and a CAD entry is created from it.
4 Time of day is defined as follows:

- Early morning: 5:00 a.m.–9:59 a.m.
- Late morning: 10:00 a.m.–11:59 a.m.
- Afternoon: noon–4:59 p.m.
- Early evening: 5:00 p.m. –9:59 p.m.
- Night: 10:00 p.m. –4:59 a.m.

Figure 5.3.3D shows that, for both years, the highest number of CAD entries were logged during the early evening, followed closely by the afternoon. These findings are partially consistent with Vera's hypothesis that 911 call volume is higher at night.

Figure 5.3.3E: Tucson breakdown of CAD entries by hour of day

	2016		2017	
Hour of day	Frequency	Percentage	Frequency	Percentage
0	14,385	3.6%	14,874	3.4%
1	11,925	3%	12,566	2.9%
2	10,068	2.5%	10,487	2.4%
3	6,763	1.7%	7,175	1.7%
4	5,510	1.4%	5,734	1.3%

5	5,703	1.4%	6,256	1.4%
6	9,419	2.4%	11,239	2.6%
7	14,129	3.5%	16,746	3.9%
8	17,078	4.3%	19,266	4.4%
9	19,238	4.8%	22,047	5.1%
10	19,318	4.8%	21,959	5.1%
11	18,660	4.7%	20,976	4.8%
12	19,720	4.9%	21,931	5%
13	19,590	4.9%	21,890	5%
14	20,951	5.3%	23,547	5.4%
15	22,227	5.6%	24,918	5.7%
16	22,540	5.7%	24,741	5.7%
17	22,860	5.7%	24,375	5.6%
18	21,867	5.5%	23,270	5.4%
19	20,155	5.1%	22,179	5.1%
20	19,635	4.9%	21,138	4.9%
21	19,644	4.9%	19,960	4.6%
22	20,335	5.1%	20,073	4.6%
23	16,943	4.2%	17,135	3.9%

Figure 5.3.3E shows that, in both years, the highest frequency of calls came in between 3:00 p.m. (Hour 15) and 5:00 p.m. (Hour 17), though there was little variation in volume from 8:00 a.m. (Hour 20) to 11:00 p.m. (Hour 23). This is inconsistent with the hypothesis that 911 call volumes are highest during the night.

Part 2: Further analyses of priority levels

The following section provides a more in-depth look at how call volumes across different contexts (e.g., hour of day, day of week, and incident type) vary by priority levels.

Figure 5.3.4A: Tucson priority levels and their definition

Priority level	Definition	Highest frequency within priority
1	An incident posing an immediate and ongoing threat to life and/or an incident posing an immediate threat to life involving the actual use or threatened use of a weapon	Violent crimes, including armed robbery
2	An incident involving a situation of imminent danger to life, or with a high potential for threat to life to escalate; either in progress or occurred within the past five minutes	Domestic violence
3	Crimes against people **or** significant property crimes, where rapid response is required; incident is in progress, occurred within the past five minutes, or may escalate to a serious situation	Requests to assist the public, including check welfare
4	Crimes requiring police response, occurred more than 10 minutes prior to dispatch	Property crimes and nuisance complaints

5	Onsite activity and 911 hang-ups	
6	No definition provided	
7	Unverified alarm reports and 911 hang-ups from pay phones	
8	Onsite activity and internal TPD resource requests	
9	Callback or alternative response call	

Figure 5.3.4B: Tucson call types, broken down by priority level

2016											
Call type	Priority level	1	2	3	4	5	6	7	8	9	Total
	Total	**2,125**	**45,879**	**87,036**	**107,018**	**8,119**	**444**	**17,996**	**69,193**	**60,847**	**398,657**
Phone (CFS)[1]	Count	2,107	45,112	83,142	79,879	1,190	1	17,993	4,097	49,718	**283,239**
	% within call type	0.7%	15.9%	29.4%	28.2%	0.4%	0.0%	6.4%	1.4%	17.6%	
	% within priority	99.2%	98.3%	95.5%	74.6%	14.7%	0.2%	100.0%	5.9%	81.7%	
Self-initiated[2]	Count	18	756	3,890	26,434	6,929	443	3	65,094	11,129	**114,696**
	% within call type	0.0%	0.7%	3.4%	23.0%	6.0%	0.4%	0.0%	56.8%	9.7%	
	% within priority	0.8%	1.6%	4.5%	24.7%	85.3%	99.8%	0.0%	94.1%	18.3%	
Walk-in[3]	Count	0	6	3	703	0	0	0	2	0	**714**
	% within call type	0.0%	0.8%	0.4%	98.5%	0.0%	0.0%	0.0%	0.3%	0.0%	
	% within priority	0.0%	0.0%	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%	
2017											
Call type	Priority level	1	2	3	4	5	6	7	8	9	Total
	Total	**2,354**	**45,547**	**88,656**	**123,923**	**8,126**	**1,064**	**22,078**	**66,592**	**76,136**	**434,476**
Phone (CFS)	Count	2,327	44,901	85,156	84,435	1,680	1	22,055	9,128	68,142	**317,825**
	% within call type	0.7%	14.1%	26.8%	26.6%	0.5%	0.0%	6.9%	2.9%	21.4%	
	% within priority	98.9%	98.6%	96.1%	68.1%	20.7%	0.1%	99.9%	13.7%	89.5%	
Self-initiated	Count	24	589	3,358	38,460	6,446	1,063	3	57,456	7,970	**115,369**
	% within call type	0.0%	0.5%	2.9%	33.3%	5.6%	0.9%	0.0%	49.8%	6.9%	
	% within priority	1.0%	1.3%	3.8%	31.0%	79.3%	99.9%	0.0%	86.3%	10.5%	
Walk-In	Count	0	6	14	857	0	0	0	0	0	**877**
	% within call type	0.0%	0.7%	1.6%	97.7%	0.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.0%	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%	

[1] Phone (CFS) refers to 911 calls for service placed by members of the community.
[2] Self-initiated refers to activities that officers proactively initiated and were not related to a 911 call for service.
[3] Walk-in refers to when a civilian reports an incident at a police station and a CAD entry is generated by TPD personnel directly from the station.

Figure 5.3.4B shows that most 911 calls for service were classified as Priority 3 or 4, which suggests that most calls are unrelated to an emergency or serious crime in progress, thus supporting the hypothesis.

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Figure 5.3.4C: Tucson 911 call for service incident types, broken down by priority level

2016										
Incident type	Priority level	1	2	3	4	5	7	8	9	Total
	Total	2,107	45,112	83,142	79,879	1,190	17,993	4,097	49,718	283,238
Alarms	Count	3	1,361	980	3,235	0	8,258	0	0	13,837
	% within incident type	0.0%	9.8%	7.1%	23.4%	0.0%	59.7%	0.0%	0.0%	
	% within priority	0.1%	3.0%	1.2%	4.0%	0.0%	45.9%	0.0%	0.0%	
Assisting the public	Count	20	5,818	19,060	784	6	0	0	0	25,688
	% within incident type	0.1%	22.6%	74.2%	3.1%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.9%	12.9%	22.9%	1.0%	0.5%	0.0%	0.0%	0.0%	
Behavioral health	Count	241	3,791	173	4	0	0	0	0	4,209
	% within incident type	5.7%	90.1%	4.1%	0.1%	0.0%	0.0%	0.0%	0.0%	
	% within priority	11.4%	8.4%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	
Callbacks	Count	0	0	5	0	0	0	0	58,77	5,882
	% within incident type	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	99.9%	
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	11.8%	
Call-related Issues[1]	Count	3	3,588	19	9	1,174	9,734	0	39,965	54,492
	% within incident Type	0.0%	6.6%	0.0%	0.0%	2.2%	17.9%	0.0%	73.3%	
	% within priority	0.1%	8.0%	0.0%	0.0%	98.7%	54.1%	0.0%	80.4%	
Complaints/ environment al conditions[2]	Count	12	1,818	7,487	19,427	0	0	0	8	28,752
	% within incident type	0.0%	6.3%	26.0%	67.6%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.6%	4.0%	9.0%	24.3%	0.0%	0.0%	0.0%	0.0%	
Domestic violence	Count	255	10758	7775	1760	0	0	0	4	20,552
	% within incident type	1.2%	52.3%	37.8%	8.6%	0.0%	0.0%	0.0%	0.0%	
	% within priority	12.1%	23.8%	9.4%	2.2%	0.0%	0.0%	0.0%	0.0%	
Drugs	Count	0	6	664	1,640	0	0	0	0	2,310
	% within incident type	0.0%	0.3%	28.7%	71.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.0%	0.8%	2.1%	0.0%	0.0%	0.0%	0.0%	
Fire	Count	0	51	3	0	0	0	0	0	54

	% within incident type	0.0%	92.7%	5.5%	0.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	
Liquor violations	Count	0	0	16	271	0	0	0	0	287
	% within incident type	0.0%	0.0%	5.6%	94.4%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.0%	0.0%	0.3%	0.0%	0.0%	0.0%	0.0%	
Medical emergencies	Count	0	12	1	0	0	0	0	0	13
	% within incident type	0.0%	92.3%	7.7%	0.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	
Missing persons	Count	1	548	563	2,923	0	0	0	1	4,036
	% within incident type	0.0%	13.6%	13.9%	72.4%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	1.2%	0.7%	3.7%	0.0%	0.0%	0.0%	0.0%	
Officer needs help	Count	15	0	4	0	0	0	0	0	19
	% within incident type	78.9%	0.0%	21.1%	0.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	
Other crimes[3]	Count	410	4,561	15,302	13,090	0	0	0	15	33,378
	% within incident type	1.2%	13.7%	45.8%	39.2%	0.0%	0.0%	0.0%	0.0%	
	% within priority	19.5%	10.1%	18.4%	16.4%	0.0%	0.0%	0.0%	0.0%	
Other (not crime)[4]	Count	8	2,938	82	324	0	0	0	3	3,355
	% within incident type	0.2%	87.6%	2.4%	9.7%	0.0%	0.0%	0.0%	0.1%	
	% within priority	0.4%	6.5%	0.1%	0.4%	0.0%	0.0%	0.0%	0.0%	
Officer status	Count	6	824	7,530	9,543	8	0	4,094	3,828	25,833
	% within incident type	0.0%	3.2%	29.1%	36.9%	0.0%	0.0%	15.8%	14.8%	
	% within priority	0.3%	1.8%	9.1%	11.9%	0.7%	0.0%	99.9%	7.7%	
Property crimes	Count	395	973	2,924	19,202	1	0	0	1	23,496
	% within incident type	1.7%	4.1%	12.4%	81.7%	0.0%	0.0%	0.0%	0.0%	
	% within priority	18.7%	2.2%	3.5%	24.0%	0.1%	0.0%	0.0%	0.0%	
Sex offenses	Count	3	153	720	413	0	0	0	7	1,296
	% within incident type	0.2%	11.8%	55.6%	31.9%	0.0%	0.0%	0.0%	0.5%	
	% within priority	0.1%	0.3%	0.9%	0.5%	0.0%	0.0%	0.0%	0.0%	
	Count	0	0	0	2	0	0	0	0	2

Status offense	% within incident type	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	
Suspicion	Count	2	613	13,232	1,309	0	1	0	5	**15,162**
	% within incident type	0.0%	4.0%	87.3%	8.6%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.1%	1.4%	15.9%	1.6%	0.0%	0.0%	0.0%	0.0%	
Traffic-related	Count	2	6,101	5,868	5,199	1	0	3	4	**17,178**
	% within incident type	0.0%	35.5%	34.2%	30.3%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.1%	13.5%	7.1%	6.5%	0.1%	0.0%	0.1%	0.0%	
Violent crimes	Count	731	1,188	572	377	0	0	0	0	**2,869**
	% within incident type	25.5%	41.4%	19.9%	13.1%	0.0%	0.0%	0.0%	0.0%	
	% within priority	34.7%	2.6%	0.7%	0.5%	0.0%	0.0%	0.0%	0.0%	
Warrants	Count	0	10	162	367	0	0	0	0	**539**
	% within incident type	0.0%	1.9%	30.1%	68.1%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.0%	0.2%	0.5%	0.0%	0.0%	0.0%	0.0%	
2017										
Incident type	Priority level	1	2	3	4	5	7	8	9	Total
	Total	2,327	44,901	85,156	84,435	1,680	22,055	9,128	68,142	317,824
Alarms	Count	7	1,301	1,016	3,027	0	8,821	0	0	**14,172**
	% within incident Type	0.0%	9.2%	7.2%	21.4%	0.0%	62.2%	0.0%	0.0%	
	% within priority	0.3%	2.9%	1.2%	3.6%	0.0%	40.0%	0.0%	0.0%	
Assisting the public	Count	18	6,211	19,401	1,076	5	0	0	2	**26,713**
	% within incident type	0.1%	23.3%	72.6%	4.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.8%	13.8%	22.8%	1.3%	0.3%	0.0%	0.0%	0.0%	
Behavioral health	Count	253	3,792	255	10	0	0	0	0	**4,310**
	% within incident type	5.9%	88.0%	5.9%	0.2%	0.0%	0.0%	0.0%	0.0%	
	% within priority	10.9%	8.4%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	
Callbacks	Count	0	1	1	0	0	0	0	6,935	**6,937**
	% within incident type	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	

	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	10.2%	
Call-related issues	Count	3	3,135	25	18	1,643	13,228	5,695	54,725	78,472
	% within incident type	0.0%	4.0%	0.0%	0.0%	2.1%	16.9%	7.3%	69.7%	
	% within priority	0.1%	7.0%	0.0%	0.0%	97.8%	60.0%	62.4%	80.3%	
Complaints/ environmental conditions	Count	12	1,716	7,435	19,191	2	5	1	7	28,369
	% within incident type	0.0%	6.0%	26.2%	67.6%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.5%	3.8%	8.7%	22.7%	0.1%	0.0%	0.0%	0.0%	
Domestic violence	Count	290	11,004	8,405	2,051	0	0	2	3	21,755
	% within incident type	1.3%	50.6%	38.6%	9.4%	0.0%	0.0%	0.0%	0.0%	
	% within priority	12.5%	24.5%	9.9%	2.4%	0.0%	0.0%	0.0%	0.0%	
Drugs	Count	0	13	649	1,642	0	0	0	0	2,304
	% within incident type	0.0%	0.6%	28.2%	71.3%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.0%	0.8%	1.9%	0.0%	0.0%	0.0%	0.0%	
Fire	Count	0	49	2	3	0	0	0	0	54
	% within incident type	0.0%	90.7%	3.7%	5.6%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	
Liquor violations	Count	0	0	20	242	0	0	0	0	262
	% within incident type	0.0%	0.0%	7.6%	92.4%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.0%	0.0%	0.3%	0.0%	0.0%	0.0%	0.0%	
Medical emergencies	Count	0	32	0	0	0	0	0	0	32
	% within incident type	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	
Missing persons	Count	0	654	487	4,056	0	0	0	13	5,210
	% within incident type	0.0%	12.6%	9.3%	77.9%	0.0%	0.0%	0.0%	0.2%	

	% within priority	0.0%	1.5%	0.6%	4.8%	0.0%	0.0%	0.0%	0.0%	
Officer needs help	Count	2	0	2	1	0	0	0	0	**5**
	% within incident type	40.0%	0.0%	40.0%	20.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	
Other crimes	Count	467	4,863	16,194	15,281	0	0	1	172	**36,978**
	% within incident Type	1.3%	13.2%	43.8%	41.3%	0.0%	0.0%	0.0%	0.5%	
	% within priority	20.1%	10.8%	19.0%	18.1%	0.0%	0.0%	0.0%	0.3%	
Other (not crime)	Count	15	2,467	51	322	0	0	0	0	**2,855**
	% within incident type	0.5%	86.4%	1.8%	11.3%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.6%	5.5%	0.1%	0.4%	0.0%	0.0%	0.0%	0.0%	
Officer status	Count	9	673	6,298	10,276	30	1	3,422	6,028	**26,737**
	% within incident type	0.0%	2.5%	23.6%	38.4%	0.1%	0.0%	12.8%	22.5%	
	% within priority	0.4%	1.5%	7.4%	12.2%	1.8%	0.0%	37.5%	8.8%	
Property crimes	Count	394	924	2,774	20,136	0	0	0	86	**24,314**
	% within incident type	1.6%	3.8%	11.4%	82.8%	0.0%	0.0%	0.0%	0.4%	
	% within priority	16.9%	2.1%	3.3%	23.8%	0.0%	0.0%	0.0%	0.1%	
Sex offense	Count	3	179	1,043	562	0	0	0	12	**1,799**
	% within incident type	0.2%	9.9%	58.0%	31.2%	0.0%	0.0%	0.0%	0.7%	
	% within priority	0.1%	0.4%	1.2%	0.7%	0.0%	0.0%	0.0%	0.0%	
Status offense	Count	0	0	0	2	0	0	0	0	**2**
	% within incident type	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	
Suspicion	Count	4	764	14,327	1,974	0	0	0	39	**17,108**
	% within incident type	0.0%	4.5%	83.7%	11.5%	0.0%	0.0%	0.0%	0.2%	

	% within priority	0.2%	1.7%	16.8%	2.3%	0.0%	0.0%	0.0%	0.1%	
Traffic-related	Count	5	5,557	5,875	3,232	0	0	7	118	**14,794**
	% within incident type	0.0%	37.6%	39.7%	21.8%	0.0%	0.0%	0.0%	0.8%	
	% within priority	0.2%	12.4%	6.9%	3.8%	0.0%	0.0%	0.1%	0.2%	
Violent crimes	Count	845	1,562	730	1,021	0	0	0	1	**4,159**
	% within incident type	20.3%	37.6%	17.6%	24.5%	0.0%	0.0%	0.0%	0.0%	
	% within priority	36.3%	3.5%	0.9%	1.2%	0.0%	0.0%	0.0%	0.0%	
Warrants	Count	0	4	166	312	0	0	0	1	**483**
	% within incident type	0.0%	0.8%	34.4%	64.6%	0.0%	0.0%	0.0%	0.2%	
	% within priority	0.0%	0.0%	0.2%	0.4%	0.0%	0.0%	0.0%	0.0%	

Note: Priority 6 is not listed because there was only one call per year in this category.
[1] This category includes incidents such as hang-ups and abandoned calls.
[2] This category includes incidents such as animal complaints, open hydrants, and disturbance of the peace.
[3] This category includes incidents such as custodial interference, cruelty to animals, and disorderly conduct.
[4] This category includes the following incidents: "other," "weapons/carrying concealed," "unknown trouble," and "task force."

Figure 5.3.4C demonstrates that the highest number of calls classified as Priority 1 were related to violent crime (more than 30 percent for both 2016 and 2017); the highest volume of calls classified as Priority 2 was related to domestic violence (approximately 24 percent in each year); the highest volume of calls classified as Priority 3 was related to requests for public assistance (approximately 23 percent in each year); and the highest number of calls classified as Priority 4 were related to property crime and complaints/environmental conditions (both categories approximately 24 percent in each year), as well as nuisance complaints (also roughly 24 percent for both years). By definition, calls classified as Priority 5, Priority 7, and Priority 9 were related to call issues (e.g., 911 hang-ups), whereas those classified as Priority 8 were all related to an officer's status.

Figure 5.3.4D: Tucson 911 call volumes at different times of the day, broken down by priority level[1]

2016										
Priority level		1	2	3	4	5	7	8	9	Total
Total		**2,107**	**45,112**	**83,142**	**79,879**	**1,190**	**17,993**	**4,097**	**49,718**	**283,238**
Early morning	Count	186	5,602	10,566	11,704	156	3,420	440	6,606	**38,680**
	% within time of Day	0.5%	14.5%	27.3%	30.3%	0.4%	8.8%	1.1%	17.1%	
	% within priority	8.8%	12.4%	12.7%	14.7%	13.1%	19.0%	10.7%	13.3%	

Late morning	Count	168	3,455	7,452	7,900	114	2,136	406	4,838	**26,469**
	% within time of day	0.6%	13.1%	28.2%	29.8%	0.4%	8.1%	1.5%	18.3%	
	% within priority	8.0%	7.7%	9.0%	9.9%	9.6%	11.9%	9.9%	9.7%	
Afternoon	Count	550	11,781	23,711	21,156	331	5,475	1,316	14,831	**79,151**
	% within time of day	0.7%	14.9%	30.0%	26.7%	0.4%	6.9%	1.7%	18.7%	
	% within priority	26.1%	26.1%	28.5%	26.5%	27.8%	30.4%	32.1%	29.8%	
Early evening	Count	628	13,747	24,688	22,257	349	4,066	1,014	15,810	**82,559**
	% within time of day	0.8%	16.7%	29.9%	27.0%	0.4%	4.9%	1.2%	19.1%	
	% within priority	29.8%	30.5%	29.7%	27.9%	29.3%	22.6%	24.7%	31.8%	
Night	Count	575	10,527	16,725	16,862	240	2,896	921	7,633	**56,379**
	% within time of day	1.0%	18.7%	29.7%	29.9%	0.4%	5.1%	1.6%	13.5%	
	% within priority	27.3%	23.3%	20.1%	21.1%	20.2%	16.1%	22.5%	15.4%	
2017										
Priority level		1	2	3	4	5	7	8	9	Total
Total		**2,327**	**44,901**	**85,156**	**84,435**	**1,680**	**22,055**	**9,128**	**68,142**	**317,824**
Early morning	Count	233	5,864	11,918	13,204	277	4,267	1,173	9,282	**46,218**
	% within time of day	0.5%	12.7%	25.8%	28.6%	0.6%	9.2%	2.5%	20.1%	
	% within priority	10.0%	13.1%	14.0%	15.6%	16.5%	19.3%	12.9%	13.6%	
Late morning	Count	188	3,805	8,110	8,175	171	2,719	966	6,737	**30,871**
	% within time of day	0.6%	12.3%	26.3%	26.5%	0.6%	8.8%	3.1%	21.8%	
	% within priority	8.1%	8.5%	9.5%	9.7%	10.2%	12.3%	10.6%	9.9%	
Afternoon	Count	608	12,055	23,779	21,502	507	6,873	2,947	21,150	**89,421**
	% within time of day	0.7%	13.5%	26.6%	24.0%	0.6%	7.7%	3.3%	23.7%	
	% within priority	26.1%	26.8%	27.9%	25.5%	30.2%	31.2%	32.3%	31.0%	
Early evening	Count	711	13,223	24,516	23,633	452	4,794	2,487	20,512	**90,328**
	% within time of day	0.8%	14.6%	27.1%	26.2%	0.5%	5.3%	2.8%	22.7%	
	% within priority	30.6%	29.4%	28.8%	28.0%	26.9%	21.7%	27.2%	30.1%	
Night	Count	587	9,954	16,833	17,921	273	3,402	1,555	10,461	**60,986**
	% within time of day	1.0%	16.3%	27.6%	29.4%	0.4%	5.6%	2.5%	17.2%	
	% within priority	25.2%	22.2%	19.8%	21.2%	16.3%	15.4%	17.0%	15.4%	

[1] Time of day is defined as follows:

- Early morning: 5:00 a.m.–9:59 a.m.
- Late morning: 10:00 a.m. –11:59 a.m.
- Afternoon: noon–4:59 p.m.
- Early evening: 5:00 p.m.–9:59 p.m.
- Night: 10:00 p.m.–4:59 a.m.

Figure 5.3.4D reveals that. in both 2016 and 2017, the largest number of Priority 1, Priority 2, Priority 3, and Priority 4 calls were received during the early evening. This is partially consistent with the hypothesis that 911 call volumes are highest at night. There was also a sizable uptick from 2016 to 2017 in Priority 8 and 9 calls, with increased volume of these priority levels increasing most dramatically during the afternoon.

Figure 5.3.4E: Tucson 911 call volumes at different hours of the day, broken down by priority level

2016										
Hour of day	Priority level	1	2	3	4	5	7	8	9	Total
	Total	2,107	45,112	83,142	79,879	1,190	17,993	4,097	49,718	283,238
0	Count	89	1,677	2,606	2,870	40	407	146	1,187	9,022
	% within hour of day	1.0%	18.6%	28.9%	31.8%	0.4%	4.5%	1.6%	13.2%	
	% within priority	4.2%	3.7%	3.1%	3.6%	3.4%	2.3%	3.6%	2.4%	
1	Count	86	1,414	2,287	2,284	34	393	117	934	7,549
	% within hour of day	1.1%	18.7%	30.3%	30.3%	0.5%	5.2%	1.5%	12.4%	
	% within priority	4.1%	3.1%	2.8%	2.9%	2.9%	2.2%	2.9%	1.9%	
2	Count	68	1,346	2,072	1,882	35	381	121	805	6,710
	% within hour of day	1.0%	20.1%	30.9%	28.0%	0.5%	5.7%	1.8%	12.0%	
	% within priority	3.2%	3.0%	2.5%	2.4%	2.9%	2.1%	3.0%	1.6%	
3	Count	58	1,057	1,571	1,403	19	309	124	598	5,139
	% within hour of day	1.1%	20.6%	30.6%	27.3%	0.4%	6.0%	2.4%	11.6%	
	% within priority	2.8%	2.3%	1.9%	1.8%	1.6%	1.7%	3.0%	1.2%	
4	Count	43	873	1,319	1,164	16	343	72	562	4,392
	% within hour of day	1.0%	19.9%	30.0%	26.5%	0.4%	7.8%	1.6%	12.8%	
	% within priority	2.0%	1.9%	1.6%	1.5%	1.3%	1.9%	1.8%	1.1%	
5	Count	42	842	1,277	1,138	23	365	67	602	4,356
	% within hour of day	1.0%	19.3%	29.3%	26.1%	0.5%	8.4%	1.5%	13.8%	
	% within priority	2.0%	1.9%	1.5%	1.4%	1.9%	2.0%	1.6%	1.2%	
6	Count	29	806	1,487	1,535	21	460	49	808	5,195

	% within hour of day	0.6%	15.5%	28.6%	29.5%	0.4%	8.9%	0.9%	15.6%	
	% within priority	1.4%	1.8%	1.8%	1.9%	1.8%	2.6%	1.2%	1.6%	
7	Count	33	1,120	2,109	2,201	35	679	78	1,342	**7,597**
	% within hour of day	0.4%	14.7%	27.8%	29.0%	0.5%	8.9%	1.0%	17.7%	
	% within priority	1.6%	2.5%	2.5%	2.8%	2.9%	3.8%	1.9%	2.7%	
8	Count	45	1,359	2,699	3,211	33	939	98	1,752	**10,136**
	% within hour of day	0.4%	13.4%	26.6%	31.7%	0.3%	9.3%	1.0%	17.3%	
	% within priority	2.1%	3.0%	3.2%	4.0%	2.8%	5.2%	2.4%	3.5%	
9	Count	37	1,475	2,994	3,619	44	977	148	2,102	**11,396**
	% within hour of day	0.3%	12.9%	26.3%	31.8%	0.4%	8.6%	1.3%	18.4%	
	% within priority	1.8%	3.3%	3.6%	4.5%	3.7%	5.4%	3.6%	4.2%	
10	Count	71	1,560	3,420	3,834	56	1,051	184	2,343	**12,519**
	% within hour of day	0.6%	12.5%	27.3%	30.6%	0.4%	8.4%	1.5%	18.7%	
	% within priority	3.4%	3.5%	4.1%	4.8%	4.7%	5.8%	4.5%	4.7%	
11	Count	97	1,895	4,032	4,066	58	1,085	222	2,495	**13,950**
	% within hour of day	0.7%	13.6%	28.9%	29.1%	0.4%	7.8%	1.6%	17.9%	
	% within priority	4.6%	4.2%	4.8%	5.1%	4.9%	6.0%	5.4%	5.0%	
12	Count	87	2,158	4,327	4,020	65	1,079	258	2,732	**14,726**
	% within hour of day	0.6%	14.7%	29.4%	27.3%	0.4%	7.3%	1.8%	18.6%	
	% within priority	4.1%	4.8%	5.2%	5.0%	5.5%	6.0%	6.3%	5.5%	
13	Count	106	2,114	4,532	4,039	66	1,130	230	2,595	**14,812**
	% within hour of day	0.7%	14.3%	30.6%	27.3%	0.4%	7.6%	1.6%	17.5%	
	% within priority	5.0%	4.7%	5.5%	5.1%	5.5%	6.3%	5.6%	5.2%	
14	Count	128	2,352	4,733	4,092	66	1,137	279	2,948	**15,735**
	% within hour of day	0.8%	14.9%	30.1%	26.0%	0.4%	7.2%	1.8%	18.7%	
	% within priority	6.1%	5.2%	5.7%	5.1%	5.5%	6.3%	6.8%	5.9%	
15	Count	98	2,529	5,022	4,282	69	1,129	291	3,310	**16,730**
	% within hour of day	0.6%	15.1%	30.0%	25.6%	0.4%	6.7%	1.7%	19.8%	
	% within priority	4.7%	5.6%	6.0%	5.4%	5.8%	6.3%	7.1%	6.7%	
16	Count	131	2,628	5,097	4,723	65	1,000	258	3,246	**17,148**

	% within hour of day	0.8%	15.3%	29.7%	27.5%	0.4%	5.8%	1.5%	18.9%	
	% within priority	6.2%	5.8%	6.1%	5.9%	5.5%	5.6%	6.3%	6.5%	
17	Count	112	2,852	5,305	4,831	64	947	210	3,830	**18,151**
	% within hour of day	0.6%	15.7%	29.2%	26.6%	0.4%	5.2%	1.2%	21.1%	
	% within priority	5.3%	6.3%	6.4%	6.0%	5.4%	5.3%	5.1%	7.7%	
18	Count	125	2,823	5,343	4,718	72	933	245	3,345	**17,604**
	% within hour of day	0.7%	16.0%	30.4%	26.8%	0.4%	5.3%	1.4%	19.0%	
	% within priority	5.9%	6.3%	6.4%	5.9%	6.1%	5.2%	6.0%	6.7%	
19	Count	131	2,776	5,044	4,333	77	791	209	2,969	**16,330**
	% within hour of day	0.8%	17.0%	30.9%	26.5%	0.5%	4.8%	1.3%	18.2%	
	% within priority	6.2%	6.2%	6.1%	5.4%	6.5%	4.4%	5.1%	6.0%	
20	Count	107	2,783	4,666	4,247	67	737	194	3,001	**15,802**
	% within hour of day	0.7%	17.6%	29.5%	26.9%	0.4%	4.7%	1.2%	19.0%	
	% within priority	5.1%	6.2%	5.6%	5.3%	5.6%	4.1%	4.7%	6.0%	
21	Count	153	2,513	4,330	4,128	69	658	156	2,665	**14,672**
	% within hour of day	1.0%	17.1%	29.5%	28.1%	0.5%	4.5%	1.1%	18.2%	
	% within priority	7.3%	5.6%	5.2%	5.2%	5.8%	3.7%	3.8%	5.4%	
22	Count	131	2,244	3,668	3,982	49	580	172	2,016	**12,842**
	% within hour of day	1.0%	17.5%	28.6%	31.0%	0.4%	4.5%	1.3%	15.7%	
	% within priority	6.2%	5.0%	4.4%	5.0%	4.1%	3.2%	4.2%	4.1%	
23	Count	100	1,916	3,202	3,277	47	483	169	1,531	**10,725**
	% within hour of day	0.9%	17.9%	29.9%	30.6%	0.4%	4.5%	1.6%	14.3%	
	% within priority	4.7%	4.2%	3.9%	4.1%	3.9%	2.7%	4.1%	3.1%	
2017										
Hour of day	Priority level	1	2	3	4	5	7	8	9	Total
	Total	**2,327**	**44,901**	**85,156**	**84,435**	**1,680**	**22,055**	**9,128**	**68,142**	**317,824**
0	Count	98	1,526	2,701	3,087	47	517	256	1,634	**9,866**
	% within hour of day	1.0%	15.5%	27.4%	31.3%	0.5%	5.2%	2.6%	16.6%	
	% within priority	4.2%	3.4%	3.2%	3.7%	2.8%	2.3%	2.8%	2.4%	
1	Count	88	1,424	2,314	2,329	47	443	215	1,287	**8,147**

	% within hour of day	1.1%	17.5%	28.4%	28.6%	0.6%	5.4%	2.6%	15.8%	
	% within priority	3.8%	3.2%	2.7%	2.8%	2.8%	2.0%	2.4%	1.9%	
2	Count	77	1,287	2,029	1,971	43	444	187	1,194	7,232
	% within hour of day	1.1%	17.8%	28.1%	27.3%	0.6%	6.1%	2.6%	16.5%	
	% within priority	3.3%	2.9%	2.4%	2.3%	2.6%	2.0%	2.0%	1.8%	
3	Count	69	1,035	1,659	1,504	23	442	155	892	5,779
	% within hour of day	1.2%	17.9%	28.7%	26.0%	0.4%	7.6%	2.7%	15.4%	
	% within priority	3.0%	2.3%	1.9%	1.8%	1.4%	2.0%	1.7%	1.3%	
4	Count	52	809	1,385	1,191	22	394	125	740	4,718
	% within hour of day	1.1%	17.1%	29.4%	25.2%	0.5%	8.4%	2.6%	15.7%	
	% within priority	2.2%	1.8%	1.6%	1.4%	1.3%	1.8%	1.4%	1.1%	
5	Count	40	733	1,355	1,274	28	486	119	802	4,837
	% within hour of day	0.8%	15.2%	28.0%	26.3%	0.6%	10.0%	2.5%	16.6%	
	% within priority	1.7%	1.6%	1.6%	1.5%	1.7%	2.2%	1.3%	1.2%	
6	Count	37	829	1,658	1,703	43	597	134	1,122	6,123
	% within hour of day	0.6%	13.5%	27.1%	27.8%	0.7%	9.8%	2.2%	18.3%	
	% within priority	1.6%	1.8%	1.9%	2.0%	2.6%	2.7%	1.5%	1.6%	
7	Count	33	1,207	2,364	2,604	67	845	257	1,919	9,296
	% within hour of day	0.4%	13.0%	25.4%	28.0%	0.7%	9.1%	2.8%	20.6%	
	% within priority	1.4%	2.7%	2.8%	3.1%	4.0%	3.8%	2.8%	2.8%	
8	Count	51	1,413	2,983	3,596	72	1,110	306	2,509	12,040
	% within hour of day	0.4%	11.7%	24.8%	29.9%	0.6%	9.2%	2.5%	20.8%	
	% within priority	2.2%	3.1%	3.5%	4.3%	4.3%	5.0%	3.4%	3.7%	
9	Count	72	1,682	3,558	4,027	67	1,229	357	2,930	13,922
	% within hour of day	0.5%	12.1%	25.6%	28.9%	0.5%	8.8%	2.6%	21.0%	
	% within priority	3.1%	3.7%	4.2%	4.8%	4.0%	5.6%	3.9%	4.3%	
10	Count	82	1,821	3,933	3,964	77	1,309	424	3,234	14,844
	% within hour of day	0.6%	12.3%	26.5%	26.7%	0.5%	8.8%	2.9%	21.8%	
	% within priority	3.5%	4.1%	4.6%	4.7%	4.6%	5.9%	4.6%	4.7%	
11	Count	106	1,984	4,177	4,211	94	1,410	542	3,503	16,027

	% within hour of day	0.7%	12.4%	26.1%	26.3%	0.6%	8.8%	3.4%	21.9%	
	% within priority	4.6%	4.4%	4.9%	5.0%	5.6%	6.4%	5.9%	5.1%	
12	Count	105	2,140	4,420	4,107	94	1,335	531	3,698	16,430
	% within hour of day	0.6%	13.0%	26.9%	25.0%	0.6%	8.1%	3.2%	22.5%	
	% within priority	4.5%	4.8%	5.2%	4.9%	5.6%	6.1%	5.8%	5.4%	
13	Count	124	2,180	4,510	4,042	88	1,357	502	3,864	16,667
	% within hour of day	0.7%	13.1%	27.1%	24.3%	0.5%	8.1%	3.0%	23.2%	
	% within priority	5.3%	4.9%	5.3%	4.8%	5.2%	6.2%	5.5%	5.7%	
14	Count	101	2,404	4,526	4,128	96	1,465	622	4,410	17,752
	% within hour of day	0.6%	13.5%	25.5%	23.3%	0.5%	8.3%	3.5%	24.8%	
	% within priority	4.3%	5.4%	5.3%	4.9%	5.7%	6.6%	6.8%	6.5%	
15	Count	133	2,588	5,077	4,408	137	1,450	667	4,780	19,240
	% within hour of day	0.7%	13.5%	26.4%	22.9%	0.7%	7.5%	3.5%	24.8%	
	% within priority	5.7%	5.8%	6.0%	5.2%	8.2%	6.6%	7.3%	7.0%	
16	Count	145	2,743	5,246	4,817	92	1,266	625	4,398	19,332
	% within hour of day	0.8%	14.2%	27.1%	24.9%	0.5%	6.5%	3.2%	22.7%	
	% within priority	6.2%	6.1%	6.2%	5.7%	5.5%	5.7%	6.8%	6.5%	
17	Count	129	2,667	5,222	5,058	87	1,230	524	5,062	19,979
	% within hour of day	0.6%	13.3%	26.1%	25.3%	0.4%	6.2%	2.6%	25.3%	
	% within priority	5.5%	5.9%	6.1%	6.0%	5.2%	5.6%	5.7%	7.4%	
18	Count	142	2,718	5,286	4,909	102	1,056	542	4,550	19,305
	% within hour of day	0.7%	14.1%	27.4%	25.4%	0.5%	5.5%	2.8%	23.6%	
	% within priority	6.1%	6.1%	6.2%	5.8%	6.1%	4.8%	5.9%	6.7%	
19	Count	162	2,709	5,113	4,797	107	1,000	534	4,079	18,501
	% within hour of day	0.9%	14.6%	27.6%	25.9%	0.6%	5.4%	2.9%	22.0%	
	% within priority	7.0%	6.0%	6.0%	5.7%	6.4%	4.5%	5.9%	6.0%	
20	Count	145	2,682	4,743	4,452	85	851	467	3,762	17,187
	% within hour of day	0.8%	15.6%	27.6%	25.9%	0.5%	5.0%	2.7%	21.9%	
	% within priority	6.2%	6.0%	5.6%	5.3%	5.1%	3.9%	5.1%	5.5%	
21	Count	133	2,447	4,152	4,417	71	657	420	3,059	15,356

	% within hour of day	0.9%	15.9%	27.0%	28.8%	0.5%	4.3%	2.7%	19.9%	
	% within priority	5.7%	5.4%	4.9%	5.2%	4.2%	3.0%	4.6%	4.5%	
22	Count	102	2,041	3,667	4,289	52	621	313	2,635	**13,720**
	% within hour of day	0.7%	14.9%	26.7%	31.3%	0.4%	4.5%	2.3%	19.2%	
	% within priority	4.4%	4.5%	4.3%	5.1%	3.1%	2.8%	3.4%	3.9%	
23	Count	101	1,832	3,078	3,550	39	541	304	2,079	**11,524**
	% within hour of day	0.9%	15.9%	26.7%	30.8%	0.3%	4.7%	2.6%	18.0%	
	% within priority	4.3%	4.1%	3.6%	4.2%	2.3%	2.5%	3.3%	3.1%	

Figure 5.3.4E shows that, in 2016, the highest number of Priority 1 calls were received during the 9:00 p.m. hour (7.3 percent of Priority 1 calls; hour 21), whereas in 2017, the peak in Priority 1 calls happened during the 7:00 p.m. hour (7 percent of Priority 1 calls; hour 19). For Priority 2 calls, in 2016, most came in during the 5:00 p.m. and 6:00 p.m. hours (hours 17 and 18, respectively), and in 2017, the highest number of calls were received during the 4:00 p.m. and 6:00 p.m. hours (hours 16 and 18). In both years, the highest number of Priority 3 calls were received during the 4:00 p.m. and 6:00 p.m. hours (hours 16 and 18), and most Priority 4 calls occurred during the 5:00 p.m. hour (hour 17). These findings are partially consistent with the hypothesis that 911 call volumes are highest at night.

Figure 5.3.4F: Tucson 911 call volumes on different days of the week, broken down by priority level

2016										
Priority level		1	2	3	4	5	7	8	9	Total
Total		**2,107**	**45,112**	**83,142**	**79,879**	**1,190**	**17,993**	**4,097**	**49,718**	**283,238**
Sunday	Count	334	6,210	10,874	11,177	158	2,180	417	6,466	**37,816**
	% within Day of Week	0.9%	16.4%	28.8%	29.6%	0.4%	5.8%	1.1%	17.1%	
	% within priority	15.9%	13.8%	13.1%	14.0%	13.3%	12.1%	10.2%	13.0%	
Monday	Count	271	6,172	11,484	11,081	174	2,617	529	7,036	**39,364**
	% within Day of Week	0.7%	15.7%	29.2%	28.1%	0.4%	6.6%	1.3%	17.9%	
	% within Priority	12.9%	13.7%	13.8%	13.9%	14.6%	14.5%	12.9%	14.2%	
Tuesday	Count	292	6,112	11,386	10,979	170	2,557	753	7,120	**39,369**
	% within day of week	0.7%	15.5%	28.9%	27.9%	0.4%	6.5%	1.9%	18.1%	
	% within priority	13.9%	13.5%	13.7%	13.7%	14.3%	14.2%	18.4%	14.3%	

Wednesday	Count	309	6,524	11,848	10,903	173	2,729	727	7,143	**40,356**
	% within day of week	0.8%	16.2%	29.4%	27.0%	0.4%	6.8%	1.8%	17.7%	
	% within priority	14.7%	14.5%	14.3%	13.6%	14.5%	15.2%	17.7%	14.4%	
Thursday	Count	283	6,306	12,204	11,224	149	2,539	755	7,041	**40,501**
	% within day of week	0.7%	15.6%	30.1%	27.7%	0.4%	6.3%	1.9%	17.4%	
	% within priority	13.4%	14.0%	14.7%	14.1%	12.5%	14.1%	18.4%	14.2%	
Friday	Count	314	7,059	13,031	11,945	177	2,862	520	7,876	**43,784**
	% within day of week	0.7%	16.1%	29.8%	27.3%	0.4%	6.5%	1.2%	18.0%	
	% within priority	14.9%	15.6%	15.7%	15.0%	14.9%	15.9%	12.7%	15.8%	
Saturday	Count	304	6,729	12,315	12,570	189	2,509	396	7,036	**42,048**
	% within day of week	0.7%	16.0%	29.3%	29.9%	0.4%	6.0%	0.9%	16.7%	
	% within priority	14.4%	14.9%	14.8%	15.7%	15.9%	13.9%	9.7%	14.2%	
2017										
Priority level		1	2	3	4	5	7	8	9	Total
Total		**2,327**	**44,901**	**85,156**	**84,435**	**1,680**	**22,055**	**9,128**	**68,142**	**317,824**
Sunday	Count	380	6,327	11,117	12,246	226	2,539	1,172	8,986	**42,993**
	% within day of week	0.9%	14.7%	25.9%	28.5%	0.5%	5.9%	2.7%	20.9%	
	% within priority	16.3%	14.1%	13.1%	14.5%	13.5%	11.5%	12.8%	13.2%	
Monday	Count	317	6,353	12,009	12,128	239	3,185	1,272	9,910	**45,413**
	% within day of week	0.7%	14.0%	26.4%	26.7%	0.5%	7.0%	2.8%	21.8%	
	% within priority	13.6%	14.1%	14.1%	14.4%	14.2%	14.4%	13.9%	14.5%	
Tuesday	Count	343	6,215	11,991	11,797	239	3,309	1,409	9,475	**44,778**
	% within day of week	0.8%	13.9%	26.8%	26.3%	0.5%	7.4%	3.1%	21.2%	
	% within priority	14.7%	13.8%	14.1%	14.0%	14.2%	15.0%	15.4%	13.9%	
Wednesday	Count	312	6,339	12,288	11,943	239	3,286	1,364	9,567	**45,338**

	% within day of week	0.7%	14.0%	27.1%	26.3%	0.5%	7.2%	3.0%	21.1%	
	% within priority	13.4%	14.1%	14.4%	14.1%	14.2%	14.9%	14.9%	14.0%	
Thursday	Count	311	6,335	12,719	11,652	246	3,382	1,457	9,949	**46,051**
	% within day of week	0.7%	13.8%	27.6%	25.3%	0.5%	7.3%	3.2%	21.6%	
	% within priority	13.4%	14.1%	14.9%	13.8%	14.6%	15.3%	16.0%	14.6%	
Friday	Count	328	6,678	12,967	12,296	226	3,434	1,359	10,359	**47,647**
	% within day of week	0.7%	14.0%	27.2%	25.8%	0.5%	7.2%	2.9%	21.7%	
	% within priority	14.1%	14.9%	15.2%	14.6%	13.5%	15.6%	14.9%	15.2%	
Saturday	Count	336	6,654	12,065	12,373	265	2,920	1,095	9,896	**45,604**
	% within day of week	0.7%	14.6%	26.5%	27.1%	0.6%	6.4%	2.4%	21.7%	
	% within priority	14.4%	14.8%	14.2%	14.7%	15.8%	13.2%	12.0%	14.5%	

Figure 5.3.4E demonstrates that, for both years, the highest number of Priority 1 calls were received on Sundays (approximately 16 percent of Priority 1 calls), the highest number of Priority 2 and Priority 3 calls were received on Fridays (approximately 15 percent of both Priority 2 and Priority 3 calls), and the highest number of Priority 4 calls were received on Fridays (approximately 15 percent of Priority 4 calls). These findings are partially consistent with the hypothesis that 911 call volumes are highest on weekends.

Appendix 5A: Detroit open data

Part 1: CAD events

Part 1 examines all CAD events, including both 911 calls for service and officer-initiated events.

Figure 5.3 5A: Detroit CAD entries, broken down by priority level[1]

	2017		2018	
Priority level	Frequency	Percentage	Frequency	Percentage
1	63,769	10.5%	75,557	9.4%
2	204,614	33.6%	257,582	32.2%
3	288,632	47.4%	416,544	52.0%
4	45,637	7.5%	42,789	5.3%
5	5,871	1.0%	7,395	0.9%
9	1	0.0	0.0%	0.0%
Missing	575	0.1%	477	0.1%

[1] Priority 1-2 calls are defined as imminent danger or life-threatening emergency, and Priority 3-6 calls are defined as quality of life and public need calls. No definition was provided for Priority 9 calls.

Figure 5.3.5A shows that the most frequently occurring priority level across all CAD activities was Priority 3, a finding consistent with the hypothesis that most calls are unrelated to a crime in progress.

Figure 5.3 5B: Detroit CAD entries, broken down by day of week

	2017		2018	
Day	Frequency	Percentage	Frequency	Percentage
Sunday	80,463	13.2%	98,615	12.3%
Monday	86,571	14.2%	112,785	14.1%
Tuesday	89,171	14.6%	118,375	14.8%
Wednesday	91,086	15.0%	123,704	15.5%
Thursday	88,767	14.6%	120,074	15.0%
Friday	89,775	14.7%	119,263	14.9%
Saturday	83,266	13.7%	107,528	13.4%

Figure 5.3.5B shows that, for both years, the highest number of CAD entries were logged on Wednesdays, a finding inconsistent with the hypothesis that 911 call volume concentrates on weekends.

Figure 5.3 5C: Detroit CAD entries, broken down by hour of day

	2017		2018	
Hour	Frequency	Percentage	Frequency	Percentage
0	23,858	3.9%	32,538	4.1%
1	21,439	3.5%	23,789	3.0%
2	17,997	3.0%	20,884	2.6%
3	15,360	2.5%	18,705	2.3%
4	13,969	2.3%	15,862	2.0%
5	12,631	2.1%	13,541	1.7%
6	12,103	2.0%	13,230	1.7%
7	16,058	2.6%	26,379	3.3%
8	22,095	3.6%	31,230	3.9%
9	25,271	4.1%	31,018	3.9%
10	28,016	4.6%	35,246	4.4%
11	29,681	4.9%	40,651	5.1%
12	30,584	5.0%	42,102	5.3%
13	31,000	5.1%	43,070	5.4%
14	29,439	4.8%	40,759	5.1%
15	31,861	5.2%	50,929	6.4%
16	37,068	6.1%	52,103	6.5%
17	36,568	6.0%	44,899	5.6%
18	33,043	5.4%	40,844	5.1%
19	30,520	5.0%	38,068	4.8%
20	29,616	4.9%	37,729	4.7%
21	28,848	4.7%	37,752	4.7%
22	26,994	4.4	33,825	4.2
23	25,080	4.1%	35,191	4.4%

Figure 5.3.5C shows that in 2017, the highest frequency of CAD entries took place during the 4:00 p.m. hour (Hour 16), whereas in 2018, the highest frequency of CAD entries took place during the 3:00 p.m. hour (Hour 15). This is inconsistent with the hypothesis that 911 call volumes are highest at night.

Part 2: Further analyses of priority levels

The following section provides a more in-depth look at how call volumes across different contexts (e.g., hour of day, day of week, and incident type) are parsed out by priority levels.

Figure 5.3 6A: Detroit call types, broken down by priority level

2017							
	Priority level	1	2	3	4	5	Missing
Call type	Total	63,769	204,614	288,632	45,637	5,871	575
911/phone calls (CFS)	Frequency	61,876	128,038	125,738	10,313	2,587	424

	% within call type	18.8%	38.9%	38.2%	3.1%	0.8%	0.1%
	% within priority	97.0%	62.6%	43.6%	22.6%	44.1%	73.7%
Officer-initiated	Frequency	1,893	76,576	162,894	35,324	3,284	151
	% within call type	0.7%	27.3%	58.2%	12.6%	1.2%	0.1%
	% within priority	3.0%	37.4%	56.4%	77.4%	55.9%	26.3%
2018							
	Priority level	1	2	3	4	5	Missing
Call type	Total	75,557	257,582	416,544	42,789	7,395	477
911/phone calls (CFS)	Frequency	73,848	119,910	116,651	8,197	2,500	322
	% within call type	23.0%	37.3%	36.3%	2.6%	0.8%	0.1%
	% within priority	97.7%	46.6%	28.0%	19.2%	33.8%	67.5%
Officer-initiated	Frequency	1,709	137,672	299,893	34,592	4,895	155
	% within call type	0.4%	28.7%	62.6%	7.2%	1.0%	0.0%
	% within priority	2.3%	53.4%	72.0%	80.8%	66.2%	32.5%

Figure 5.3.6A shows that, although most calls for service were classified as Priority 2 or 3 in both years, the majority of self-initiated activity was classified as Priority 3. These findings are consistent with Vera's hypothesis that the majority of calls do not involve incidents in progress and/or active emergencies.

Figure 5.3 6B: Detroit incident types, broken down by priority level

2017							
Incident type	Priority	1	2	3	4	5	Missing
	Total count	63,769	204,614	288,632	45,637	5,871	575
Assault and battery	Frequency	289	30,281	0	0	0	1
	% within incident	0.9%	99.1%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.5%	14.8%	0.0%	0.0%	0.0%	0.2%
Auto accident injury unknown	Frequency	66	10,526	0	0	0	0
	% within incident	0.6%	99.4%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.1%	5.1%	0.0%	0.0%	0.0%	0.0%
Bus boarding	Frequency	0	0	13,244	0	0	0
	% within incident	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	4.6%	0.0%	0.0%	0.0%
Disturbance	Frequency	2,644	92	49,040	1	0	1
	% within incident	5.1%	0.2%	94.7%	0.0%	0.0%	0.0%
	% within priority	4.1%	0.0%	17.0%	0.0%	0.0%	0.2%
Felonious IP	Frequency	14,810	370	0	1	0	0
	% within incident	97.6%	2.4%	0.0%	0.0%	0.0%	0.0%
	% within priority	23.2%	0.2%	0.0%	0.0%	0.0%	0.0%
Investigate person	Frequency	250	67	28,566	0	0	0
	% within incident	0.9%	0.2%	98.9%	0.0%	0.0%	0.0%

	% within priority	0.4%	0.0%	9.9%	0.0%	0.0%	0.0%
Larceny report	Frequency	4	2	1	12,773	0	0
	% within incident	0.0%	0.0%	0.0%	99.9%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	28.0%	0.0%	0.0%
Remarks	Frequency	0	17	12,150	0	0	1
	% within incident	0.0%	0.1%	99.9%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	4.2%	0.0%	0.0%	0.2%
Special attention	Frequency	0	0	80,648	0	0	0
	% within incident	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	27.9%	0.0%	0.0%	0.0%
Vehicle tow	Frequency	0	0	25,014	0	0	0
	% within incident	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	8.7%	0.0%	0.0%	0.0%
Traffic stop	Frequency	0	67,052	0	0	0	0
	% within incident	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	32.8%	0.0%	0.0%	0.0%	0.0%
Unknown problem	Frequency	303	24,678	0	1	0	1
	% within incident	1.2%	98.8%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.5%	12.1%	0.0%	0.0%	0.0%	0.2%
2018							
Incident type	**Priority**	**1**	**2**	**3**	**4**	**5**	**Missing**
	Total count	22657	289530	327849	12967	1	16
Assault and battery	Frequency	595	25,335	0	0	0	0
	% within incident	2.3%	97.7%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.8%	9.8%	0.0%	0.0%	0.0%	0.0%
Auto accident injury unknown	Frequency	122	10,304	0	0	0	1
	% within incident	1.2%	98.8%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.2%	4.0%	0.0%	0.0%	0.0%	0.2%
Disturbance	frequency	4,809	14	46,893	0	0	2
	% within incident	9.3%	0.0%	90.7%	0.0%	0.0%	0.0%
	% within priority	6.4%	0.0%	11.3%	0.0%	0.0%	0.4%
Felonious IP	Frequency	15,830	280	0	0	0	0
	% within incident	98.3%	1.7%	0.0%	0.0%	0.0%	0.0%
	% within priority	21.0%	0.1%	0.0%	0.0%	0.0%	0.0%
Instigate person	Frequency	416	29	30,649	0	0	2
	% within incident	1.3%	0.1%	98.6%	0.0%	0.0%	0.0%
	% within priority	0.6%	0.0%	7.4%	0.0%	0.0%	0.4%
Larceny report	Frequency	3	0	1	12,967	0	0
	% within incident	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	30.3%	0.0%	0.0%
Remarks	Frequency	1	8	49,649	0	1	5

	% within incident	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	11.9%	0.0%	0.0%	1.0%
Special attention	Frequency	0	0	118,165	0	0	1
	% within incident	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	28.4%	0.0%	0.0%	0.2%
Start of shift	Frequency	0	0	58,252	0	0	3
	% within incident	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	14.0%	0.0%	0.0%	0.6%
Vehicle tow	Frequency	0	0	24,240	0	0	0
	% within incident	0.0%	0.0%	100.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	5.8%	0.0%	0.0%	0.0%
Traffic stop	Frequency	0	128,347	0	0	0	0
	% within incident	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	49.8%	0.0%	0.0%	0.0%	0.0%
Unknown problem	Frequency	881	25,213	0	0	0	2
	% within incident	3.4%	96.6%	0.0%	0.0%	0.0%	0.0%
	% within priority	1.2%	9.8%	0.0%	0.0%	0.0%	0.4%

[1] Priority 9 is unlisted because there was only one case in 2017 and none in 2018, was removed from this table.

Figure 5.3.6B demonstrates that, in both years, the highest number of calls classified as Priority 1 were related to felonious assaults (46 percent in 2017 and 41 percent in 2018); most calls classified as Priority 2 were traffic stops (41.8 percent in 2017 and 62.4 percent in 2018); the greatest frequency of Priority 3 calls were classified as special attention (37.8 percent in 2017 and 35.1 percent in 2018); and most Priority 4 calls were larceny reports (57.7 percent in 2017 and 61.9 percent in 2018). There were no priority 5 calls logged in 2017, but nearly 100 percent of those logged in 2018 were classified as investigate auto.

Figure 5.3 6C: Detroit calls volumes on different days of the week, broken down by priority level

2017							
Day of the week	Priority	1	2	3	4	5	Missing
	Total	63,769	204,614	288,632	45,637	5,871	575
Sunday	Frequency	9,719	27,934	36,945	5,152	653	60
	% within day of week	15.2%	13.7%	12.8%	11.3%	11.1%	10.4%
	% within priority	12.1%	34.7%	45.9%	6.4%	0.8%	0.1%
Monday	Frequency	8,767	28,186	41,227	7,464	835	91
	% Within Day of Week	13.7%	13.8%	14.3%	16.4%	14.2%	15.8%
	% within priority	10.1%	32.6%	47.6%	8.6%	1.0%	0.1%
Tuesday	Frequency	8,701	29,165	43,005	7,308	892	100
	% within day of week	13.6%	14.3%	14.9%	16.0%	15.2%	17.4%
	% within priority	9.8%	32.7%	48.2%	8.2%	1.0%	0.1%
Wednesday	Frequency	8,916	29,989	44,177	6,967	933	104
	% within day of week	14.0%	14.7%	15.3%	15.3%	15.9%	18.1%

	% within priority	9.8%	32.9%	48.5%	7.6%	1.0%	0.1%
Thursday	Frequency	8,787	29,396	42,878	6,716	918	72
	% within day of week	13.8%	14.4%	14.9%	14.7%	15.6%	12.5%
	% within priority	9.9%	33.1%	48.3%	7.6%	1.0%	0.1%
Friday	Frequency	9,174	30,781	42,205	6,639	881	95
	% within day of week	14.4%	15.0%	14.6%	14.5%	15.0%	16.5%
	% within priority	10.2%	34.3%	47.0%	7.4%	1.0%	0.1%
Saturday	Frequency	9,705	29,163	38,195	5,391	759	53
	% within day of week	15.2%	14.3%	13.2%	11.8%	12.9%	9.2%
	% within priority	11.7%	35.0%	45.9%	6.5%	0.9%	0.1%
2018							
Day of the Week	Priority	1	2	3	4	5	Missing
	Total	75,557	257,582	416,544	42,789	7,395	477
Sunday	Frequency	11,471	30,763	50,652	4,823	861	45
	% within day of week	15.2%	11.9%	12.2%	11.3%	11.6%	9.4%
	% within priority	11.6%	31.2%	51.4%	4.9%	0.9%	0.0%
Monday	Frequency	10,730	34,675	58,946	7,252	1,071	111
	% within day of week	14.2%	13.5%	14.2%	16.9%	14.5%	23.3%
	% within priority	9.5%	30.7%	52.3%	6.4%	0.9%	0.1%
Tuesday	Frequency	10,209	37,641	62,611	6,721	1,116	77
	% within day of week	13.5%	14.6%	15.0%	15.7%	15.1%	16.1%
	% within priority	8.6%	31.8%	52.9%	5.7%	0.9%	0.1%
Wednesday	Frequency	10,166	40,504	65,302	6,474	1,191	67
	% within day of week	13.5%	15.7%	15.7%	15.1%	16.1%	14.0%
	% within priority	8.2%	32.7%	52.8%	5.2%	1.0%	0.1%
Thursday	Frequency	10,452	39,441	62,847	6,184	1,096	54
	% within day of week	13.8%	15.3%	15.1%	14.5%	14.8%	11.3%
	% within priority	8.7%	32.8%	52.3%	5.2%	0.9%	0.0%
Friday	Frequency	10,751	39,051	62,041	6,243	1,103	74
	% within day of week	14.2%	15.2%	14.9%	14.6%	14.9%	15.5%
	% within priority	9.0%	32.7%	52.0%	5.2%	0.9%	0.1%
Saturday	Frequency	11,778	35,507	54,145	5,092	957	49
	% within day of week	15.6%	13.8%	13.0%	11.9%	12.9%	10.3%
	% within priority	11.0%	33.0%	50.4%	4.7%	0.9%	0.0%

Figure 5.3.6C demonstrates that, in both years, the highest number of Priority 1 calls were received on Saturdays and Sundays; the highest number of Priority 2 and 3 calls were received on Wednesdays, with the exception of Priority 2 calls in 2017, of which there were slightly more on Fridays. In both 2017 and 2018, the highest frequency of Priority 4 calls occurred on Mondays, and most of the Priority 5 calls were received on Tuesdays. These findings are partially consistent with the hypothesis that 911 call volumes are highest on the weekends.

Appendix 5B: New Orleans open data

Part 1 CAD events

Part 1 examines all CAD events, including both 911 calls for service and officer-initiated events.

Figure 5.3.7A: New Orleans CAD Entries broken down by priority level

2016			2017		
Priority level	Frequency	Percent	Priority level	Frequency	Percent
0	21,227	5.3%	0	31,694	7.1%
1	263,317	65.2%	1	309,986	69.8%
2	119,465	29.6%	2	102,321	23.0%
3	56	0.0%	3	109	0.0%

Figure 5.3.7A shows that the majority of calls in both years were labeled Priority 1, which are considered non-emergency calls for service. Priority 3 is considered the highest priority, Priority 2 is designated for emergency calls for service, and Priority 0 calls do not require a police presence.

Figure 5.3.7B: New Orleans CAD entries, broken down by day of week

	2016		2017	
Day	Frequency	Percentage	Frequency	Percentage
Sunday	23,427	14.7%	25,930	14.8%
Monday	20,867	13.1%	22,313	12.8%
Tuesday	25,706	16.1%	28,188	16.1%
Wednesday	20,810	13.0%	22,861	13.1%
Thursday	23,480	14.7%	25,952	14.8%
Friday	23,279	14.6%	24,964	14.3%
Saturday	21,995	13.8%	24,754	14.2%

Figure 5.3.7B shows that, in both years, the highest number of CAD entries were logged on Tuesdays. In 2016, the lowest number of CAD entries were logged on Wednesdays, and in 2017, Mondays saw the lowest number of entries. These results are inconsistent with the hypothesis that 911 call volume concentrates on weekends.

Figure 5.3.7C: New Orleans CAD Entries, broken down by hour of day

	2016		2017	
Hour	Frequency	Percentage	Frequency	Percentage
0	16,091	4.0%	18,771	4.2%
1	13,445	3.3%	15,662	3.5%
2	11,102	2.7%	12,554	2.8%
3	9,222	2.3%	10,944	2.5%
4	8,838	2.2%	9,395	2.1%
5	7,934	2.0%	8,894	2.0%
6	8,610	2.1%	8,607	1.9%

7	12,006	3.0%	12,602	2.8%
8	15,857	3.9%	17,327	3.9%
9	17,229	4.3%	18,720	4.2%
10	18,143	4.5%	19,728	4.4%
11	19,354	4.8%	21,379	4.8%
12	20,470	5.1%	22,529	5.1%
13	20,351	5.0%	22,348	5.0%
14	19,120	4.7%	20,116	4.5%
15	21,441	5.3%	23,233	5.2%
16	23,741	5.9%	25,513	5.7%
17	23,518	5.8%	25,299	5.7%
18	21,474	5.3%	23,958	5.4%
19	20,110	5.0%	23,420	5.3%
20	20,870	5.2%	23,155	5.2%
21	20,669	5.1%	21,976	4.9%
22	17,992	4.5%	18,692	4.2%
23	16,478	4.1%	19,289	4.3%

Figure 5.3.7C shows that, in both years, the highest frequency of CAD entries took place at the 4:00 p.m. and 5:00 p.m. hours (Hours 16 and 17, respectively). This is inconsistent with the hypothesis that 911 call volumes are highest during the night. In both years, the lowest number of entries took place during the 5:00 a.m. and 6:00 a.m. hours (Hours 5 and 6).

Figure 5.3.7D: New Orleans CAD entries, broken down by geographic sector

	2016		2017	
Sector	Frequency	Percentage	Frequency	Percentage
0	912	0.2%	2,330	1%
1	55,184	13.7%	61,364	14%
2	41,412	10.2%	46,934	11%
3	65,548	16.2%	70,843	16%
4	34,265	8.5%	41,547	9%
5	41,030	10.2%	45,441	10%
6	47,892	11.9%	58,817	13%
7	57,657	14.3%	56,471	13%
8	60,165	14.9%	60,364	14%

Figure 5.3.7D shows that, in both years, sector 3 had the highest number of CAD entries.

Part 2 Further analyses of priority levels

The following section provides a more in-depth look at how call volumes across different contexts (e.g., hour of day, day of week, and incident type) are parsed out by priority levels. Code 3 is considered the highest priority and is reserved for officer needs assistance. Code 2 calls are considered "emergency" calls for service. Code 1 calls are considered "non-emergency" calls for service. Code 0 calls do not require a police presence. In practice, NOPD priorities are further differentiated using a letter designation, with "A" being the highest priority within that level, but, sub-priorities containing letters were collapsed into their corresponding number categories for the purposes of this analysis.

Figure 5.3.8A: New Orleans call types, broken down by priority level

2016						2017					
Priority level		0	1	2	3	Priority level		0	1	2	3
Total		21,226	263,282	119,453	56	Total		31,643	309,968	102,310	109
Phone (CFS)	Count	12,700	187,322	114,146	196	Phone (CFS)	Count	19,006	209,467	96,746	107
	% within call type	4.0%	59.6%	36.4%	0.1%		% within call type	5.8%	64.4%	29.8%	0.0%
	% within priority	59.8%	71.2%	95.6%	97.0%		% within priority	60.1%	67.6%	94.6%	98.2%
Self-initiated	Count	8,526	75,960	5,307	6	Self-initiated	Count	12,637	100,519	5,564	2
	% within call type	9.5%	84.6%	5.9%	0.0%		% within call type	10.6%	84.7%	4.7%	0.0%
	% within priority	40.2%	28.9%	4.4%	3.0%		% within priority	40.0%	32.4%	5.4%	1.8%

Figure 5.3.8A shows that, in both years, most CAD entries for each priority level were calls for service.

Figure 5.3.8B: New Orleans incident types, broken down by priority level[2]

2016					2017				
Priority level		0	1	2	Priority level		0	1	2
Total		21,227	263,317	119,465	Total		31,694	309,986	102,321
Complaint other	Count	108	89,225	9,669	Complaint other	Count	163	79,238	8,476
	% within call type	0.1%	90.1%	9.8%		% within call type	0.2%	90.2%	9.7%
	% within priority	0.5%	33.9%	8.09%		% within priority	0.5%	25.6%	8.3%
Burglar alarm	Count	1	16,374	28,586	Burglar alarm	Count	15	17,353	18,023
	% within call type	0.0%	36.4%	63.6%		% within call type	0.0%	49.0%	50.9%
	% within priority	0.0%	6.2%	23.9%		% within priority	0.1%	5.6%	17.6%
Disturbance (other)	Count	0	19,553	10,379	Disturbance (other)	Count	3	20,759	7,039
	% within call type	0.0%	65.3%	34.7%		% within call type	0.0%	74.7%	25.3%
	% within priority	0.0%	7.4%	8.7%		% within priority	0.0%	6.7%	6.9%

Auto accident	Count	1	14,044	7,620	Auto accident	Count	0	14,806	6,601
	% within call type	0.0%	64.8%	35.2%		% within call type	0.0%	69.2%	30.8%
	% within priority	0.0%	5.3%	6.4%		% within priority	0.0%	4.8%	6.5%
Traffic incident	Count	2	36,500	1,629	Traffic incident	Count	0	42,831	1,551
	% within call type	0.0%	95.72%	1.36%		% within call type	0.0%	96.5%	3.5%
	% within priority	0.0%	13.86%	1.36%		% within priority	0.0%	13.8%	1.5%
Suspicious person	Count	0	2,746	13,339	Suspicious person	Count	0	3,796	12,216
	% within call type	0.0%	17.1%	82.9%		% within call type	0.0%	23.7%	76.3%
	% within priority	0.0%	1.0%	11.2%		% within priority	0.0%	1.2%	11.9%
Domestic disturbance	Count	0	3,219	7,312	Domestic disturbance	Count	0	3,544	8,014
	% within call type	0.0%	30.6%	69.4%		% within call type	0.0%	30.7%	69.3%
	% within priority	0.0%	1.2%	6.1%		% within priority	0.0%	1.1%	7.8%
Hit and run	Count	2	7,918	1,305	Hit and run	Count	3	8,341	1,060
	% within call type	0.0%	85.83%	14.15%		% within call type	0.03%	88.70%	11.27%
	% within priority	0.0%	3.0%	1.1%		% within priority	0.01%	2.69%	1.04%
Mental health	Count	0	1,592	3,685	Mental health	Count	0	1423	3873
	% within call type	0.0%	30.2%	69.8%		% within call type	0.00%	26.87%	73.13%
	% within priority	0.0%	0.6%	3.1%		% within priority	0.00%	0.46%	3.79%
	Count	12,697	12	0		Count	18793	9	0

Warr with stop release	% within call type	99.9%	0.1%	0.0%	Warr with stop release	% within call type	99.95%	0.05%	0.00%
	% within priority	59.8%	0.0%	0.0%		% within priority	59.30%	0.00%	0.00%
Medical, including sexual assault kit	Count	0	225	6,199	Medical, including sexual assault kit	Count	0	433	6497
	% within call type	0.00%	3.50%	96.5%		% within call type	0.00%	6.25%	93.75%
	% within priority	0.0%	0.1%	5.2%		% within priority	0.00%	0.14%	6.35%
Silent 911	Count	0	178	4,016	Silent 911	Count	0	388	2731
	% within call type	0.0%	4.2%	95.8%		% within call type	0.00%	12.44%	87.56%
	% within priority	0.0%	0.1%	3.4%		% within priority	0.00%	0.13%	2.67%
Return for additional info	Count	94	8,885	9	Return for additional info	Count	219	12925	4
	% within call type	1.1%	98.9%	0.1%		% within call type	1.67%	98.30%	0.03%
	% within priority	0.4%	3.4%	0.0%		% within priority	0.69%	4.17%	0.00%
Domestic battery (simple and aggravated)	Count	1	1,362	3,003	Domestic battery (simple and aggravated)	Count	2	1370	3447
	% within call type	0.0%	31.2%	68.8%		% within call type	0.0%	28.4%	71.5%
	% within priority	0.0%	0.5%	2.5%		% within priority	0.0%	0.4%	3.4%
Simple battery	Count	3	3,018	947	Simple battery	Count	2	3,548	704
	% within call type	0.1%	76.1%	23.9%		% within call type	0.1%	83.4%	16.6%
	% within priority	0.0%	1.2%	0.8%		% within priority	0.0%	1.1%	0.7%
	Count	116	3,971	219		Count	619	3,079	157

Simple criminal damage	% within call type	2.7%	92.2%	5.1%	Simple criminal damage	% within call type	16.1%	79.9%	4.1%
	% within priority	0.6%	1.5%	0.2%		% within priority	2.0%	1.0 %	0.2%
Noise complaint	Count	0	4,063	2	Noise complaint	Count	0	4,565	5
	% within call type	0.0%	99.9%	0.1%		% within call type	0.0%	99.9%	0.1%
	% within priority	0.00%	1.5%	0.0%		% within priority	0.0%	1.5%	0.0%
Lost property	Count	4,637	80	1	Lost property	Count	3,823	72	0
	% within call type	98.3%	1.7%	0.0%		% within call type	98.2%	1.9%	0.0%
	% within priority	21.8%	0.0%	0.0%		% within priority	12.1%	0.0%	0.0%
Theft (including Auto)	Count	1,999	10,155	255	Theft (including auto)	Count	5,422	6,934	206
	% within call type	16.1%	81.8%	2.1%		% within call type	43.2%	55.2%	1.6%
	% within priority	9.4%	3.9%	0.2%		% within priority	17.1%	2.2%	0.2%
All other crimes	Count	1,566	40,197	21,290	All other crimes	Count	2,630	52,386	21,717
	% within call type	2.5%	63.8%	33.8%		% within call type	3.4%	68.3%	28.3%
	% within priority	7.4%	15.3%	17.8%		% within priority	8.3%	16.9%	21.2%
N/A					Area and business check	Count	0	32,186	0
						% within call type	0.0%	100.0%	0.0%
						% within priority	0.0%	10.4%	0.0%

[2] Priority 3 calls are not included in this table. There were 56 in 2016 and 109 in 2017, and they were all coded as Officer Needs Assistance, Life in Danger.

Figure 5.3.8B demonstrates that the highest volume of calls classified as Priority 2 was related to burglar alarms (23.93 percent in 2016, 17.61 percent in 2017); the highest number of calls classified as Priority 1 were related to complaints (33.89 percent in 2016, 25.56 percent in 2017); the highest volume of calls classified as Priority 0 were coded as warr (i.e., warrant) with stop release (approximately 59 percent in both years). The decline in Priority 1 complaints may be due to the newly added categories of area and business checks, which accounted for roughly 10 percent of Priority 1 calls in 2017.

Figure 5.3.8C: New Orleans call types, broken down by day[3]

2016					2017				
Day of Week	Priority Level	0	1	2	Day of Week	Priority Level	0	1	2
	Total	21,226	263,282	119,453		Total	31,643	272,625	102,310
Sunday	Count	1,278	15,472	6,675	Sunday	Count	1,950	15,897	5,972
	% within call type	5.5%	66.1%	28.5%		% within call type	8.2%	66.7%	25.1%
	% within priority	6.0%	5.9%	5.6%		% within priority	6.2%	5.8%	5.8%
Monday	Count	1,038	13,733	6,091	Monday	Count	1,537	13,584	5,211
	% within call type	5.0%	65.8%	29.2%		% within call type	7.6%	66.8%	25.6%
	% within priority	4.9%	5.2%	5.1%		% within priority	4.9%	5.0%	5.1%
Tuesday	Count	1,223	16,720	7,744	Tuesday	Count	2,076	17,141	6,600
	% within call type	4.8%	65.1%	30.1%		% within call type	8.0%	66.4%	25.6%
	% within priority	5.8%	6.4%	6.5%		% within priority	6.6%	6.3%	6.5%
Wednesday	Count	1,184	13,593	6,029	Wednesday	Count	1,682	14,148	5,150
	% within call type	5.7%	65.3%	29.0%		% within call type	8.0%	67.4%	24.5%
	% within priority	5.6%	5.2%	5.1%		% within priority	5.3%	5.2%	5.0%
Thursday	Count	1,209	15,245	7,024	Thursday	Count	1,877	16,106	5,953
	% within call type	5.2%	64.9%	29.9%		% within call type	7.8%	67.3%	24.9%
	% within priority	5.7%	5.8%	5.9%		% within priority	5.9%	5.9%	5.8%
Friday	Count	1,226	14,892	7,154	Friday	Count	1,754	15,238	5,932
	% within call type	5.3%	64.0%	30.7%		% within call type	7.7%	66.5%	25.9%
	% within priority	5.8%	5.7%	6.0%		% within priority	5.5%	5.6%	5.8%
Saturday	Count	1,137	13,958	6,899	Saturday	Count	1,843	15,450	5,606
	% within call type	5.2%	63.5%	31.4%		% within call type	8.1%	67.5%	24.5%

	% within priority	5.4%	5.3%	5.8%		% within priority	5.8%	5.7%	5.5%

[3] Data on the small sample of priority 3 calls was excluded from this analysis.

Figure 5.3.8C demonstrates that, in both years, high numbers of Priority 2, Priority 1, and Priority 0 calls were received on Tuesdays, though in 2016, a slightly higher number of Priority 0 calls were received on Sundays. These findings are partially consistent with the hypothesis that 911 call volumes are highest on weekends.

Appendix 5C: Seattle open data

Part 1 CAD events

Part 1 examines all CAD events, including both 911 calls for service and officer-initiated events.

Figure 5.3.9A: Seattle CAD entries, broken down by priority level[1]

	2016		2017	
Priority	Frequency	Percentage	Frequency	Percentage
1	49,587	6.0%	50,664	6.1%
2	95,221	11.4%	97,955	11.8%
3	142,512	17.1%	139,604	16.8%
4	10,941	1.3%	10,678	1.3%
5	9,568	1.1%	8,950	1.1%
6	2,282	0.3%	1,458	0.2%
7	72,090	8.7%	89,878	10.8%
8	0	0.0%	1	0.0%
9	25,962	3.1%	25,993	3.1%

[1] Priority 1 calls are urgent incidents that pose obvious danger to the life of a citizen or officer; Priority 2 calls are urgent altercations that could develop into more serious situations if not policed quickly; Priority 3 refers to matters requiring prompt attention, such as investigations or minor incident complaints in which response time is not critical; Priority 4 incidents are mischief or nuisance complaints; Priority 5 incidents are calls handled by officers assigned to the internet/telephone reporting unit; Priority 6 incidents are call events handled by call-takers assigned in the communications sections; Priority 7 incidents are officer initiated call events for proactive work, including traffic stops, suspicious stops, premise checks, and directed patrol activities. No definitions were provided for Priority Levels 8 or 9.

Figure 5.3.9A demonstrates that, in both 2016 and 2017, the Priority 3 call volume was highest, followed by Priority 2. This is consistent with the hypothesis that the majority of calls are not made regarding in-progress events and that the majority of calls are for non-emergency incidents.

Figure 5.3.9B: Seattle CAD entries broken down by day of week

	2016		2017	
Day of week	Frequency	Percentage	Frequency	Percentage
Sunday	48,740	5.8%	52,959	6.4%
Monday	57,393	6.9%	59,315	7.1%
Tuesday	60,812	7.3%	62,216	7.5%
Wednesday	60,417	7.2%	63,441	7.6%
Thursday	60,515	7.3%	63,353	7.6%
Friday	63,193	7.6%	65,522	7.9%
Saturday	57,093	6.9%	58,375	7.0%

Figure 5.3.9B demonstrates that the majority of calls for 2016 and 2017 occurred on Fridays. There is minimal variation in call volume between Monday and Saturday. In both 2016 and 2017, the majority of calls took place on Fridays. While in 2016, the second most frequent days

calls were received was on Tuesdays. In 2017, Wednesdays had the second largest number of calls.

Figure 5.3.9C: Seattle CAD entries broken down by hour of day

	2016		2017	
Hour	Frequency	Percentage	Frequency	Percentage
0	13,275	3.3%	14,229	3.3%
1	11,928	2.9%	12,839	3.0%
2	9,902	2.4%	10,358	2.4%
3	7,164	1.8%	7,136	1.7%
4	9,336	2.3%	10,028	2.4%
5	7,694	1.9%	8,524	2.0%
6	9,877	2.4%	9,894	2.3%
7	16,985	4.2%	16,787	3.9%
8	17,224	4.2%	17,704	4.2%
9	19,447	4.8%	19,842	4.7%
10	19,932	4.9%	20,036	4.7%
11	20,862	5.1%	21,485	5.1%
12	24,557	6.0%	26,069	6.1%
13	23,991	5.9%	25,548	6.0%
14	22,009	5.4%	23,140	5.4%
15	23,783	5.8%	24,573	5.8%
16	25,425	6.2%	25,326	6.0%
17	20,796	5.1%	20,865	4.9%
18	18,454	4.5%	19,065	4.5%
19	16,306	4.0%	17,828	4.2%
20	18,638	4.6%	20,109	4.7%
21	17,920	4.4%	19,058	4.5%
22	17,300	4.2%	18,602	4.4%
23	15,358	3.8%	16,136	3.8%

Figure 5.3.9C demonstrates that the call volume is highest during the 4:00 p.m. hour (Hour 16) in both years followed by noon and 1:00 p.m. (Hours 12 and 13, respectively). This does not support the hypothesis that the majority of calls are placed during the evening and overnight. Call volume variation is minimal between from 8am to 11 pm (Hour 23).

Part 2: Further analyses of priority levels

The following section provides a more in-depth look at how call volumes across different contexts (e.g., hour of day, day of week, and incident type) are parsed out by priority levels.

Figure 5.3.10A: Seattle call types, broken down by priority level

2016									
Call type	Priority	1	2	3	4	5	6	7	9
911	Frequency	38,629.0	64,502.0	37,612.0	2,232.0	729.0	129.0	0.0	1.0
	% within call type	26.9%	44.8%	26.1%	1.6%	0.5%	0.1%	0.0%	0.0%
	% within priority	77.9%	67.7%	26.4%	20.4%	7.6%	5.7%	0.0%	0.0%
Alarm call (not police alarm)	Frequency	170.0	2,073.0	10,674.0	3.0	0.0	0.0	0.0	0.0
	% within call type	1.3%	16.0%	82.6%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.3%	2.2%	7.5%	0.0%	0.0%	0.0%	0.0%	0.0%
FK error	Frequency	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
	% within call type	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
In-person complaint	Frequency	1.0	2.0	14.0	0.0	0.0	0.0	0.0	0.0
	% within call type	5.9%	11.8%	82.4%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
On view	Frequency	3,205.0	11,492.0	36,691.0	4,312.0	194.0	0.0	72,069.0	25,652.0
	% within call type	2.1%	7.5%	23.9%	2.8%	0.1%	0.0%	46.9%	16.7%
	% within priority	6.5%	12.1%	25.7%	39.4%	2.0%	0.0%	100.0%	98.8%
Police (Varda) alarm	Frequency	24.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	% within call type	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Proactive (officer-initiated)	Frequency	0.0	2.0	2.0	0.0	0.0	0.0	0.0	0.0
	% within call type	0.0%	50.0%	50.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Scheduled event	Frequency	0.0	3.0	3.0	0.0	0.0	0.0	0.0	0.0
	% within call type	0.0%	50.0%	50.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Telephone (other not 911)	Frequency	7,558.0	17,146.0	57,516.0	4,394.0	8,645.0	2,153.0	21.0	309.0
	% within call type	7.7%	17.5%	58.8%	4.5%	8.8%	2.2%	0.0%	0.3%
	% within priority	15.2%	18.0%	40.4%	40.2%	90.4%	94.3%	0.0%	1.2%
2017									
Call type	**Priority**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**9**
911	Frequency	39,001.0	68,361.0	37,334.0	1,447.0	657.0	64.0	2.0	1.0
	% within call type	26.6%	46.5%	25.4%	1.0%	0.4%	0.0%	0.0%	0.0%
	% within priority	77.0%	69.8%	26.7%	13.6%	7.3%	4.4%	0.0%	0.0%
Alarm call (not police alarm)	Frequency	193.0	2,216.0	11,325.0	8.0	1.0	1.0	0.0	0.0
	% within call type	1.4%	16.1%	82.4%	0.1%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.4%	2.3%	8.1%	0.1%	0.0%	0.1%	0.0%	0.0%
FK error	Frequency	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
	% within call type	0.0%	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
In-person complaint	Frequency	0.0	1.0	5.0	0.0	0.0	0.0	0.0	0.0
	% within call type	0.0%	16.7%	83.3%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
On view	Frequency	3,301.0	11,369.0	34,526.0	4,821.0	21.0	1.0	89,852.0	25,808.0
	% within call type	1.9%	6.7%	20.3%	2.8%	0.0%	0.0%	52.9%	15.2%
	% within priority	6.5%	11.6%	24.7%	45.1%	0.2%	0.1%	100.0%	99.3%
Police (Varda) alarm	Frequency	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	% within call type	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Proactive (officer-initiated)	Frequency	0.0	2.0	3.0	0.0	0.0	0.0	0.0	0.0
	% within call type	0.0%	40.0%	60.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Scheduled event	Frequency	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0
	% within call type	0.0%	50.0%	50.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Telephone (other not 911)	Frequency	8,164.0	16,004.0	56,410.0	4,402.0	8,271.0	1,392.0	24.0	184.0
	% within call type	8.6%	16.9%	59.5%	4.6%	8.7%	1.5%	0.0%	0.2%
	% within priority	16.1%	16.3%	40.4%	41.2%	92.4%	95.5%	0.0%	0.7%

Figure 5.3.10A demonstrates that the in both 2016 and 2017, Priority 2 calls were the highest volume of 911 calls, making up just less than half of the calls. Though Priority 1 and Priority 3 calls each made up approximately 25 percent of calls in 2017, in 2016, there were more than twice as many Priority 1 calls than Priority 3 calls (29 percent and 12 percent, respectively). In any event, the combined high frequency of Priority 2 and 3 calls supports the hypothesis that the majority of calls are made for incidents not involving a crime in progress.

Figure 5.3.10B: Seattle incident types broken down by priority level

2016									
Incident type	Priority	1	2	3	4	5	6	7	9
	Total count	49,587	95,221	142,512	10,941	9,568	2,282	72,090	25,962
Burglary alarm residence	Frequency	6	134	6,247	0	0	0	0	0
	% within incident	0.1%	2.1%	97.8%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.1%	4.4%	0.0%	0.0%	0.0%	0.0%	0.0%
Disturbance	Frequency	1,339	9,598	9,507	0	0	0	0	0
	% within incident	6.5%	46.9%	46.5%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	2.7%	10.1%	6.7%	0.0%	0.0%	0.0%	0.0%	0.0%
Follow-Up	Frequency	41	614	7,058	0	0	0	0	0
	% within incident	0.5%	8.0%	91.5%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.1%	0.6%	5.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Auto collision no injuries	Frequency	54	436	4,681	0	0	0	0	0
	% within incident	1.0%	8.4%	90.5%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.1%	0.5%	3.3%	0.0%	0.0%	0.0%	0.0%	0.0%
Nuisance- mischief	Frequency	3	55	10,309	13	0	0	0	0
	% within incident	0.0%	0.5%	99.3%	0.1%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.1%	7.2%	0.1%	0.0%	0.0%	0.0%	0.0%
Off-duty employment	Frequency	0	0	0	0	0	0	0	14,195
	% within incident	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	54.7%
Premise check- on view	Frequency	0	0	0	0	0	0	39,164	0
	% within incident	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	54.3%	0.0%

Shoplift theft	Frequency	69	5,639	398	1	0	0	0	0
	% within incident	1.1%	92.3%	6.5%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.1%	5.9%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%
Suspicious person	Frequency	551	7,943	16,908	0	0	0	0	0
	% within incident	2.2%	31.3%	66.6%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	1.1%	8.3%	11.9%	0.0%	0.0%	0.0%	0.0%	0.0%
Suspicious stop- on view	Frequency	0	0	0	0	0	0	9,282	0
	% within incident	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	12.9%	0.0%
Traffic stop- on view	Frequency	0	0	0	0	0	0	19,425	0
	% within incident	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	26.9%	0.0%
Trespassing	Frequency	52	9,900	125	0	0	0	0	0
	% within incident	0.5%	98.2%	1.2%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.1%	10.4%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
2017									
Incident type	**Priority**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**9**
	Total count	50,664	97,955	139,604	10,678	8,950	1,458	89,878	25,993
Burglary alarm residence	Frequency	14	97	6,254	0	0	0	0	0
	% Within Incident	0.2%	1.5%	98.3%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.1%	4.5%	0.0%	0.0%	0.0%	0.0%	0.0%
Direct patrol activity	Frequency	0	0	0	0	0	0	14,917	0
	% within incident	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	16.6%	0.0%
Disturbance	Frequency	1,156	10,543	9,093	0	0	0	0	0
	% within incident	5.6%	50.7%	43.7%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	2.3%	10.8%	6.5%	0.0%	0.0%	0.0%	0.0%	0.0%
Follow-up	Frequency	15	507	6,776	0	0	0	0	0
	% within incident	0.2%	6.9%	92.8%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.5%	4.9%	0.0%	0.0%	0.0%	0.0%	0.0%
Nuisance- mischief	Frequency	8	113	10,651	2	0	0	0	0
	% within incident	0.1%	1.0%	98.9%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.0%	0.1%	7.6%	0.0%	0.0%	0.0%	0.0%	0.0%
Off-duty employment	Frequency	0	0	0	0	0	0	0	13,918
	% within incident	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	53.5%
Premise check- on view	Frequency	0	0	1	0	0	0	40,271	0
	% within incident	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	44.8%	0.0%
Shoplift- theft	Frequency	75	5,846	480	1	0	0	0	0
	% within incident	1.2%	91.3%	7.5%	0.0%	0.0%	0.0%	0.0%	0.0%

	% within priority	0.1%	6.0%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%
Suspicious person	Frequency	410	8,241	14,534	3	0	0	0	0
	% within incident	1.8%	35.5%	62.7%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.8%	8.4%	10.4%	0.0%	0.0%	0.0%	0.0%	0.0%
Suspicious stop- on view	Frequency	0	1	0	0	0	0	12,011	0
	% within incident	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	13.4%	0.0%
Traffic stop- on view	Frequency	0	0	0	0	0	0	22,626	0
	% within incident	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%	0.0%
	% within priority	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	25.2%	0.0%
Trespassing	Frequency	61	10,713	131	0	0	0	0	0
	% within incident	0.6%	98.2%	1.2%	0.0%	0.0%	0.0%	0.0%	0.0%
	% within priority	0.1%	10.9%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%

Figure 5.3.10B demonstrates that the highest frequency of total calls is Priority 3, followed by Priority 2, making up over 30 percent and approximately 23 percent of calls respectively, for both 2016 and 2017. And while Priority 2 and 3 calls had a large spread of incident types associated with them, nuisance calls comprise approximately 7 percent of Priority 3 calls in both years, while disturbance made up more than 10 percent of Priority 2 calls in both years. This finding does not support the hypothesis that a majority of calls for service were nuisance-based incidents, whereas the majority of calls being Priority 2 and 3 supports the hypothesis that most calls are not crimes in progress.

Figure 5.3.10C: Seattle day of the week, broken down by priority level

2016									
Day of the week	Priority	1	2	3	4	5	6	7	9
	Total count	49,587	95,221	142,512	10,941	9,568	2,282	72,090	25,962
Sunday	Frequency	7,077	12,231	16,726	1,625	540	304	8,413	1,824
	% within day	14.5%	25.1%	34.3%	3.3%	1.1%	0.6%	17.3%	3.7%
	% within priority	14.3%	12.8%	11.7%	14.9%	5.6%	13.3%	11.7%	7.0%
Monday	Frequency	6,631	13,348	20,738	1,538	1,667	347	9,620	3,504
	% within day	11.6%	23.3%	36.1%	2.7%	2.9%	0.6%	16.8%	6.1%
	% within priority	13.4%	14.0%	14.6%	14.1%	17.4%	15.2%	13.3%	13.5%
Tuesday	Frequency	7,031	13,726	21,239	1,580	1,721	326	10,793	4,396
	% within day	11.6%	22.6%	34.9%	2.6%	2.8%	0.5%	17.7%	7.2%
	% within priority	14.2%	14.4%	14.9%	14.4%	18.0%	14.3%	15.0%	16.9%
Wednesday	Frequency	6,666	13,911	21,183	1,524	1,697	332	10,681	4,423
	% within day	11.0%	23.0%	35.1%	2.5%	2.8%	0.5%	17.7%	7.3%
	% within priority	13.4%	14.6%	14.9%	13.9%	17.7%	14.5%	14.8%	17.0%
Thursday	Frequency	6,964	13,697	21,402	1,451	1,685	326	10,809	4,181
	% within day	11.5%	22.6%	35.4%	2.4%	2.8%	0.5%	17.9%	6.9%
	% within priority	14.0%	14.4%	15.0%	13.3%	17.6%	14.3%	15.0%	16.1%

Friday	Frequency	7,516	14,543	21,677	1,514	1,579	329	11,402	4,633
	% within day	11.9%	23.0%	34.3%	2.4%	2.5%	0.5%	18.0%	7.3%
	% within priority	15.2%	15.3%	15.2%	13.8%	16.5%	14.4%	15.8%	17.8%
Saturday	Frequency	7,702	13,765	19,547	1,709	679	318	10,372	3,001
	% within day	13.5%	24.1%	34.2%	3.0%	1.2%	0.6%	18.2%	5.3%
	% within priority	15.5%	14.5%	13.7%	15.6%	7.1%	13.9%	14.4%	11.6%

Day of the week	Priority	1	2	3	4	5	6	7	9
	Total count	50,664	97,955	139,604	10,678	8,950	1,458	89,878	25,993
Sunday	Frequency	7,546	12,928	17,010	1,641	735	235	10,850	2,014
	% within day	14.2%	24.4%	32.1%	3.1%	1.4%	0.4%	20.5%	3.8%
	% within priority	14.9%	13.2%	12.2%	15.4%	8.2%	16.1%	12.1%	7.7%
Monday	Frequency	6,757	13,540	20,296	1,440	1,581	205	12,101	3,395
	% within day	11.4%	22.8%	34.2%	2.4%	2.7%	0.3%	20.4%	5.7%
	% within priority	13.3%	13.8%	14.5%	13.5%	17.7%	14.1%	13.5%	13.1%
Tuesday	Frequency	6,910	14,066	20,569	1,422	1,514	226	13,317	4,191
	% within day	11.1%	22.6%	33.1%	2.3%	2.4%	0.4%	21.4%	6.7%
	% within priority	13.6%	14.4%	14.7%	13.3%	16.9%	15.5%	14.8%	16.1%
Wednesday	Frequency	6,996	14,410	20,878	1,409	1,460	192	13,652	4,444
	% within day	11.0%	22.7%	32.9%	2.2%	2.3%	0.3%	21.5%	7.0%
	% within priority	13.8%	14.7%	15.0%	13.2%	16.3%	13.2%	15.2%	17.1%
Thursday	Frequency	7,113	14,516	20,937	1,417	1,441	190	13,479	4,260
	% within day	11.2%	22.9%	33.0%	2.2%	2.3%	0.3%	21.3%	6.7%
	% within priority	14.0%	14.8%	15.0%	13.3%	16.1%	13.0%	15.0%	16.4%
Friday	Frequency	7,498	14,703	21,169	1,570	1,431	187	14,170	4,794
	% within day	11.4%	22.4%	32.3%	2.4%	2.2%	0.3%	21.6%	7.3%
	% within priority	14.8%	15.0%	15.2%	14.7%	16.0%	12.8%	15.8%	18.4%
Saturday	Frequency	7,844	13,792	18,745	1,779	788	223	12,309	2,895
	% within day	13.4%	23.6%	32.1%	3.0%	1.3%	0.4%	21.1%	5.0%
	% within priority	15.5%	14.1%	13.4%	16.7%	8.8%	15.3%	13.7%	11.1%

Figure 5.3.10B demonstrates that the highest frequency of calls in both 2016 and 2017 were Priority 3 incidents (more than 30% for each year). This supports the hypothesis that most calls are for non-emergency related events, as Priority 3 events are incidents in which time is not deemed critical. For Priority 1 calls, the highest frequency for both years occurred on Saturdays, whereas Priority 2 calls' highest frequency occurs on Friday. Similarly, for both years, Priority 3 calls had the highest frequency on Fridays. Though this partially supports the hypothesis that the majority of calls occur on weekends, variation across call volume by day is minimal, so it is difficult to support this hypothesis definitively.

Conclusion

After observing section 5.3, which takes a more granular exploration of the descriptive data, it becomes evident that most of the findings in relation to Vera's hypotheses are consistent with what emerged in section 5.2. After observing the descriptive statistics across sites that included priority levels in their data, certain trends emerge. Specifically, across all five sites, the majority of calls are for nonemergency and nonviolent crime-based incidents, which supports the original hypothesis. The hypothesis that the majority of calls occur on weekends, is partially supported across all sites, but consistently the lack of variation over days makes it difficult to fully support this hypothesis. Although there is support for the hypothesis regarding the urgency of most calls, the categorizations of the incidents are sporadic across sites, this leads to an inability to support the hypothesis that the majority of calls for service regard nuisance-based incidents.

Chapter 6: 911 Outcomes Analysis Report

Section 1: Findings

Marilyn Sinkewicz, Frankie Wunschel, and Abdul Rad

The purpose of this section is to inform ongoing efforts of police departments to understand how computer-aided dispatch (CAD) information relates to enforcement outcomes. The analysis focuses on one of the most frequently applied enforcement outcomes—arrest. It provides empirical evidence about potential avenues for optimizing the use of police resources, mental health supports, and other diversion strategies.

Research questions

This study investigates the following research questions:

- Are 911 calls more likely to result in arrest versus other outcomes, such as citations, warrants, summonses, justice system diversion [e.g., social service, program, or community service referral, issuing verbal warnings]? Does this vary by call volume, incident-type, time of day, and geographic location?
- What are the predictors of 911 calls that result in arrest?

Based on the limited extant literature, as well as on expert knowledge, researchers hypothesized that CAD events are less likely to result in arrest if they occur in response to low-level offenses, mental health crises, noncriminal incidents, and nuisance complaints, compared to higher-level incidents, such as violent crimes and domestic violence. See “Findings from the Literature” on page 32.

Data and analytic approach

To examine these questions, researchers from the Vera Institute of Justice (Vera) used data supplied by the research sites—the Camden County Police Department (CCPD), the Tucson Police Department (TPD), and their respective public safety communications agencies. Each site provided data from its Records Management Systems (RMS) about arrests that resulted from CAD events. Researchers then matched RMS data on arrests to CAD data, also provided by the sites. The matched data allowed the estimation of the extent to which CAD-related factors, such as call type, incident type, geographic location, and other variables gathered by call-takers and dispatchers predicted arrest. Both sites supplied RMS and CAD data for 2016 and 2017. The pooled data from both years included 501,851 CAD events for Camden and 850,764 for Tucson, which resulted in 23,718 and 87,339 arrests for Camden and Tucson, respectively. In the future, as more data becomes available, research can explore other CAD event outcomes, such as citations and uses of force, as well as patterns and trends over longer periods of time.

This study took a three-pronged analytic approach, summarized below. A brief overview of the relevant analytic strategy is included in each section of the analysis. Additionally, a detailed description of the overall methodology is provided in Chapter 6.2, Appendix 6B.

1. *Typology of arrests that resulted from CAD events*. In addition to providing descriptive statistics, the researchers constructed a typology that organizes the multitude of arrests for each site into discrete and manageable categories and produces a profile of the representative arrest for each category. This exercise is analogous to the way that botanists organize plants into species to describe meaningful differences among their categories.

2. *Spatial analysis showing the geographic distribution of arrests*. The researchers produced maps for each site, which display the location of the arrests, overlaid with the race/ethnicity of the person arrested and the geographic sector-level call volume.

3. *Predictors of arrest*. Researchers conducted regression analysis to estimate the associations between whether an event resulted in arrest and factors collected by CAD call-takers and dispatchers, including call type, incident type, district, and time of day.

Findings

Cross-Site Comparisons for Camden, NJ and Tucson, AZ

The findings revealed differences between Camden and Tucson. For example:

- From 2016 to 2017, in Camden, the number of CAD events decreased by 19 percent, whereas those events that resulted in arrest increased by 13 percent. The reverse trend occurred in Tucson. Although total CAD events increased by 9 percent, CAD events that resulted in arrest decreased by 13 percent.
- The vast majority of Camden's population was identified as either Hispanic or Black. Tucson's primary race-ethnic groups were white and Hispanic.

Despite important differences between Camden and Tucson, this study showed similar patterns across the two sites. For example, the following findings were consistent:

- Compared to 911 calls, officer-initiated events were more likely to result in arrest.
- Mental health/medical incidents were diverted away from further contact with the justice system to a considerable extent.
- Notably, the likelihood that noncriminal incidents ended in arrest was substantial.
- The time of day that incidents occurred was associated with their likelihood of ending in arrest.

The full results from the Camden and Tucson analyses are presented below, followed by a cross-site summary. The conclusion highlights the key findings, implications for policy and practice, and future directions. The appendices contain tables with supporting data and analysis, as well as a description of the methodology.

Camden County Police Department 911 outcomes analysis

This section begins with a brief overview of the characteristics of CAD events in 2016 and 2017, followed by an analysis of the arrests that resulted from those CAD events. The components include a taxonomy of arrests, maps showing the geographic distribution of arrests, and an analysis of the strength of predictors of arrest in data collected by call-takers and dispatchers.

Characteristics of CAD events

A comprehensive analysis of CAD events is available in previous chapters of this report. The information presented below shows the percentage of CAD events that resulted in arrest as well as the descriptive characteristics of these events including call type, incident type, district, time of day, and neighborhood poverty.

Figure 6.1.1 Camden, NJ: CAD events for 2016 and 2017, by arrest status

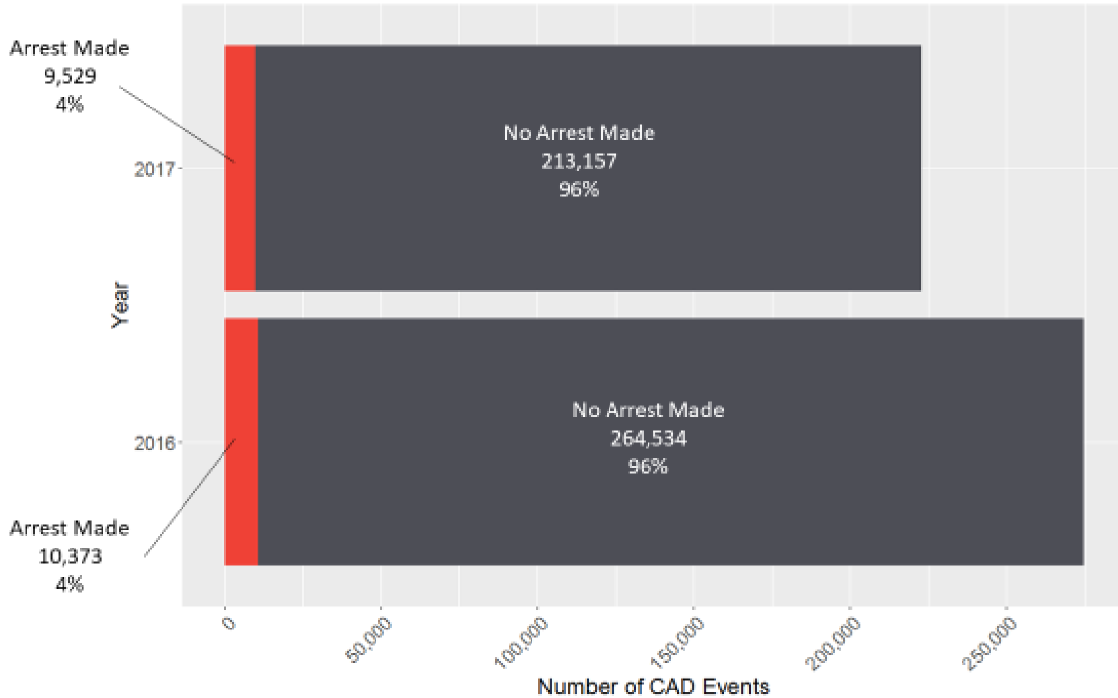

Figure 6.1.1 shows the extent of CAD events in Camden for 2016 (bottom panel) and 2017 (top panel), by arrest status, meaning whether the event resulted in arrest(s). Between 2016 and 2017, total CAD events decreased by 19 percent, from 274,907 to 222,686. However, during the same period, the percentage of CAD events that resulted in arrest(s), 3.8 percent in 2016 and 4.3 percent in 2017, demonstrates an overall increase of 13 percent.

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Figure 6.1.2. Camden, NJ: CAD events for 2016 and 2017, by call type

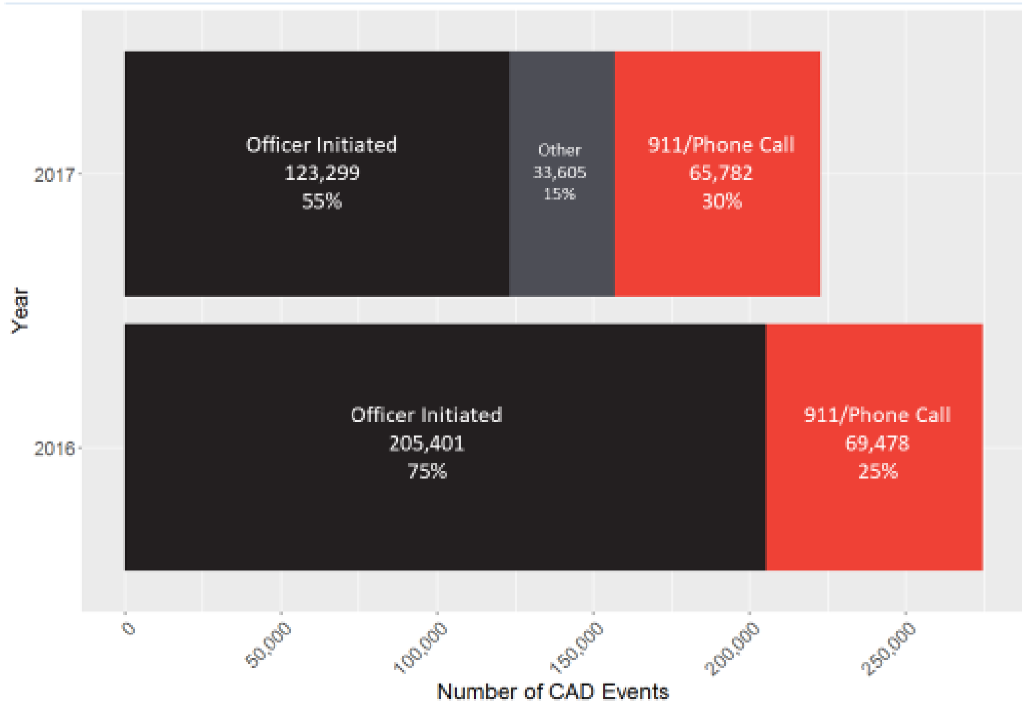
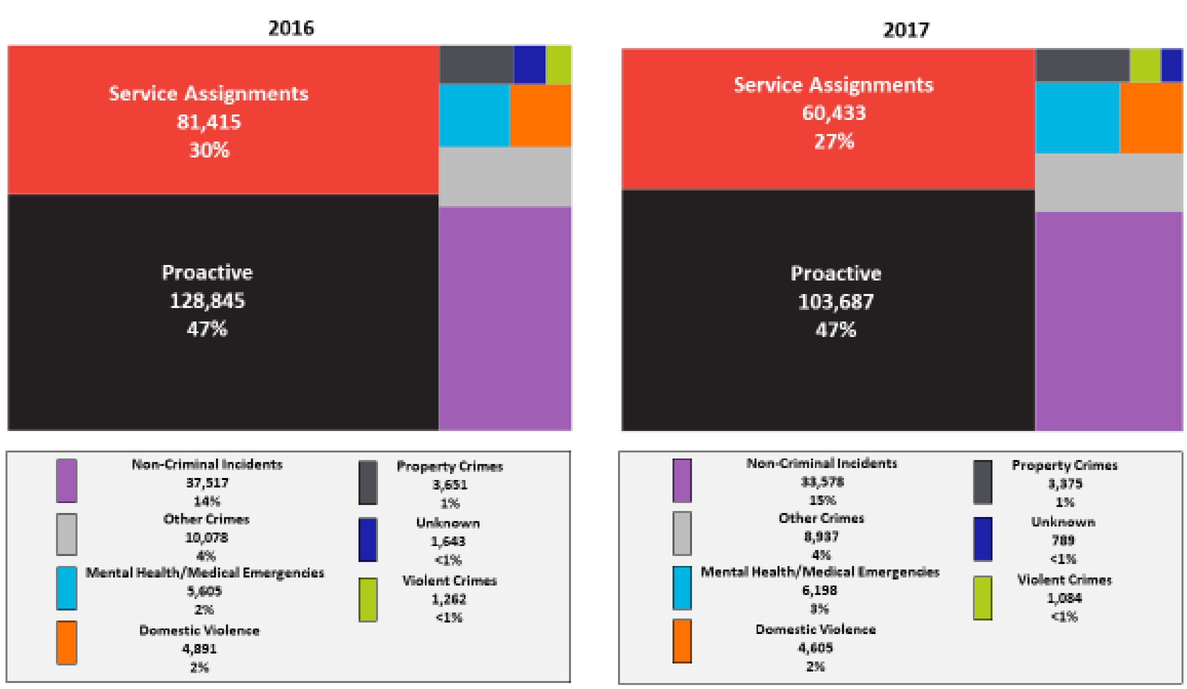


Figure 6.1.2 describes the CAD events by call type. In both 2016 and 2017, most events were officer-initiated, about thrice and twice as many as events from 911 calls, respectively. A new call type 'Other' was introduced in 2017, which accounted for 15 percent of events.

Figure 6.1.3. Camden, NJ: CAD events for 2016 and 2017, by incident type



Note: Percentages may not total 100 due to rounding.

Figure 6.1.3 shows the distribution of CAD events by incident type. In both 2016 (left panel) and 2017 (right panel), about 90 percent of CAD events consisted of three incident types: service assignments, proactive, and noncriminal incidents.[214] The remaining six categories each made a substantially lower contribution: from 0.5 percent (violent crimes) to 4 percent (other crimes) of total CAD events.

Figure 6.1.4. Camden, NJ: CAD events for 2016 and 2017, by district.

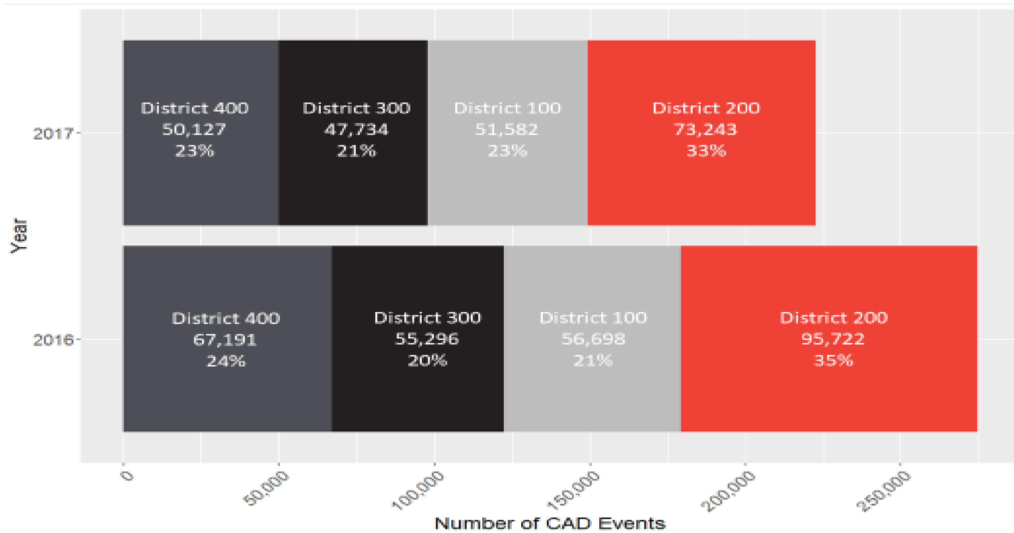


Figure 6.1.4 shows the distribution of CAD events by district. In both 2016 and 2017, fully one-third of CAD events occurred in District 200. The remaining two-thirds of events were distributed about evenly among Districts 100, 300, and 400 (see figures 6.17 and 6.18).

Additional analyses (see Figure 6.A1 in Chapter 6.2, Appendix 6A) indicate that most CAD events occurred later in the day. In 2016, the highest number of events took place in the early evening and night, whereas in 2017, the prevalence of events that occurred at night declined by 35 percent; therefore, afternoon and early evening saw the highest number of events that year. Regarding neighborhood poverty, in both 2016 and 2017, CAD events were most prevalent in low-poverty sectors and least prevalent in high-poverty sectors.

<u>Arrests resulting from CAD events</u>

The descriptive analysis of arrests that resulted from CAD events in 2016 and 2017 is based on RMS data. The unit of analysis is arrests. Researchers merged RMS arrest data with the corresponding CAD data pertaining to the arrests. The merged dataset is referred to as RMS-CAD data (See "Data and variables" in Chapter 6.2, Appendix 6B).

The data provided by the Camden County Police Department (CCPD) included:

- *Arrest-related demographics*:
  - sex (female/male), race/ethnicity (Black, white, Hispanic), and age (years) of the person arrested; and
  - majority race/ethnic group and poverty level of the sector in which the arrest occurred.
- *Geographic location and time of the call*:

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[214] Based on guidance from the police departments, researchers aggregated 'call for service' (CFS) codes into meaningful categories. See Section 2, Appendix 6B: Methodology on page 272 for details.

- district; and
- time of day.

- *Other information*:
  - call type;
  - incident type; and
  - total number of charges related to the arrest. [215]

Taxonomy of arrests

To begin to understand the vast amount of RMS data on arrests resulting from CAD events, researchers conducted a cluster analysis to sort arrests of a similar kind into their respective categories. Cluster analysis is commonly used to develop taxonomies—that is, to organize observed data into meaningful categories. It is an exploratory, atheoretical tool that aims to sort observations into groups, such that the degree of association between the observations is maximal if they belong to the same group, and minimal otherwise. The resulting taxonomy provided initial insights into the many arrests made by CCPD.

The cluster analysis was based on pooled 2016-2017 RMS data, which contained observations for all the arrests that resulted from CAD events (N=23,537). Information from the CAD data was merged with the RMS data to produce an arrest file, called RMS-CAD data in this report (see Chapter 6.2, Appendix 6B). Thus, the unit of analysis was an arrest. Because a single CAD event could result in more than one arrest, the number of records in the RMS-CAD file was larger than the number of records in the CAD or CAD-RMS file.

Figure 6.1.5. Camden, NJ: Taxonomy of arrests that resulted from CAD events

Cluster	1	2	3	4	5	6	7
Call Type	911/Phone Call	Officer Initiated	Officer Initiated	Officer Initiated	Officer Initiated	Officer Initiated	Officer Initiated
Incident Type	Service Assignments	Proactive	Proactive	Proactive	Proactive	Proactive	Proactive
District	400	300	200	400	200	100	200
Time of Day	Afternoon	Early Evening	Early Evening	Night	Night	Afternoon	Early Evening
Majority Race in CAD Event Sector	Black	Hispanic	Black	Black	Black	Hispanic	Black
Povery Level in CAD Event Sector	Low	Low	Medium	Low	Medium	Medium	Medium
Sex of Person Arrested	Male	Male	Male	Male	Female	Male	Male
Race/Ethnicity of Person Arrested	Black	Hispanic	Black	Black	Black	White	Black
Age in Years of Person Arrested	39.8	27.6	52.8	25.0	23.9	30.5	28.1
Total Charges from CAD Event	1.6	1.5	1.4	1.6	1.4	1.6	1.7
Cluster Size	1,980	3,696	3,654	3,375	1,851	4,407	4,574

[215] Arrests in which a person self-identified or was otherwise identified as Hispanic were coded as Hispanic. For example, both a person who identified as a white Hispanic and one who identified as a nonwhite Hispanic were coded as Hispanic. People identified as non-Hispanic white were coded as white, and those identified as non-Hispanic Black were coded as Black. Sector is a geographical zone of the city defined by the Camden County Police Department (CCPD). A sector is smaller in area than a police district (sectors can be aggregated into districts), and it comprises multiple census tracts. Census data from 2017 was used to impute the majority race-ethnic group residing in the sector as well as the percentage of people living below the poverty line in the sector. For ease of interpretation, a three-level categorical poverty variable was constructed: low, medium, and high poverty. CCPD delineated the city of Camden into four districts for the purpose of reporting information about police activities. Based on the hour of the call, researchers constructed a five-level categorical variable to indicate time of day: early morning, late morning, afternoon, early evening, and night. Call type indicates the source of the call. Based on guidance from CCPD, researchers constructed a 12-level categorical variable for incident type. Incident type represents the aggregation of 100 final CFS codes into 12 meaningful categories. See Chapter 6.2, Appendix 6B for details about the coding of these variables.

The results of the cluster analysis are displayed in Figure 6.1.5. In Camden, the 23,537 arrests that resulted from CAD events during 2016 and 2017 clustered into seven categories. Each row in Figure 6.1.5 describes the representative arrest for that category. This taxonomy offered CCPD a way to understand the most common profiles of the thousands of arrests made each year, based on the characteristics described in the preceding section (e.g., call type, incident code, location, time of day, demographics, and number of charges.)

Figure 6.1.5 describes the seven most prevalent profiles that emerged from over 20,000 arrests, setting the stage for the spatial analysis and statistical modeling in the next sections. It shows that, in most clusters, the representative arrests originated from officer-initiated events. The representative arrest in all seven clusters occurred in either low or medium poverty areas. In only one cluster, the representative person arrested was female. In six of the seven clusters, the representative incident type was proactive. Other findings include the following:

Sex. As mentioned, the representative person arrested in all but one cluster was male.[216]

Age. In five clusters, the representative arrest pertained to young adults in their 20s and early 30s. Only two clusters (1 and 3) represented middle-aged people 39.8 years and 52.8 years of age, respectively.

Race/ethnicity. In five of the seven clusters, the representative person arrested was identified as Black; the representative people arrested in clusters 2 and 6 were Hispanic and white, respectively. Cluster 6 was the only cluster in which the identified race/ethnic group of the person arrested (white) did not match the majority race/ethnic group in the sector where the CAD event was initiated (Hispanic).

Poverty. None of the representative arrests in any of the seven clusters occurred in a sector identified as high poverty. Four of the seven clusters involved medium poverty sectors.

Call type and incident code. As mentioned, the representative call type in six of seven clusters was officer-initiated. In those six clusters, the incident type was proactive. Cluster 1 differed in that the representative arrest originated with a 911 call, and the incident type was service assignment.

Total charges. The representative arrest in each cluster resulted in multiple charges (mean = 1.6 total charges) with little variation across clusters.

Geographic distribution of arrests

Researchers plotted the geographic distribution of arrests resulting from CAD events on maps using ArcGIS software.[217] Figures 6.1.6 and 6.1.7 below provide visual displays of arrests for 2016 and 2017, respectively. Each point represents the location of an arrest, with the color of the dot indicating the ascribed race/ethnicity of the person arrested. The colors indicate the volume of CAD events in each sector, with darker colors representing larger call volumes.

[216] Based on arrest data compiled by the Vera Institute of Justice, the ratio of male to female arrests was 3.6 (N=18,614) to 1 (N=5,101). Vera Institute of Justice, "Demographics: How Do Arrest Trends Vary Across Demographic Groups?" https://arresttrends.vera.org/demographics.

[217] ArcGIS is mapping software used to create spatial visualizations using demographic data. ArcGIS Online, www.arcgis.com.

Figure 6.1.6. Camden, NJ: Arrests that resulted from CAD events, by race/ethnicity of the person arrested and sector call volume

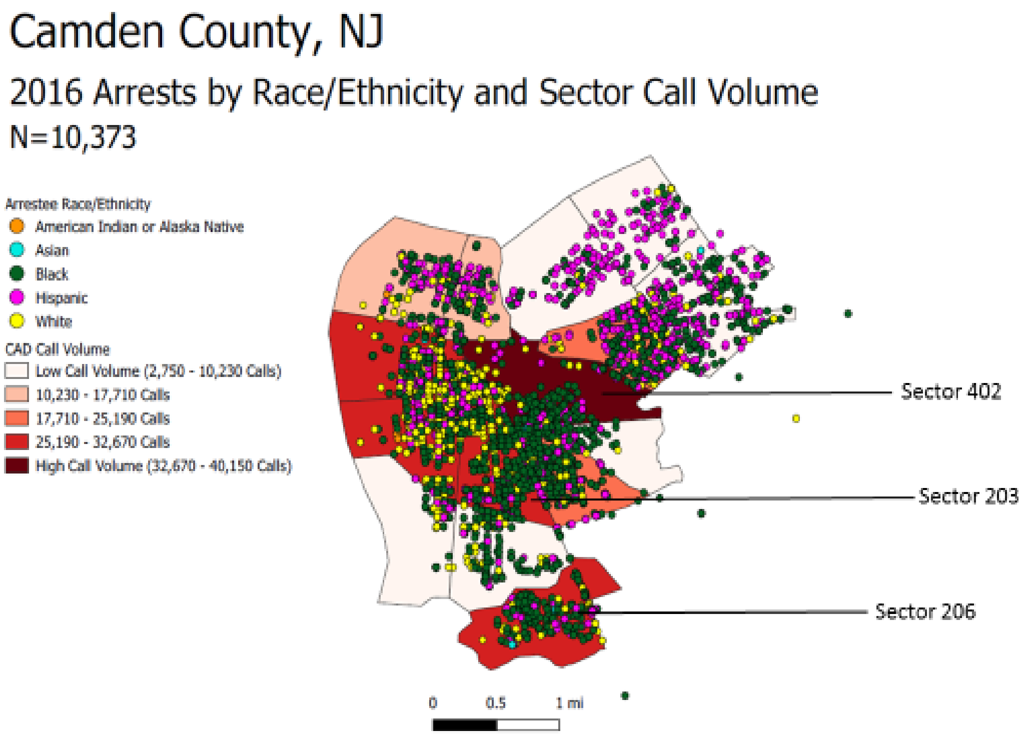
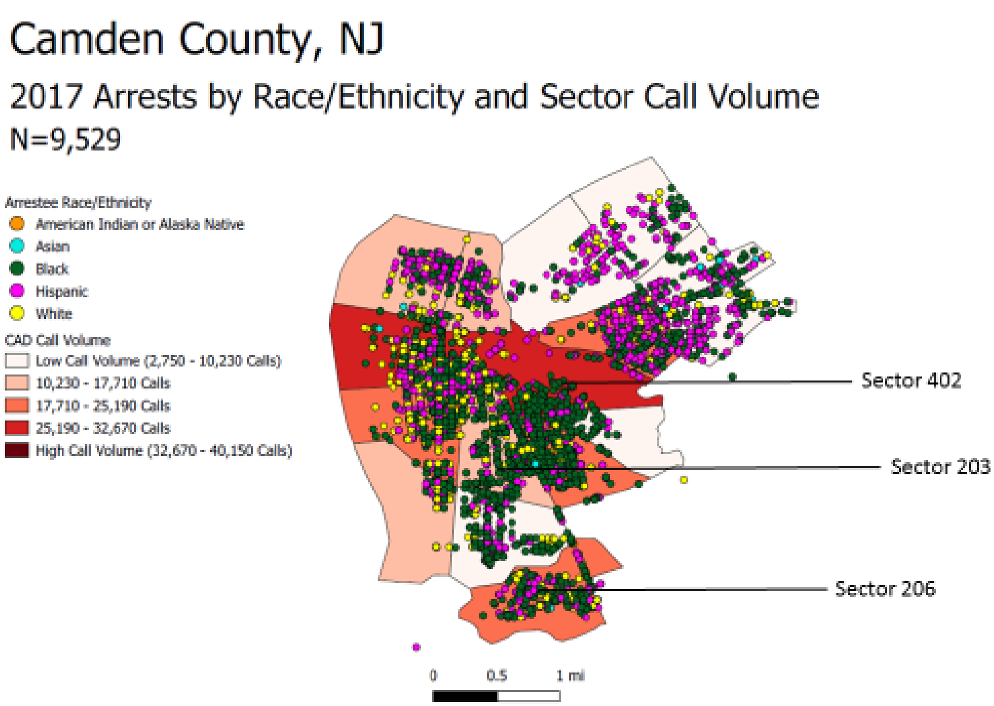


Figure 6.1.7. Camden, NJ: Arrests that resulted from CAD events, by race-ethnicity of the person arrested and sector call volume



The maps above illustrate the following patterns and trends:

Location of arrests. In both 2016 and 2017, arrests were generally scattered throughout the city, except for the western perimeter, which shows a notable dearth of arrests.

Call volume. The change in colors of the sectors over the study period shows that several sectors experienced decreased call volume from 2016 to 2017 (e.g., sectors 402, 203, and 206). However, the most southwest sector of the city experienced increased call volume during this period, as indicated by the change from very light pink in 2016 to slightly darker pink in 2017. Arrests generally occurred in sectors with higher call volume (darker colors), with some notable exceptions, such as the two sectors in the northeast, which experienced a substantial number of arrests despite low call volume.

Race/ethnicity. The color of the dots suggests that arrests of people from the same race/ethnic group tended to cluster in particular geographic areas. For example, arrests of people identified as Black race/ethnicity (green dots) occurred primarily in the south-central part of the city, whereas arrests of Hispanic people (purple dots) clustered in the northern part of the city.

Predictors of arrest

This analysis used statistical models to examine whether information gathered by CAD call-takers and dispatchers predicted arrest. Researchers employed the analytic strategy summarized below for both Camden and Tucson. It is followed by the results from statistical models that estimate associations between CAD event factors and whether the CAD event resulted in arrest(s).

Analytic strategy for Camden and Tucson

Researchers examined the question of whether the information collected by CAD call-takers and dispatchers had predictive value for arrests using the following analytic strategy. A detailed description of the methodology is provided in Chapter 6.2, Appendix 6B.

Data and variables. For the study period 2016 and 2017, researchers merged CAD data with RMS data (CAD-RMS dataset). Thus, CAD events were the unit of analysis. The outcome of interest was whether a CAD event resulted in arrest(s). This variable was coded dichotomously (yes/no). The predictors of interest in this analysis were call characteristics (call type and incident type), location (district), and time (time of day). Confounding covariates included majority race/ethnic group and percentage of people living below the poverty line, both at the sector-level, as well as year (2016 or 2017).

Statistical models. Researchers used multivariate logistic regression models to estimate associations between the outcome (arrest) and predictors of interest. All models controlled for covariates. The reference group for each categorical variable functioned as the basis for comparison to the other categories in that variable. For example, for the categorical variable *incident type*, violent crimes is the reference group against which all other incident types are compared. For Camden, the final model did not include majority race-ethnic group at the sector level because sensitivity analyses indicated that its predictive value was explained away (mediated) by poverty.

Stratified analysis. For each city (Camden and Tucson), researchers conducted additional analyses in which the statistical models described above were run on two subsamples of the CAD data based on call type: 1) 911 calls, and 2) officer-initiated events. This more granular analysis allowed researchers to focus on discrete predictors of arrest related to each of these call types.

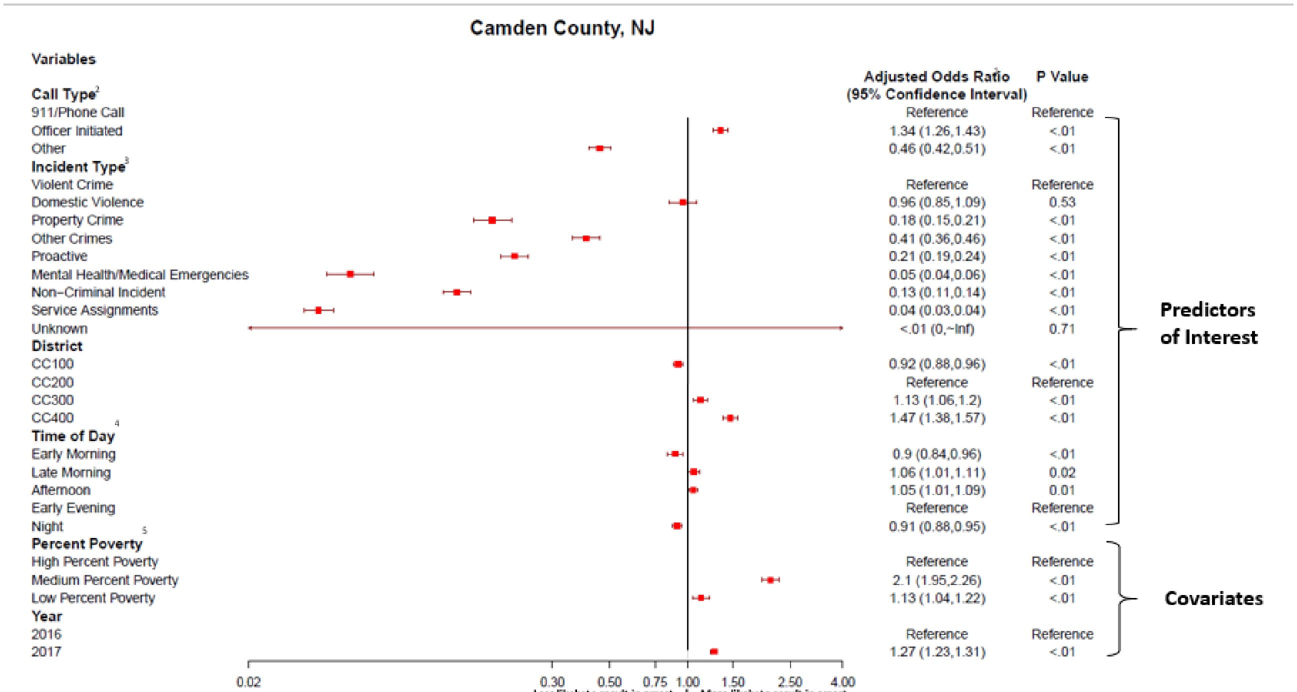
Adjusted odds ratios. The results are reported as adjusted odds ratios (AORs). 'Adjusted' means that the results account for the influence of potentially confounding covariates (described above) on the association between the outcome and predictors of interest. In other words, the reported AORs take into account the impact of the potential confounders and are, therefore, the net/adjusted estimates. Odds ratios greater than 1 (e.g., AOR=3.5) indicate that the category of interest is more likely than the reference category to be associated with arrest. Odds ratios less than 1 (e.g., AOR=0.5) indicate that the category of interest is less likely than the reference category to be associated with arrest.

Statistical significance. Only results that are statistically significant at or above a 95 percent confidence level are discussed ($p<0.05$), meaning that there is at least a 95 percent probability that the results are not due to chance.

Camden, NJ. Does data collected by CAD call-takers and dispatchers predict arrest?

Figure 6.1.8 below is a graphical representation of the associations between arrest and the information collected by call-takers and dispatchers. The left-hand column shows the predictors of interest and the covariates. The two right-hand columns show the results of the logistic regression model: adjusted odds ratios (AORs), confidence intervals, and p-values. AOR means the association between arrest and the predictor of interest is net of the covariates (poverty and year) as well as the other variables in the model (call type, incident code, district, and time of day). The AORs and confidence intervals are plotted in the middle of the figure. The location of the red dots on the *x*-axis corresponds to the direction and size of the association between arrest and the predictor, and the line through the dot represents the size of the confidence interval. A longer line represents greater uncertainty about whether the association is due to chance.

Figure 6.1.8. Camden, NJ: CAD event predictors of arrest



[1] Adjusted odds ratios from logistic regression.
[2] Call Type: Only call types with some probability of arrest were included in the analysis.
[3] Incident codes were aggregated into 9 categories based on CCPD input.
[4] Time of Day: 5-level variable based on the time of day a CAD event occurred: Early Morning (5:00am-9:00am), Late Morning (9:00am to 12:00pm), Afternoon (12:00pm-5:00pm), Early Evening (5:00pm-10:00pm) and Night (10:00pm-5:00am).
[5] Poverty: Percentage of people living below the poverty line in the sector in which the CAD event originated. (American Community Survey 2017): High Poverty (Greater than 49%), Medium Poverty (37% -49%) and Low Poverty (Less Than 37%).

Call type. The odds that officer-initiated events resulted in arrest were 34 percent higher than for 911 calls (AOR=1.34), meaning that officer-initiated activities were more likely to lead to arrest than 911 calls for service from community members. This finding raises questions about the difference in approach between an officer-initiated event and a 911 call for service.

Incident type. The odds that domestic violence incidents resulted in arrest were not substantially or statistically significantly different from violent crimes. This finding is not surprising, given that New Jersey, like many other states, has a mandatory arrest protocol for many domestic violence occurrences. The odds that mental health/medical emergency codes resulted in arrest were much lower than those for violent crimes (AOR=0.05). This result suggests that, in Camden, most incidents involving mental health are diverted away from further contact with the justice system. All other incident types (property, other, proactive, noncriminal, and service assignment) had lower odds of arrest than violent crimes.

District. The odds of CAD events resulting in arrest did not vary substantially by district, except in CC400, where the odds of arrest were almost 50 percent higher than in CC200 (AOR=1.47).

Time of day. Compared to early evening, CAD events that occurred during the early morning and night had lower odds of arrest, whereas events that occurred in late morning and afternoon had slightly higher odds of arrest.

Camden, NJ. Unpacking predictors of arrest: 911 calls and officer-initiated events.

The circumstances that motivate 911 calls and officer-initiated events may be qualitatively different. For example, 911 calls reflect the needs and perceptions of the public. These may range from first reactions to perceived threats and problems to avenues of last resort for individual people, families, and communities dealing with circumstances and crises beyond their control. On the other hand, officer-initiated activities may be based on police officers' expert knowledge and experience regarding when and how to prevent, deflect, or defuse situations that have the potential to escalate.

Therefore, to better understand CAD predictors of arrest, Vera researchers stratified the analyses by call type. Discrete analyses were conducted for 911 calls and for officer-initiated events. Detailed results are shown in Figures 6.2.2 and 6.2.3 in Chapter 6.2, Appendix 6A. The key findings are summarized below. They account for all factors in the full regression model, which include incident type, district, and time of day, as well as controls for poverty and year.

Incident type

- Domestic violence. For 911 calls, the odds of arrest were not substantially or statistically significantly different for domestic violence compared to violent crimes, whereas for officer-initiated events, the odds were more than 50 percent higher for domestic violence than for violent crimes (AOR=1.52). This finding may be related to the mandatory arrest protocol for many domestic violence occurrences in New Jersey. This protocol may be more likely to play a role in officer-initiated events than calls for service from the public. In the latter situation, officers may have more opportunity to de-escalate and divert the people in conflict.
- Mental health/medical. For both officer-initiated events and 911 calls, the odds of arrest were consistently much lower for mental health/medical than for violent crimes. This finding suggests that, regardless of the source of the CAD event, mental and physical health incidents are often diverted away from the justice system.

- Proactive, property, service. For both officer-initiated events and 911 calls, the odds were lower that proactive incidents resulted in arrest compared to violent crimes. However, the odds were much lower for officer-initiated events (AOR=0.18) relative to 911 calls (AOR= 0.46), suggesting that proactive incidents initiated by officers may be better suited to de-escalation tactics than similar incidents originating from 911 calls. The same pattern was evident for property crimes and service assignments.
- Noncriminal. The opposite pattern emerged for noncriminal incidents (911 calls AOR=0.08; officer-initiated events AOR=0.23). Nonetheless, one could expect that noncriminal incidents would rarely result in arrest. Therefore, this finding highlights the importance of clear communication among 911 call-takers, dispatchers, and responding officers. If officers obtain call-taker information from the CAD system and/or directly from dispatchers that appropriately conveys the context of the situation, they may be more prepared to successfully divert and de-escalate noncriminal incidents.

District

- 911 calls were more likely to result in arrest in district CC100 than in CC200 (AOR=1.12). By contrast, officer-initiated events were less likely to result in arrest in CC100 than in CC200 (AOR=0.84). This finding suggests that the likelihood of CAD events leading to arrest varies within districts, based on the origin of CAD events.

Tucson Police Department 911 outcomes analysis

This section begins with a brief overview of the characteristics of CAD events in 2016 and 2017. It is followed by an analysis of the arrests that resulted from those CAD events. The components include a taxonomy of arrests, maps showing the geographic distribution of arrests, and an analysis of the of the strength of predictors of arrest in data collected by call-takers and dispatchers.

Characteristics of CAD events

A comprehensive analysis of CAD events is available in previous chapters of this report. The information presented below shows the percentage of CAD events that resulted in arrest, as well as the descriptive characteristics of these events, including call type, incident type, district, time of day, and neighborhood poverty.

Figure 6.1.9. Tucson, AZ: CAD events for 2016 and 2017, by arrest status

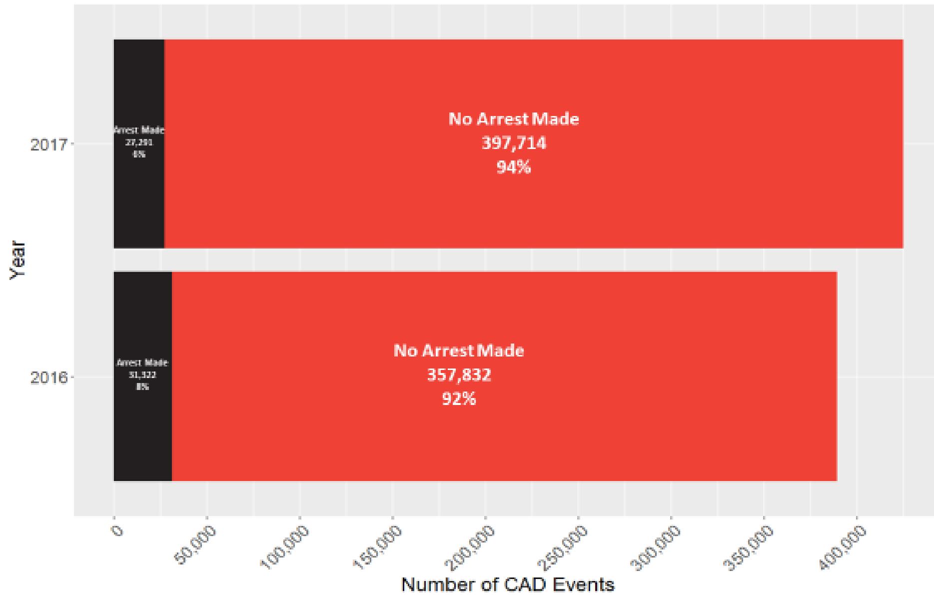
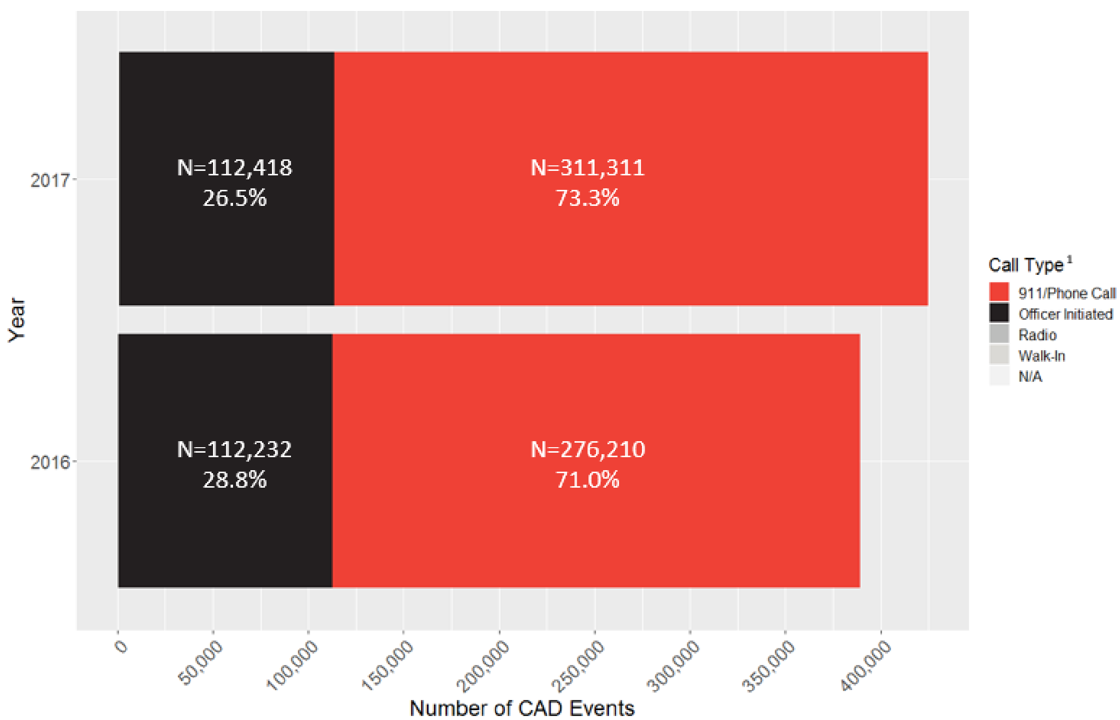


Figure 6.1.9 shows the extent of CAD events in Tucson for 2016 (bottom panel) and 2017 (top panel), by arrest status (i.e., whether the event resulted in one or more arrests). Between 2016 and 2017, total CAD events increased by 9 percent, from 389,154 to 425,005. However, compared to 2016, a smaller percentage of CAD events resulted in arrest in 2017.

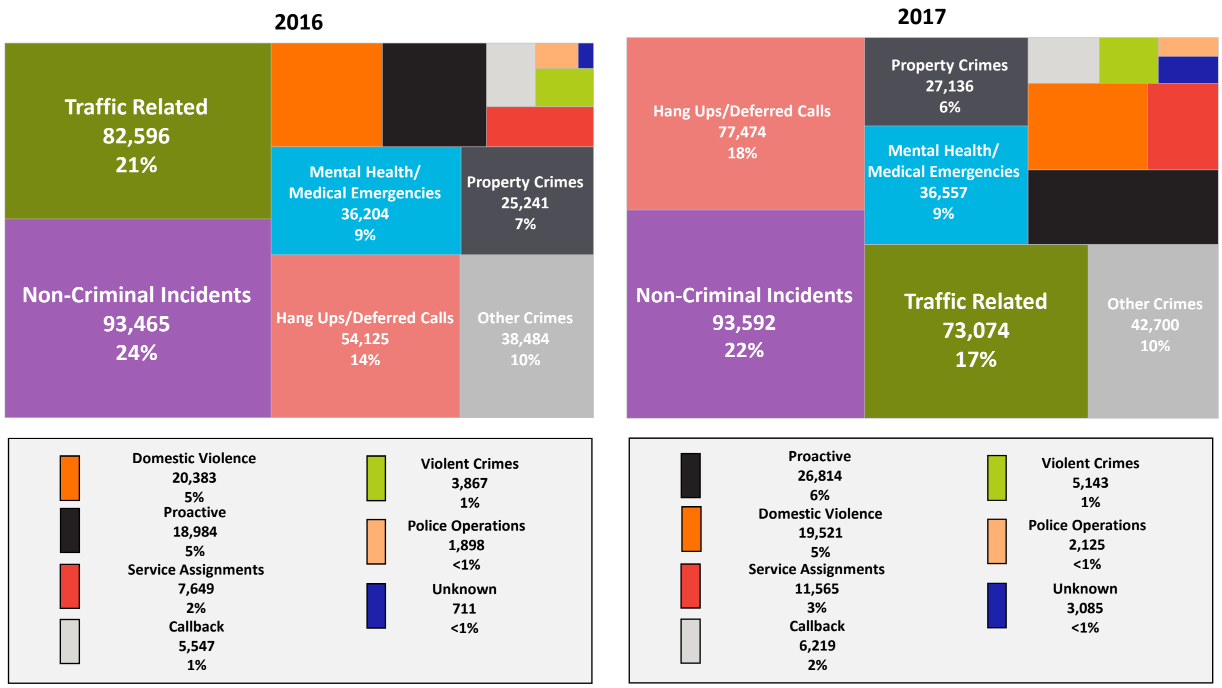
Figure 6.1.10. Tucson, AZ: CAD events for 2016 and 2017, by call type



[1]In 2016 0 radio based calls were made making up ~0% of all CAD events, 712 walk-in calls were made making up 0.2% of all CAD events. In 2017 2 radio calls were made making up ~0% of all CAD events, 877 walk-in calls were made making up 0.2% of all CAD events

Figure 6.1.10 describes the CAD events by call type. In both 2016 and 2017, of the bulk of events were 911 phone calls from the public, about 2.5 times as many as officer-initiated events.

Figure 6.1.11. Tucson, AZ: CAD events for 2016 and 2017, by incident type



Note: Percentages may not total 100 due to rounding.

Figure 6.1.11 shows the distribution of CAD events by incident type. In both 2016 (left panel) and 2017 (right panel), more than two-thirds of CAD events consisted of four incident types: noncriminal, traffic related, hang-ups/deferred calls, and other crimes. Mental health and medical incidents composed 9 percent of CAD events in both years. The remaining eight categories each made a substantially lower contribution: from police operations (less than 1 percent) to property crimes (6 percent of total CAD events).

Figure 6.1.12. Tucson, AZ: CAD events for 2016 and 2017, by district

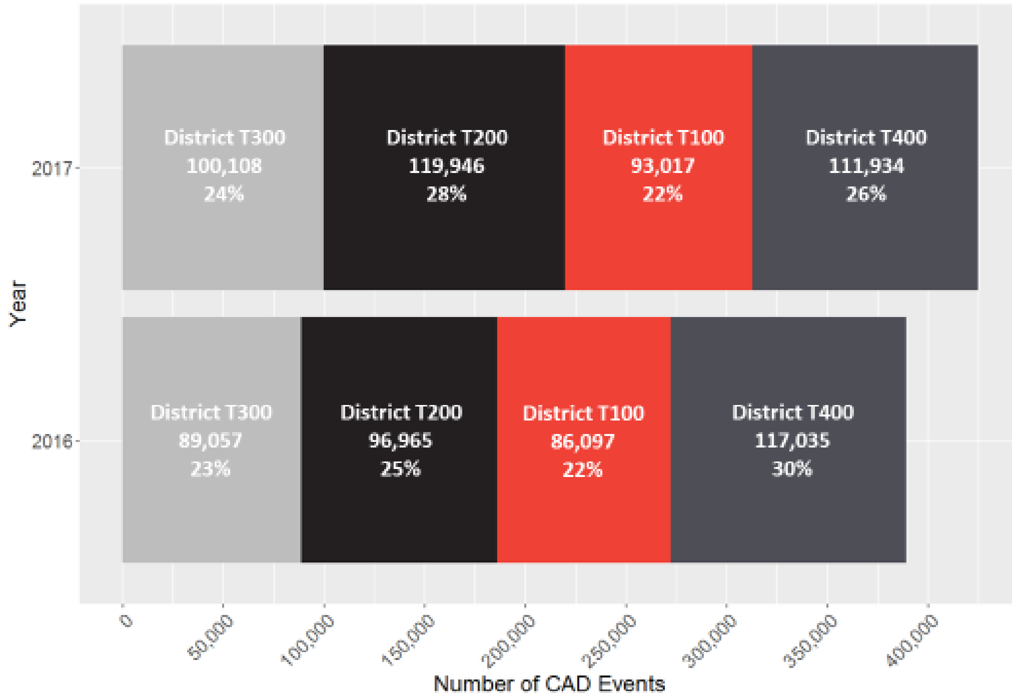


Figure 6.1.12 shows the distribution of CAD events by district. In 2016, events were most prevalent in district T400 (30 percent), whereas in 2017, most events occurred in district T200 (28 percent). The remaining events were distributed about evenly among the other districts.

Additional analyses (see Chapter 6.2, Appendix 6A) showed that the patterns were similar for both 2016 and 2017 concerning time of day. Many CAD events occurred in the afternoon and early evening, whereas calls were least prevalent in the early morning. Regarding neighborhood poverty, in both 2016 and 2017, CAD events were most prevalent in medium-poverty sectors and least prevalent in low-poverty sectors. Race/ethnic differences were similar in both years, as well. CAD events were about 40 percent more prevalent in majority-white sectors than in majority-Hispanic sectors.

<u>Arrests resulting from CAD Events</u>

The descriptive analysis of arrests that resulted from CAD events in 2016 and 2017 is based on RMS data. The unit of analysis is arrests. Researchers merged RMS arrest data with the corresponding CAD data pertaining to these arrests. The merged dataset is referred to as RMS-CAD data (see “Data and variables” in Chapter 6.2, Appendix 6B).

The data was provided by the Tucson Police, communications, and City Informational Technology Departments. It included:

- *Arrest-related demographics*:
    - sex (female/male), race/ethnicity (Black, white, Hispanic), and age (years) of the person arrested; and
    - majority race-ethnic group and poverty level of the sector in which the arrest occurred.
- *Geographic location and time of the call*:

- district; and
- time of day.

- *Other information*:

  - call type;
  - incident type; and
  - total number of charges related to the arrest. [218]

Taxonomy of arrests

Researchers conducted a cluster analysis to explore the large volume of RMS data on arrests resulting from CAD events. Generally, cluster analysis is used to develop taxonomies that organize observed data into meaningful categories. It sorts observations into groups, such that the degree of association between the observations is maximal if they belong to the same group, and minimal otherwise. Vera researchers used this analytic tool to provide initial insights into the wide range and number of arrests made by TPD during the study period.

The cluster analysis was based on pooled 2016-2017 RMS data, which contains observations for all the arrests that resulted from a CAD event that occurred during the two-year period (N=73,819). Information from the CAD data was merged with the RMS data to produce an arrest file referred to as RMS-CAD data in this report (see Chapter 6.2, Appendix 6B). Thus, the unit of analysis is an arrest. Because a single CAD event could result in more than one arrest, the number of records in the RMS-CAD file was larger than the number of records in the CAD or CAD-RMS file.

In Tucson, the 73,819 arrests that resulted from CAD events during 2016 and 2017 clustered into seven categories. Each row in Figure 6.1.13 describes the representative arrest for one of the seven categories. This taxonomy provided TPD with an understanding of the most common profiles of the thousands of arrests made each year, based on the characteristics described in the preceding section (call type, incident code, location, time of day, demographics, and number of charges).

[218] Arrests in which a person self-identified or was otherwise identified as Hispanic were coded as Hispanic. For example, both a person who identified as a white Hispanic and one who identified as a nonwhite Hispanic were coded as Hispanic. Persons identified as non-Hispanic white were coded as white, and those identified as non-Hispanic Black were coded as Black. TPD delineated the city of Tucson into four districts for the purpose of reporting information about police activities. Based on the hour of the call, researchers constructed a five-level categorical variable to indicate time of day: early morning, late morning, afternoon, early evening, and night. Call type indicates the source of the call. Based on guidance from TPD, researchers constructed a 12-level categorical variable for incident type. Incident type represents the aggregation of 100 final CFS codes into 12 meaningful categories. See Chapter 6.2, Appendix 6B for a detailed description of the variables and how codes were constructed.

Figure 6.1.13. Tucson, AZ: Taxonomy of arrests that resulted from CAD events

Cluster	1	2	3	4	5	6	7
Call Type	Officer Initiated	911/Phone Call	911/Phone Call	911/Phone Call	911/Phone Call	Officer Initiated	911/Phone Call
Incident Type	Proactive	Non-Criminal	Non-Criminal	Non-Criminal	Other Crimes	Traffic Related	Non-Criminal
District	T300	T100	T100	T400	T100	T200	T400
Time of Day	Night	Early Evening	Afternoon	Early Evening	Late Morning	Night	Afternoon
Majority Race in CAD Event Sector	White	Hispanic	Hispanic	White	Hispanic	White	White
Povery Level in CAD Event Sector	Medium	High	High	Medium	Medium	High	Medium
Sex of Person Arrested	Male	Male	Male	Male	Male	Male	Male
Race/Ethnicity of Person Arrested	White	White	Hispanic	Hispanic	Hispanic	Hispanic	White
Age in Years of Person Arrested	52.0	48.6	23.1	19.3	30.2	28.4	32.0
Total Charges from CAD Event	1.5	1.5	1.6	1.5	1.6	1.5	1.5
Cluster Size	7,049	8,666	13,278	10,824	8,336	11,933	13,733

Figure 6.1.13 shows that, in most clusters, the representative arrest originated with a 911 call. These arrests occurred in medium- and high-poverty areas. Other key findings are as follows:

Call type. In only two clusters (1 and 6), the representative arrest was officer-initiated rather than a 911 call.

Incident code. In the two clusters (1 and 6) where the representative arrest was officer-initiated, the incident codes were proactive and traffic-related, respectively. Four clusters (2, 3, 4, and 7) involved incident codes categorized by call-takers and dispatchers as noncriminal. The potential incoherence in the finding that incidents categorized as noncriminal result in arrest raises the question of how well the initial information responding officers receive from call-takers and dispatchers maps onto the situation officers meet when they arrive in the field. Perhaps the CFS code was entered incorrectly. If so, was it subsequently changed? Another possibility is that the information provided to the call-taker by the caller was not credible or accurate. In any event, this finding merits further consideration.

District. The most prevalent district (three of seven clusters) was T100.

Poverty. None of the clusters involved low poverty sectors.

Race/ethnicity. In three of the seven clusters, the representative person arrested was identified as white, whereas in four clusters, the person was Hispanic. In three clusters, the identified race/ethnic group of the person arrested did not match the majority race/ethnic group in the sector where the CAD event was initiated.

Sex. As mentioned, the representative arrest across all clusters involved males.[219]

[219]Based on arrest data compiled by the Vera Institute of Justice, the ratio of male to female arrests was 3.6 (N=18,614) to 1 (N=5,101). Vera Institute of Justice, "Demographics: How Do Arrest Trends Vary Across Demographic Groups?" https://arresttrends.vera.org/demographics.

Age. In five clusters, the representative arrest reflected young adults in their 20s and early 30s. Only two clusters (1 and 2) represented middle-aged people 52.0 years and 48.6 years of age, respectively.

Total charges. The representative arrest in each cluster resulted in multiple charges (mean=1.5 total charges) with little variation across clusters.

<u>*Geographic distribution of arrests*</u>

Researchers plotted the geographic distribution of arrests resulting from CAD events on maps using ArcGIS. Figures 6.1.14 and 6.1.15 below provide visual displays of arrests for 2016 and 2017, respectively. Each dot represents the location of an arrest, with the color of the dot indicating the ascribed race/ethnicity of the person arrested. The colors indicate the volume of CAD events (911 CFS and officer-initiated events) in each sector, with darker colors representing larger call volumes.

Figure 6.1.14. Tucson, AZ: Arrests that resulted from CAD events, by race/ethnicity of the person arrested and sector call volume, 2016

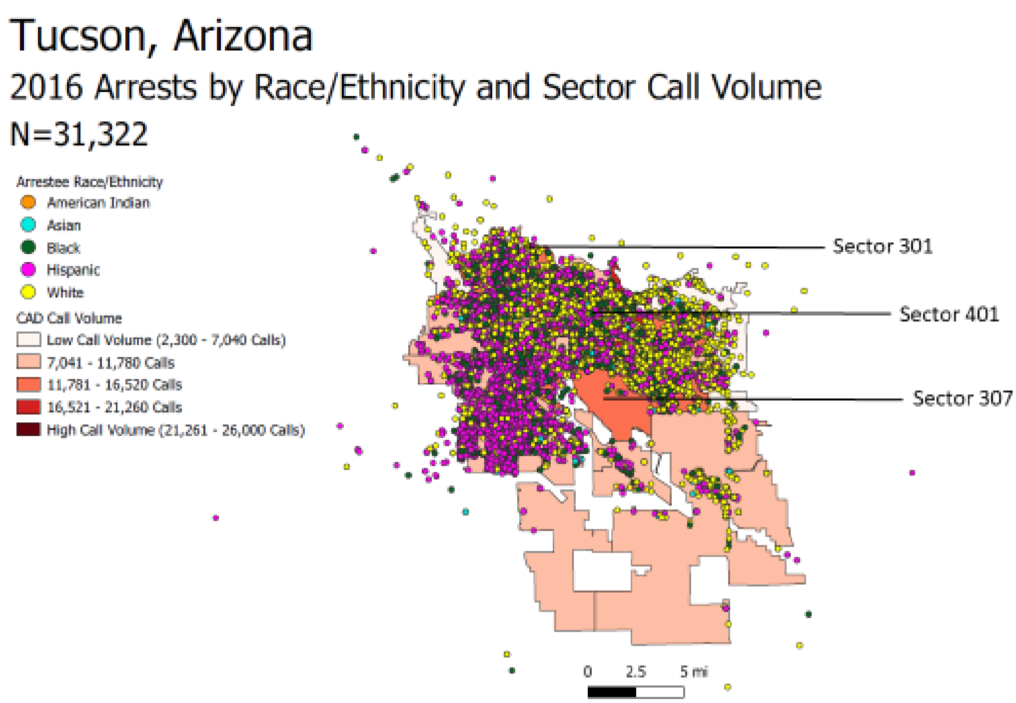
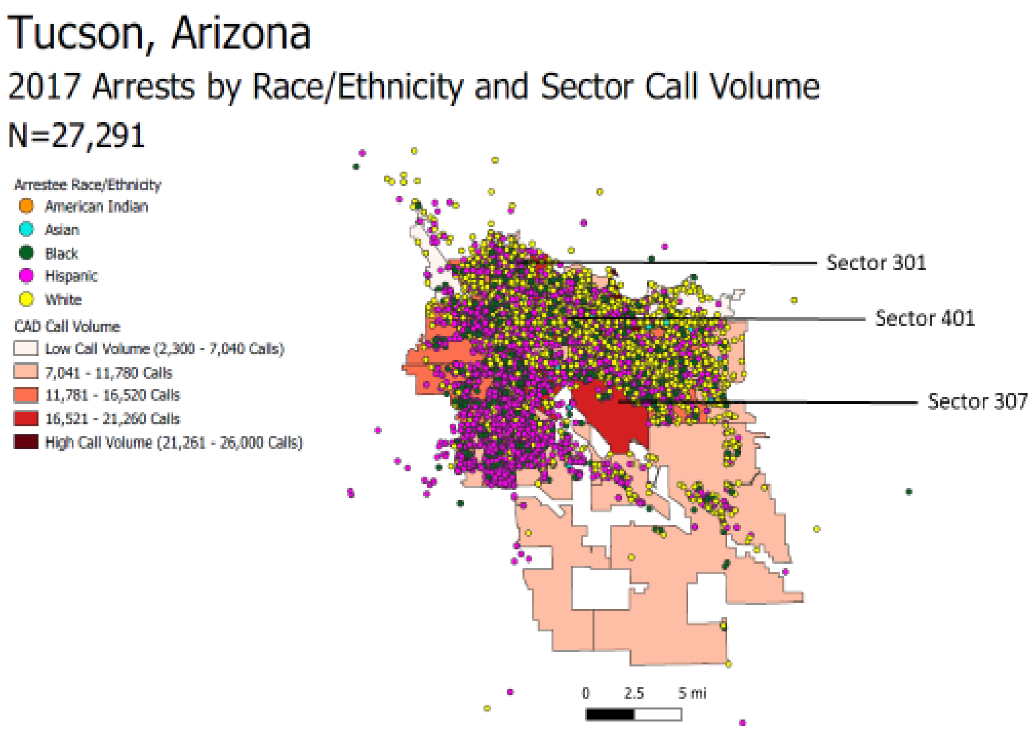


Figure 6.1.15. Tucson, AZ: Arrests that resulted from CAD events, by race-ethnicity of the person arrested and sector call volume, 2017



The maps above illustrate the following patterns and trends:

Location of arrests. In both 2016 and 2017, arrests occurred primarily in the northern half of the city.

Call volume. The change in colors of the sectors (darker colors indicate higher call volumes) shows that calls became more prevalent in some sectors in the northern half of Tucson from 2016 to 2017 (e.g., sectors 301, 401, and 307). Arrests generally occurred in sectors with higher call volumes, although some sectors, such as sector 307, experienced moderate to high call volume with relatively few arrests.

Race/ethnicity. The color of the dots suggests that people arrested in the northeastern sectors of the city were mainly identified as white (yellow dots), whereas those arrested in the northwestern sectors were mainly identified as Hispanic (purple dots).

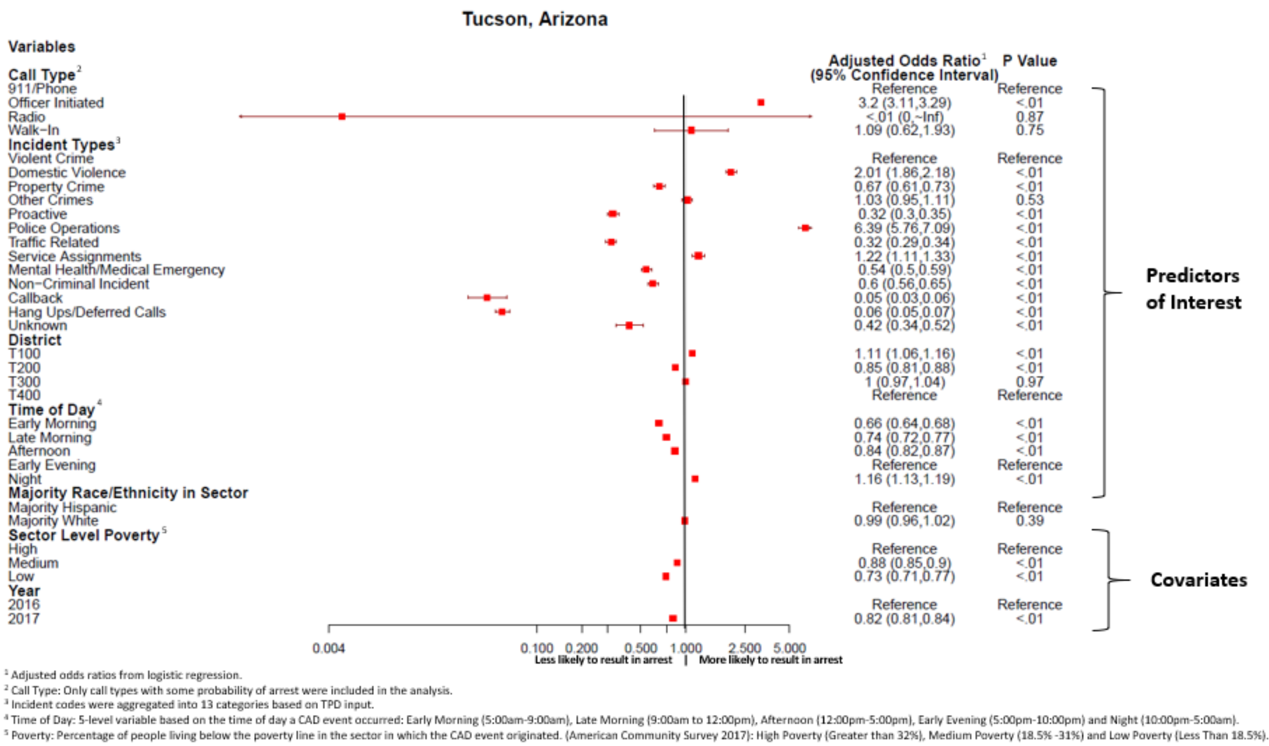
Predictors of arrest

The following analyses examined whether information gathered by CAD call-takers and dispatchers was predictive of arrest. A detailed description of the methodology is provided in Chapter 6.2, Appendix 6B. The findings below are based on statistical models that estimate associations between the characteristics of CAD events and whether the CAD event resulted in arrest(s).

Tucson, AZ. Does data collected by CAD call-takers and dispatchers predict arrest?

Figure 6.1.16 below is a graphical representation of the associations between arrest (the outcome of interest) and information collected by call-takers and dispatchers. The left-hand column shows the predictors of interest and the covariates. The two right-hand columns show the results of the logistic regression model: adjusted odds ratios (AORs), confidence intervals, and *p*-values. AOR means the association between arrest and the predictor of interest is net of the covariates (poverty and year), as well as the other variables in the model (call type, incident code, district, and time of day). The adjusted odds ratios and confidence intervals are plotted in the middle of the figure. The location of the red dots on the *x*-axis corresponds to the direction and size of the association between arrest and the predictor, and the line through the dot represents the size of the confidence interval. A longer line represents greater uncertainty about whether the association is due to chance.

Figure 6.1.16. Tucson, AZ: Predictors of arrest



Call type. Compared to 911 calls, the odds were more than three times greater that officer-initiated events resulted in arrest (AOR=3.20). This means that officer-initiated activities were more likely to result in arrest than 911 calls for service from community members. This finding raises questions about the difference in approach taken for an officer-initiated event compared to a 911 call for service.

Incident type. The odds that domestic violence codes resulted in arrest were twice as great as those for violent crimes (AOR=2.01). This is not surprising given that Arizona, like many other states, has a mandatory arrest protocol for many domestic violence specific occurrences. The odds of arrest were more than six times greater for police operations (AOR=6.39) than for violent crimes. This difference may be partially explained by the fact that police operations include warrant-based arrests and similar activities. The odds of arrest were about one-fifth greater for service assignments (AOR=1.22) than for violent crimes. Property crimes (AOR=0.67) were less likely to result in arrest than violent crimes, whereas the probability of proactive and traffic-related incidents resulting in arrest was even lower (AOR=0.32). The odds of arrest were much lower for mental health/medical incidents (AOR=0.54) than for violent crimes. This finding may reflect successful efforts of Tucson's mental health crisis intervention initiatives. Compared to violent crimes, noncriminal incidents were less likely to result in arrest (AOR=0.60), suggesting that such incidents may be well-suited to increased diversion efforts. See further analysis and discussion of this issue below.

District. The odds that CAD events resulted in arrest did not vary substantially by district.

Time of day. Compared to early evening, the odds of arrest were lower at most other times of day, except at night, when CAD events were more likely to result in arrest (AOR=1.16).

Tucson, AZ. Unpacking predictors of arrest: 911 calls and officer-initiated events.

The circumstances that motivate 911 calls for service and officer-initiated events may be qualitatively different. For example, 911 calls reflect the needs and perceptions of the public. Such perceptions may range from impulsive reactions to perceived threats and problems to an avenue of last resort for individual people, families, and communities facing circumstances and crises beyond their control. Alternatively, officer-initiated activities could be based on the expert knowledge and experience of police officers about when and how to prevent or intervene early to defuse situations with the potential to escalate.

Therefore, to better understand CAD predictors of arrest, Vera researchers stratified the analyses by call type to conduct discrete analyses for 911 calls and for officer-initiated events. Detailed results are shown in Figures 16.2.5 and 16.2.6 in Chapter 6.2, Appendix 6A. The key findings are summarized below. The findings presented account for all factors in the full regression model, which include incident type, district, and time of day, in addition to controls for race, poverty, and year.

Incident type

- Domestic violence. For 911 calls, the odds of arrest were twice as great for domestic violence incidents compared to violent crimes. For officer-initiated events, there was no statistically significant difference between odds of arrest for incidents classified as domestic violence and for those classified as violent crimes. This finding suggests that the mandatory arrest protocol for many domestic violence occurrences plays a larger role in calls for service from the public than in officer-initiated events. In the latter situation, officers may have more opportunity to de-escalate tensions and divert the people involved away from further justice system contact.

- Mental health/medical. For both officer-initiated events and 911 calls, the odds of arrest were lower for mental health/medical incidents than for violent crimes. This finding may be partly due to the role of Tucson's Crisis Response Center, which provides an alternative to arrest and jail booking. Nonetheless, the odds of arrest for mental health/medical versus violent crimes were far lower concerning officer-initiated events than 911 calls.

- Police operations. For both officer-initiated events and 911 calls, the odds were greater that police operations incidents resulted in arrest compared to those for violent crimes. However, the association was much stronger for officer-initiated events (AOR=11.87) relative to 911 calls (AOR=2.34). This finding may be an artifact of the coding structure, given the qualitative difference in the way this incident type code was used in officer-initiated events versus 911 calls. Further investigation is needed.

- Noncriminal. For 911 calls, the odds of arrest for noncriminal incidents were lower than for violent crime (AOR=0.53). For officer-initiated incidents, there was no statistically significant difference. Yet one might expect that noncriminal incidents would rarely result in arrest. Therefore, this finding highlights the importance of supporting efforts to improve 911 call-taker, dispatcher, and responding officer communication. If officers are provided call-taker information from the CAD system and/or directly from dispatchers that appropriately conveys the context of the situation, they may be more prepared to effectively de-escalate and divert noncriminal incidents.

District

- 911 calls were less likely to result in arrest in district T300 than in T400 (AOR=0.92). The opposite pattern was evident for officer-initiated events (AOR=1.15). This finding highlights the district-level variance in likelihood of arrest, based on the origin of CAD events.

Cross-site comparison between Camden, NJ and Tucson, AZ

Comparisons between Camden and Tucson reveal some similar patterns in the predictors of arrest. For example, across both cities mental health/medical incidents were less likely to result in arrest compared to violent crime incidents. This finding may reflect a broad emphasis on diversion away from the justice system to mental health and medical services and supports.

However, other patterns are more nuanced. Property crime incidents, for example, are less likely to result in arrest compared to violent crime incidents in Camden, regardless of whether the event is generated by a 911 call or officer-initiated activity. By contrast, in Tucson, property crime incidents are less likely to result in arrest only if they are generated by a 911 call. Failing to account for these nuances could potentially result in over-generalized implications that may have unintended consequences or fail to yield the desired results.

The cross-site analysis also highlights the limits of cross-site comparisons due to differences in the characteristics of the sites. For example, the racial/ethnic composition of the two cities is very different. Comparisons are also limited because the nature, scope, and structure of the data varies between sites.

Key findings include the following:

Concepts and codes. There are differences in the ways that Camden and Tucson deploy and code their call-taking, dispatching, and officer response, as well as how their underlying data management and information systems operate. Thus, incident types, disposition codes, and other CAD variables are not always uniform or directly comparable. This study provides initial information about the issues that need to be addressed in order to standardize data within and between sites, as well as across the field more broadly. Future research is required to specify pathways to harmonize data.[220]

[220] The process of harmonizing data involved aligning the coding of a concept, such as call type, that is operationalized differently in the data received from Camden and Tucson.

Race/ethnicity. The primary race/ethnic groups in Camden are Hispanic and Black, whereas in Tucson, they are Hispanic and white. Thus, researchers should consider the local context when conceptualizing and operationalizing concepts and factors such as race/ethnicity.[221]

Incident codes: Compared to violent crimes, in Tucson, the odds of arrest were greater for domestic violence events, whereas in Camden, there was no statistically significant difference.[222] In Tucson, the odds of arrest were lower for mental health/medical incidents, noncriminal events, and property crimes than for violent crimes. The same pattern was evident in Camden. However, the difference was much greater in Camden compared to Tucson.

Time of Day. Compared to early evening, the odds of arrest were lower during other times of day in Tucson, except at night, when the odds of arrest were higher. By contrast, in Camden, the odds of arrest were higher in the late morning and afternoon than in the early evening, and lower at night and in the early morning.

Conclusion and future directions

The field currently lacks sufficient empirical evidence to guide police departments' use of call-taker and dispatcher collected data to streamline resources and improve public safety. The purpose of the current study is to begin closing that gap by working with the Camden, NJ and Tucson, AZ police and communications departments. Vera researchers analyzed available administrative data and conducted an initial exploration of the associations between CAD information and enforcement outcomes, specifically arrest.

To Vera's knowledge, this is the first research that merged, harmonized, and analyzed multiple sources of data from two large police departments about 911 events and their outcomes. The study provides new information on two fronts.

First, the analysis produced initial empirical evidence about how data collected by call-takers and dispatchers relates to officer response and activity on the ground.

Key findings include:

- Some associations between CAD data and the probability of arrest were expected. For example, mental health/medical incidents were less likely to end in arrest than violent crime incidents. This suggests that an increasing focus on mental health awareness, training, and diversion may be promising approaches. Research that examines trends over a longer study period is needed to provide more robust evidence.
- Other associations deserve further examination. For instance, even though both Arizona and New Jersey have mandatory arrest protocols for many domestic violence specific occurrences, in Tucson, domestic violence incidents were more likely to result in arrest than violent crimes, whereas in Camden, there was no statistically significant difference in the odds of arrest.[223] The current study

[221] Preliminary sensitivity analyses (not shown) indicated that, in the Camden data, race/ethnicity was strongly correlated with poverty; the association between race/ethnicity and arrest was explained away (mediated) when poverty was included in the statistical model. By contrast, both race/ethnicity and poverty meaningfully explained variation in the Tucson data.
[222] The implications of this finding should be considered in the following context: both Arizona and New Jersey have a statewide mandatory arrest protocol for many domestic violence specific occurrences.
[223] It is important to note that, though both New Jersey and Arizona possess mandatory arrest protocol for domestic violence occurrences, they contain different provisions, which should be explored in further research.

cannot explain such findings, but it does point them out so they can be examined further.

- Findings related to noncriminal incidents give reason for pause. In both sites, they were less likely than violent crime incidents to end in arrest. However, more nuanced analyses showed wide variation in the likelihood of arrest, depending on whether the event was officer-initiated or motivated by a 911 call. Further research is warranted to understand the seeming 'mismatch' between what was described as a noncriminal incident at the beginning of the event and the eventual outcome—arrest.

- Importantly, the study provided essential practical information in a user-friendly format. Researchers produced data visualizations that overlay the geography of arrests, race/ethnicity, and call volume in addition to maps of both Camden and Tucson for 2016 and 2017.

Second, the findings revealed the sizable and relatively untapped potential of this data. They suggest how it can be optimized to become a key resource for management and officers on the ground. This research highlights potential new variables and data sources for consideration, as well as recommendations to improve the quality of the current data.

For example, several key findings include:

- Collaboration within and between police and communications departments could improve the scope and quality of the data. The study shed light on best practices that could facilitate data harmonization and extend the analytics.

- Further geo-spatial visualization is possible with the current data. Now that the groundwork has been laid, the mapping component of the research could be vastly expanded and refined.

- Data is currently available to go beyond 'arrest' and examine the number and types of charges related to the arrests.

- New data is needed to conduct more robust analyses, including trends over time. For example, call-takers' interpretations of what information to record in CAD system variables and narrative fields are essential. Similarly, information on dispatchers' decisions about when to send officers to the field, and with what information, could play an important role in the analysis.

- New variables, such as known disabilities and/or support systems, repeat calls, interest in non-police response, and nearby social services, could be systematically added to the CAD data.

- There is an important opportunity to use the current findings, along with future research, to develop evidence-based criteria and rubrics that would enable police and communications departments to assess the strengths and limitations of their CAD data to inform police response.

Section 2: Appendices

Marilyn Sinkewicz, Frankie Wunschel, and Abdul Rad

Appendix 6A: Supporting figures

Figure 6.2.1: Camden, NJ. Characteristics of CAD events

	2,016	**2,017**	**Total**
Total CAD events	274,907	222,686	497,593
Arrest status			
No arrest made	264,534	213,157	477,691
Arrest made	10,373	9,529	19,902
Call type			
911/phone call	69,478	65,782	135,260
Officer-initiated	205,401	123,299	328,700
Other	28	33,605	33,633
Incident type			
Violent crime	1,262	1,084	2,346
Domestic violence	4,891	4,605	9,496
Property crimes	3,651	3,375	7,026
Other crimes	10,078	8,937	19,015
Proactive	128,845	103,687	232,532
Mental health/medical Emergencies	5,605	6,198	11,803
Non-criminal incidents	37,517	33,578	71,095
Service assignments	81,415	60,433	141,848
Unknown	1,643	789	2,432
District			
CC100	56,698	51,582	108,280
CC200	95,722	73,243	168,965
CC300	55,296	47,734	103,030
CC400	67,191	50,127	117,318
Time of day			
Early morning	20,550	19,587	40,137
Late morning	30,383	33,343	63,726
Afternoon	69,951	64,827	134,778
Early evening	81,427	57,857	139,284
Night	72,596	47,072	119,668

Sector-level majority race-ethnic group			
Black	159,528	119,973	279,501
Hispanic	111,994	99,316	211,310
Sector-level poverty			
Low	140,939	110,098	251,037
Medium	108,162	91,588	199,750
High	22,421	17,603	40,024

Note: Missing data are not reported in this table. Therefore, counts of total events by category may not total 274,907 for 2016 and 222,686 for 2017.

Figure 6.2.2: Camden, NJ. Predictors of arrest: 911 calls

	911 CALLS			
	Adjusted odds ratio	P-value	N	Percentage
PREDICTORS OF INTEREST				
Incident type				
Violent crimes	Reference	Reference	2,049	1.5
Domestic violence	0.93	.254	9,133	6.8
Property crimes	0.19	<.001	5,888	4.4
Other crimes	0.40	<.001	16,487	12.2
Proactive	0.46	<.001	4,940	3.7
Mental health/medical emergencies	0.06	<.001	9,019	6.7
Non-criminal incidents	0.08	<.001	54,428	40.2
Service assignments	0.13	<.001	31,621	23.4
Unknown	0.00	.847	1,695	1.3
District				
CC100	1.12	.007	29,028	21.5
CC200	Reference	Reference	44,335	32.8
CC300	1.09	.112	31,200	23.1
CC400	1.31	<.001	30,697	22.7
Time of day				
Early morning	0.80	<.001	16,548	12.2
Late morning	0.96	.341	17,774	13.1
Afternoon	0.98	.547	36,371	26.9
Early evening	Reference	Reference	35,421	26.2
Night	1.00	.926	29,146	21.5
COVARIATES				
Poverty level				
High poverty level	Reference	Reference	10,821	8.2
Medium poverty level	1.06	.352	53,632	40.5
Low poverty level	0.93	.213	68,089	51.4
Year				

2016	Reference	Reference	69,478	51.4
2017	1.10	.001	65,782	48.6

Note: Percentages may not total 100 due to rounding.

Figure 6.2.3: Camden, NJ. Predictors of arrest: Officer-initiated events

	OFFICER-INITIATED EVENTS			
	Adjusted odds ratio	***p*-value**	**N**	**Percentage**
PREDICTORS OF INTEREST				
Incident type				
Violent crimes	Reference	Reference	252	0.1
Domestic violence	1.52	.035	287	0.1
Property crimes	0.10	<.001	932	0.3
Other crimes	0.44	<.001	2,190	0.7
Proactive	0.18	<.001	201,973	61.4
Mental health/medical emergencies	0.04	<.001	2,123	0.6
Non-criminal incidents	0.23	<.001	14,402	4.4
Service assignments	0.01	<.001	105,805	32.2
Unknown	0.00	.817	736	0.2
District				
CC100	0.84	<.001	70,440	21.4
CC200	Reference	Reference	113,433	34.5
CC300	1.12	.007	64,713	19.7
CC400	1.60	<.001	80,114	24.4
Time of day				
Early morning	0.93	.098	20,737	6.3
Late morning	1.06	.053	40,371	12.3
Afternoon	1.07	.008	94,959	28.9
Early evening	Reference	Reference	88,183	26.8
Night	0.90	<.001	84,450	25.7
COVARIATES				
Poverty level				
High poverty level	Reference	Reference	26,690	8.2
Medium poverty level	2.87	<.001	129,969	39.9
Low poverty level	1.31	<.001	168,681	51.8
Year				
2016	Reference	Reference	205,401	62.5
2017	1.39	<.001	123,299	37.5

Note: Percentages may not total 100 due to rounding.

Figure 6.2.4: Tucson, AZ. Characteristics of CAD events, by year

	2,016	2,017	Total
Total CAD events	389,154	425,005	814,159
Arrest status			
No arrest occurred	357,832	397,714	755,546
Arrest occurred	31,322	27,291	58,613
Call type			
911/phone call	276,202	311,311	587,513
Officer-initiated	112,232	112,418	224,650
Radio	0	2	2
Walk-in	712	877	1,589
Incident type			
Violent crime	3,867	5,143	9,010
Domestic violence	20,383	19,521	39,904
Property crime	25,241	27,136	52,377
Other crimes	38,484	42,700	81,184
Proactive	18,984	26,814	45,798
Police operations	1,898	2,125	4,023
Traffic-related	82,596	73,074	155,670
Service assignments	7,649	11,565	19,214
Mental health/medical emergency	36,204	36,557	72,761
Callback	5,547	6,219	11,766
Non-criminal incident	93,465	93,592	187,057
Hang-ups/deferred calls	54,125	77,474	131,599
Unknown	711	3,085	3,796
District			
T100	86,097	93,017	179,114
T200	96,965	119,946	216,911
T300	89,057	100,108	189,165
T400	117,035	111,934	228,969
Time of day			
Early morning	45,349	52,463	97,812
Late morning	55,707	63,163	118,870
Afternoon	101,827	113,747	215,574
Early evening	101,939	108,886	210,825
Night	84,332	86,746	171,078
Sector-level majority race-ethnic group			
Hispanic	145,731	162,406	308,137
White	203,982	234,101	438,083
Sector-level poverty			
High	124,177	142,589	266,766
Medium	159,352	180,453	339,805
Low	66,184	73,465	139,649

Note: Missing data are not reported in this table. Therefore, total events by category counts may not total 389,154 for 2016 and 425,005 for 2017.

Figure 6.2.5: Tucson, AZ. Predictors of arrest: 911 calls

	911 CALLS			
	Adjusted odds ratio	*p*-value	N	Percentage
PREDICTORS OF INTEREST				
Incident type				
Violent crime	Reference	Reference	8,268	1.4
Domestic violence	2.02	<.001	39,259	6.7
Property crime	0.62	<.001	48,030	8.2
Other crimes	0.92	.034	75,972	12.9
Proactive	0.21	<.001	1,233	0.2
Police operations	2.34	<.001	1,409	0.2
Traffic-related	0.54	<.001	31,572	5.4
Service assignments	1.39	<.001	15,537	2.6
Mental health/medical emergency	0.61	<.001	67,030	11.4
Non-criminal incident	0.53	<.001	154,830	26.4
Callback	0.04	<.001	11,069	1.9
Hang -ups/deferred calls	0.06	<.001	131,589	22.4
Unknown	0.66	<.001	1,715	0.3
District				
T100	1.06	.046	131,289	22.3
T200	0.75	<.001	166,262	28.3
T300	0.92	<.001	141,222	24.0
T400	Reference	Reference	148,700	25.3
Time of day				
Early morning	0.96	.095	58,146	9.9
Late morning	0.96	.056	80,445	13.7
Afternoon	0.98	.225	164,293	28.0
Early evening	Reference	Reference	169,580	28.9
Night	1.11	<.001	115,049	19.6
COVARIATES				
Majority race in sector				
Majority Hispanic	Reference	Reference	228,602	40.5
Majority white	0.91	<.001	336,283	59.5
Poverty level				
High poverty	Reference	Reference	196,751	34.8
Medium poverty level	0.91	<.001	105,662	18.7
Low poverty level	0.80	<.001	262,472	46.5
Year				
2016	Reference	Reference	276,202	47.0
2017	0.85	<.001	311,311	53.0

Note: Percentages may not total 100 due to rounding.

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Figure 6.2.6: Tucson, AZ. Predictors of arrest: Officer-initiated events

	OFFICER-INITIATED EVENTS			
	Adjusted odds ratio	***p*-value**	**N**	**Percentage**
PREDICTORS OF INTEREST				
Incident type				
Violent crime	Reference	Reference	729	0.3
Domestic violence	0.75	.059	625	0.3
Property crime	0.85	.146	4,298	1.9
Other crimes	2.21	<.001	5,102	2.3
Proactive	0.34	<.001	44,564	19.9
Police operations	11.87	<.001	2,593	1.2
Traffic-related	0.31	<.001	124,063	55.4
Service assignments	0.93	.492	3,657	1.6
Mental health/medical emergency	0.13	<.001	5,673	2.5
Non-criminal incident	0.83	.069	32,038	14.3
Callback	0.08	<.001	685	0.3
Hang -ups/deferred calls	0.00	.871	1	0.0
Unknown	0.19	<.001	62	0.0
District				
T100	1.19	<.001	47,646	26.2
T200	1.03	.329	49,412	27.2
T300	1.15	<.001	4,775	2.6
T400	Reference	Reference	79,833	43.9
Time of day				
Early morning	0.42	<.001	39,506	17.6
Late morning	0.50	<.001	37,856	16.9
Afternoon	0.61	<.001	50,226	22.4
Early evening	Reference	Reference	41,107	18.3
Night	1.19	<.001	55,955	24.9
COVARIATES				
Majority race in sector				
Majority Hispanic	Reference	Reference	79,196	43.9
Majority white	1.09	.001	101,330	56.1
Poverty level				
High poverty level	Reference	Reference	69,715	38.6
Medium poverty level	0.84	<.001	76,957	42.6
Low poverty level	0.63	<.001	33,854	18.8
Year				
2016	Reference	Reference	112,232	50.0
2017	0.79	<.001	112,418	50.0

Note: Percentages may not total 100 due to rounding.

Appendix 6B: Methodology

The methodological overview begins with a description of the data and variables. It is followed by an explanation of the descriptive analyses, including the cluster and spatial analyses. It concludes with a description of the statistical models used to estimate predictors of arrest.

Data

The two research sites, the Camden County Police Department (CCPD) and the Tucson Police Department (TPD), along with their respective public safety communications agencies, each provided data for the study. The study period included the years 2016 and 2017; data was collected between July 1, 2016 and June 30, 2018.

Each research site extracted information from two data systems:

- The computer-aided dispatch (CAD) system contains information gathered by call-takers and dispatchers while they process calls for service from the public. A CAD event can also originate with the officers (e.g., motor vehicle stop, pedestrian stop, or suspicious person stop). Only CAD events that required law enforcement dispatch were included in this study. The pooled data from both years included 497,593 CAD events for Camden and 850,764 CAD events for Tucson. Of these events, 19,902 and 87,339 resulted in one or more arrest for Camden and Tucson, respectively.
- The Records Management System (RMS) contains enforcement information that is collected primarily by responding officers who record the outcomes and activities resulting from CAD events. This study focused on arrests. Arrest data from the RMS system was provided for each CAD event. Some CAD events ended in multiple arrests. Therefore, the pooled data from both years included 23,537 and 73,819 arrests for Camden and Tucson, respectively.

Data from the CAD and RMS systems was merged in two ways to produce different datasets that were needed for a range of analyses:

- CAD-RMS dataset. Arrest information from the RMS system was linked to relevant CAD events—that is, those CAD events that resulted in one or more arrest—using a common identifier. (CAD events that did not result in arrest were not linked to RMS data.) Then, RMS information about the arrest was merged with the CAD data to produce a new CAD-RMS dataset, in which the unit of analysis was the CAD event. The CAD-RMS data was used in descriptive analyses of CAD events. Additionally, the statistical models used to assess CAD predictors of arrest drew on the CAD-RMS data.
- RMS-CAD dataset. Using a common identifier, researchers linked CAD event information from the CAD system to arrests in the RMS system that resulted from those events. They then merged the CAD data with the RMS data to produce a new RMS-CAD dataset. Researchers used the new combined data to conduct descriptive analyses of the arrests, in which the unit of analysis was the arrest.

Variables

The variables used in this study included the following:

<u>CAD event data</u>

- Call type: Researchers constructed categorical variables for Camden and Tucson. Camden's call type variable had two levels: 911 calls and officer-initiated events. Tucson's had four: 911 calls, officer-initiated events, radio calls, and walk-ins.

- Incident type: Based on guidance from the police departments, researchers constructed a nine-level categorical variable for Camden and a 13-level incident type variable for Tucson to aggregate final 'call for service' (CFS) codes into meaningful categories. The detail and aggregate codes for Camden are shown in the left-hand panel below, and the codes for Tucson are in the right-hand panel below.

CAMDEN CODES	TUCSON CODES
Category: Violent crime	Category: Violent crimes
CRIME (AGGRAVATED ASSAULT)	ARMED ROBBERY/ATTEMPT
CRIME (ARMED ROBBERY)	ARMED ROBBERY/RESIDENCE
CRIME (ROBBERY)	ASSAULT
CRIME (SEXUAL ASSAULT)	ASSAULT VICTIM
CRIME IN PROGRESS (ASSAULT)	ASSAULT, AGGRAVATED/DRIVEBY SHOOTING
CRIME IN PROGRESS (PERSON SHOT)	ASSAULT, AGGRAVATED/OTHER
CRIME IN PROGRESS (ROBBERY)	ASSAULT, AGGRAVATED/PEACE OFFICER (NON-SERIOUS INJ)
CRIME IN PROGRESS (SEXUAL ASSAULT)	ASSAULT, AGGRAVATED/PEACE OFFICER (SERIOUS INJURY)
Category: Domestic violence	ASSAULT/MINOR INJURY
DOMESTIC INVOLVING PARENT/CHILD WITH INJURY OR OFFENDER PRESENT	ASSAULT/NO INJURY
DOMESTIC INVOLVING PARENT/CHILD WITH INJURY OR OFFENDER PRESENT (IP)	BANK HOLDUP ALARM
DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT	CAR JACKING/GTA BY FORCE
DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT (IP)	CRIME (AGGRAVATED ASSAULT)
DOMESTIC NO INJURIES & OFFENDER NOT PRESENT	CRIME (ARMED ROBBERY)
DOMESTIC NO INJURIES & OFFENDER NOT PRESENT (IP)	CRIME (ARMED ROBBERY/ALARM)
CRIME (CHILD ABUSE)	CRIME (BANK ROBBERY ALARM)
Category: Property crime	CRIME (CODE 43)
CRIME (THEFT / LARCENY)	CRIME (ROBBERY)
CRIME IN PROGRESS (BURGLARY)	CRIME (SEXUAL ASSAULT)
CRIME (BURGLARY)	CRIME IN PROGRESS (ASSAULT)
CRIME (CRIMINAL MISCHIEF)	CRIME IN PROGRESS (PERSON SHOT)
Other crimes	CRIME IN PROGRESS (ROBBERY)
CRIME IN PROGRESS (OTHER)	CRIME IN PROGRESS (SEXUAL ASSAULT)
CRIME (OTHER)	DRIVE BY SHOOTING
INTOXICATED DRIVER	FIGHT
VICE COMPLAINT (DRUGS)	FIGHT WITH LARGE GROUP
VICE COMPLAINT (GAMBLING)	FIGHT WITH WEAPONS
VICE COMPLAINT (PROSTITUTION)	HIGHWAY ROBBERY/JUST OCCURRED
Category: Complaints/environmental conditions	HOMICIDE/MURDER
ANIMAL CARCASS	KIDNAPPING
ANIMAL COMPLAINT	MAN OR FIGHT W/KNIFE
HAZARDOUS MATERIAL INCIDENT	MAN WITH GUN
INVESTIGATE SMOKE CONDITION	MOLESTING
OPEN HYDRANT	PERSON WITH A FIREARM
DISTURBANCE OF THE PEACE	PERSON/FIGHT W/GUN
TRAFFIC COMPLAINT	PURSE SNATCH
Traffic-related	ROBBERY/COMMERCIAL HOUSE
DIRECT TRAFFIC	ROBBERY/CONVENIENCE STORE
HIT AND RUN (NO INJURIES)	ROBBERY/HIGHWAY
MOTOR VEHICLE CRASH (EMERGENT)	ROBBERY/MISCELLANEOUS
MOTOR VEHICLE CRASH (NON-EMERGENT)	ROBBERY/SERVICE STATION
TOW TRUCK NEEDED	SEX OFFENSES
Category: Missing persons	SEX OFFENSES/CHILD MOLESTING
MISSING ADULT	SEX OFFENSES/EXPOSURE
MISSING ADULT (SPECIAL NEEDS INDIVIDUAL)	SEX OFFENSES/LEWD & LASCIVIOUS ACTS
MISSING CHILD	SEX OFFENSES/MOLESTING
Category: Proactive	SEX OFFENSES/OBSCENE PHONE CALLS
PEDESTRIAN STOP	SEX OFFENSES/OTHER (ADULTERY, INCEST, STAT RAPE, ETC)
TRAFFIC STOP	SEXUAL ASSAULT
PROPERTY CHECK	SEXUAL ASSAULT ATTEMPT

PROPERTY CHECK (BUSINESS)
PROPERTY CHECK (PARK)
PROPERTY CHECK (RESIDENCE)
Category: Service assignments/statuses
SERVICE ASSIGNMENT (CLOTHING REMOVAL)
SERVICE ASSIGNMENT (COURT)
SERVICE ASSIGNMENT (FOUND PROPERTY)
SERVICE ASSIGNMENT (GUARDING PRISONER)
SERVICE ASSIGNMENT (INTERNAL AFFAIRS)
SERVICE ASSIGNMENT (MEETING SUPERVISOR)
SERVICE ASSIGNMENT (OTHER)
SERVICE ASSIGNMENT (PAPERWORK)
SERVICE ASSIGNMENT (TRAINING)
SERVICE ASSIGNMENT (TRANSPORT)
SERVICE ASSIGNMENT (UNION ACTIVITY)
SERVICE ASSIGNMENT (VEHICLE DEFICIENCY)
LATRINE
15 MINUTE BREAK
30 MINUTE BREAK
ASSIST UNIT
ATTEMPT TO SERVE (CRIMINAL WARRANT)
ATTEMPT TO SERVE (RESTRAINING ORDER)
BOMB SCARE
COMPUTER EQUIPMENT FAILURE
DECEASED PERSON (NATURAL)
DECEASED PERSON (UNKNOWN CIRCUMSTANCES)
FIGHT
MEET COMPLAINANT
MENTOR SESSION
NOTIFICATION
OUT OF SERVICE
OUT OF SERVICE - BODY WORN CAMERA
PERSON WITH A FIREARM
RECORDS INDICATE WANTED OR STOLEN
RECOVERY OF A STOLEN AUTO
SECONDARY EMPLOYMENT
TERRORISTIC THREATS
VEHICLE WASH
CRIME CONDITION CHECK
FUEL
Reports
REPORT OF A STOLEN AUTO
REPORT OF A STRUCTURE FIRE (OCCUPIED)
REPORT OF A STRUCTURE FIRE (VACANT)
REPORT OF A VEHICLE FIRE
Category: Suspicion
SUSPICIOUS PERSON (ADULT)
SUSPICIOUS PERSON (JUVENILE)
SUSPICIOUS PERSON/PROWLER CALL
SUSPICIOUS VEHICLE (ABANDON)
SUSPICIOUS VEHICLE (OCCUPIED)
SUSPICIOUS VEHICLE (UN-OCCUPIED)
Category: Medical
EMS CALL (LIFE THREATENING)
EMS CALL NON-EMERGENT (OTHER)
Category: Behavioral health
EMOTIONALLY DISTURBED PERSON
INTOXICATED PEDESTRIAN
Category: Hang-ups and deferred calls
911 HANG UP
DEFERRED CALL
Separate (no assigned category)
EMERGENCY CALL FOR HELP FROM POLICE OFFICER

SEXUAL ASSAULT ATTEMPT
SEXUAL ASSAULT/ATTEMPT
SEXUAL ASSAULT/ATTEMPTED RAPE
SEXUAL ASSAULT/OTHER
SHOOTING
SHOOTING VICTIM
SHOTS FIRED
STABBING
STRONG ARM ROBBERY
SUICIDAL WITH WEAPONS
Category: Property crimes
ARSON FIRE
ARSON/OTHER
ARSON/RESIDENTIAL STRUCTURE
BURGLAR ALARM (BUSINESS)
BURGLAR ALARM (PANIC)
BURGLAR ALARM (RESIDENTIAL)
BURGLARY ATTEMPT
BURGLARY IN PROGRESS
BURGLARY- INTERIOR HAS BEEN CHECKED
BURGLARY- INTERIOR NOT CHECKED
BURGLARY/ATTEMPTED FORCIBLE ENTRY
BURGLARY/FORCIBLE ENTRY
BURGLARY/UNLAWFUL ENTRY - NO FORCE
CRIME (BURGLARY)
CRIME (CRIMINAL MISCHIEF)
CRIME (THEFT / LARCENY)
CRIME IN PROGRESS (BURGLARY)
FENCE FIRE
FIRE
FIRE/RESIDENTIAL STRUCTURE (FIRE NOT ARSON)
FIRE/RESIDENTIAL STRUCTURE (FIRE ORIGIN UNKNOWN)
GTA ATTEMPT
GTA/RECOVERY
GTA/RECOVERY FOR OTHR JURISDICTION
GTA/STOLEN
LARCENY
LARCENY ATTEMPT
LARCENY- METAL THEFT
LARCENY/ALL OTHERS
LARCENY/AUTO PARTS & ACCESSORIES
LARCENY/BICYCLES
LARCENY/FROM ANY COIN OPERATED MACHINE
LARCENY/FROM BUILDING OPEN TO THE PUBLIC
LARCENY/FROM MOTOR VEHICLES (EXCEPT 0605)
LARCENY/FROM RESIDENCE
LARCENY/POCKET PICKING
LARCENY/PURSE SNATCHING
LARCENY/SHOPLIFTING
RECOVERED GTA
RECOVERY OF A STOLEN AUTO
SHOPLIFTER IN CUSTODY
STOLEN MOTOR VEHICLE
STOLEN MOTOR VEHICLE LOCATION
STOLEN PLATE
STOLEN PROPERTY LOCATED
TILL TAP
VEHICLE FIRE
Category: Domestic violence
10-31 WITH WEAPON
ASSAULT, AGGRAVATED/OTHER - DOMESTIC VIOLENCE
ASSAULT/MINOR INJURY-DOMESTIC VIOLENCE
CHILD NEGLECT
CRIME (CHILD ABUSE)
CRIMINAL DAMAGE/INTENTIONAL VANDALISM - DOM VIOL
CRIMINAL DAMAGE/INTENTIONAL VANDALISM - DOM VIOL
CUSTODIAL INTERFERENCE
DISORDERLY CONDUCT/DISTURBING THE PEACE DV

DISORDERLY CONDUCT/FAMILY FIGHT
DOMESTIC INVOLVING PARENT/CHILD WITH INJURY OR OFFENDER PRESENT
DOMESTIC INVOLVING PARENT/CHILD WITH INJURY OR OFFENDER PRESENT (IP)
DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT
DOMESTIC INVOLVING TWO ADULTS WITH INJURY OR OFFENDER PRESENT (IP)
DOMESTIC NO INJURIES & OFFENDER NOT PRESENT
DOMESTIC NO INJURIES & OFFENDER NOT PRESENT (IP)
FAMILY FIGHT/DOMESTIC VIOLENCE
FAMILY FIGHT/DOMESTIC VIOLENCE BREWING
FAMILY FIGHT/DOMESTIC VIOLENCE- OVER. PARTIES SEPARATED
HEALTH WELFARE AND MORALS
OFFENSES AGAINST FAMILY & CHILDREN/NEGLECT
OFFENSES AGAINST FAMILY & CHILDREN/OTHER
OFFENSES AGAINST FAMILY & CHILDREN/PHYSICAL ABUSE
OFFENSES AGNST FAMILY & CHLDRN/CSTDL INTRFRNCE DV
OFFENSES AGNST FAMILY & CHLDRN/CUSTODIAL INTERFERE
OTHER OFFENSES/DATING VIOLENCE
OTHER OFFENSES/OTHER FELONIES DV
OTHER OFFENSES/OTHER MISDEMEANORS DV
Category: Other crimes
ABUSE
ABUSE OF ELDERLY
ANIMAL BITES/OTHER
ANIMAL BITES/OTHER DOMESTIC ANIMAL
BOMB SCARE
BOMB THREAT
CITY CODE VIOLATION
COMMERCIALIZED SEX/OTHER
COMMERCIALIZED SEX/PANDERING
COUNTERFEIT
COURT ORDER VIOLATION
COURT ORDER VIOLATION- SUSPECT NOT PRESENT
COURT ORDER/ORDER OF PROTECTION
CRIME (OTHER)
CRIME IN PROGRESS (OTHER)
CRIMINAL DAMAGE/GRAFFITI
CRIMINAL DAMAGE/INTENTIONAL VANDALISM
CRIMINAL DAMAGE/MALICIOUS MISCHIEF
CRUELTY TO ANIMALS
CURFEW VIOLATION
DEATH THREATS
DISORDERLY CONDUCT
DISORDERLY CONDUCT/DISTURBING THE PEACE
DISORDERLY CONDUCT/FIGHTING
DISORDERLY CONDUCT/OTHER (TRESPASSING)
DISTURBANCE
DISTURBANCE OF THE PEACE
DISTURBANCE/NO CRIMINAL VIOLATION
DISTURBANCE/OTHER
DRINKING IN PUBLIC
EMBEZZLED VEHICLE
EMBEZZLEMENT
EMBEZZLEMENT/FROM EMPLOYER
EMBEZZLEMENT/OTHER
EMBEZZLEMENT/RENTAL PROPERTY
FAILURE TO PAY
FIGHT BREWING
FIRECRACKERS
FIREWORKS
FORGERY & COUNTERFEITING/COUNTERFEITING
FORGERY & COUNTERFEITING/FORGERY
FRAUD
FRAUD/BOGUS CHECKS
FRAUD/CONFIDENCE GAME
FRAUD/DEFRAUDING
FRAUD/IDENTITY THEFT
FRAUD/OTHER
HARASSMENT
HATE CRIME

HUMAN TRAFFICKING/COMMERCIAL SEX ACTS
ILLEGAL DUMPING
INDECENT EXPOSURE
JUVENILE VIOLATIONS/HEALTH, WELFARE, MORALS
JUVENILE VIOLATIONS/OTHER
LIQUOR LAW VIOLATION
LIQUOR LAWS/DRINKING IN PUBLIC
LIQUOR LAWS/MINOR IN POSSESSION
LIQUOR LAWS/OTHER
LOUD MUSIC
LOUD NOISE
LOUD PARTY
NARCOTIC DRUG LAWS/POSSESSION
NARCOTIC DRUG LAWS/POSSESSION OF PARAPHERNALIA
NARCOTIC DRUG LAWS/SALE
NARCOTICS VIOLATION
NEIGHBOR PROBLEM
OTHER
OTHER OFFENSES/ESCAPE
OTHER OFFENSES/OTHER FELONIES
OTHER OFFENSES/PHONE CALLS
PANHANDLING
PREDATOR
PROWLER
RACING VEHICLE
RECKLESS DRIVING
RED TAG ISSUED
ROAD RAGE
RUNAWAY JUVENILE
RUNAWAY JUVENILE/ESCAPEE FROM INSTITUTION
RUNAWAY JUVENILE/FROM INSTITUTION OR FOSTER HOME
RUNAWAY JUVENILE/FROM PARENT OR GUARDIAN
RUNAWAY JUVENILE/LOCATION
RUNAWAY JUVENILE/RETURNED
SHOT HEARD
SKATE BOARDERS
STOLEN PROPERTY/POSSESSION
TERRORISTIC THREATS
THREATS
THREATS OF PHYSICAL HARM, SUSPECT IN AREA
THREATS- SUSPECT GONE
TRESPASSING
TROUBLE WITH CUSTOMER
UNKNOWN TROUBLE
UNLAWFUL POSSESSION OF MARIJUNA
UNWANTED PERSON
URINATING IN PUBLIC
VAGRANCY/BEGGING
VANDALISM
VICE COMPLAINT (DRUGS)
VICE COMPLAINT (GAMBLING)
VICE COMPLAINT (PROSTITUTION)
VICIOUS DOG
WEAPONS VIOLATION
WEAPONS/CARRYING CONCEALED
WEAPONS/CARRYING CONCEALED
WEAPONS/ILLEGAL
WEAPONS/OTHER
Category: Proactive
10-80 FIELD INTERVIEW/SUBJECT IN VEHICLE
10-81 FIELD INTERVIEW
BICYCLE TRAFFIC
COMMUNITY ENGAGEMENT/CITY PARK PATROL
COMMUNITY ENGAGEMENT/COFFEE WITH A COP
COMMUNITY ENGAGEMENT/COMMUNITY PROJECT ASSIGNMENT
COMMUNITY ENGAGEMENT/CRIME PREVENTION MEETING/FAIR
COMMUNITY ENGAGEMENT/DEPARTMENT EVENT/MEMORIAL-AWARDS
COMMUNITY ENGAGEMENT/GAIN/NNO
COMMUNITY ENGAGEMENT/NEIGHBORHOOD ASSOC MEETING
COMMUNITY ENGAGEMENT/NEIGHBORHOOD WATCH MEETING
COMMUNITY ENGAGEMENT/RECRUITING EVENT

COMMUNITY ENGAGEMENT/SCHOOL EVENT
COMMUNITY ENGAGEMENT/SECURITY SURVEY-BUSINESS
COMMUNITY ENGAGEMENT/SECURITY SURVEY-RESIDENTIAL
COMMUNITY ENGAGEMENT/SPECIAL CHECK ACTIVITY
COMMUNITY ENGAGEMENT/TARGETED ENFORCEMENT
COMMUNITY ENGAGEMENT/WARD OFFICE/WARD MEMBER MEETING
FLAG DOWN
FOLLOW UP
NEIGHBORHOOD PRESERVATION/JUNK MOTOR VEHICLE
NEIGHBORHOOD PRESERVATION/OTHER
NEIGHBORHOOD PRESERVATION/WEED ENFORCEMENT
PEDESTRIAN STOP
PEDESTRIAN TRAFFIC
PUBLIC HAZARD/TRAFFIC
SPECIAL CHECK
STOP AND FIELD INTERVIEW
VOLUNTARY FIELD INTERVIEW
Category: Mental health/medical emergencies
ANIMAL BITES/DOG
ANIMAL BITES/DOG
ANIMAL RELATED EVENT
CHECK WELFARE
CIVIL MATTER/OTHER
DECEASED PERSON (NATURAL)
DECEASED PERSON (UNKNOWN CIRCUMSTANCES)
DROWNING
DRUNK PERSON
EMOTIONALLY DISTURBED PERSON
EMS CALL (LIFE THREATENING)
EMS CALL NON-EMERGENT (OTHER)
FOUND CHILD
FOUND PERSON
FOUND/ADULT
INTOXICATED PEDESTRIAN
LARC RUN
LOST CHILD
LOST/ADULT
MAC TEAM ASSIST
MAN DOWN
MEDICAL REJECTION
MEDS ASSIST
MENTAL CASES/OTHER
MENTAL CASES/TRANSPORTED TO TREATMENT FACILITY
MENTAL HEALTH UNIT
MENTAL PATIENT
MISSING ADULT
MISSING ADULT (SPECIAL NEEDS INDIVIDUAL)
MISSING CHILD
MISSING ELDERLY PERSON
MISSING IMPAIRED PERSON
MISSING JUVENILE- 12 YOA OR UNDER
MISSING PERSON
MISSING PERSON- SUICIDAL
OPERATION DEEP FREEZE
OVERDOSE
PUBLIC ASSIST
PUBLIC ASSIST/CHECK WELFARE
PUBLIC ASSIST/OTHER
REQUEST FOR POLICE
REQUEST POLICE ASSIST
RUNAWAY JUVENILE- SUICIDAL
RUNAWAY JUVENILE WITH IMPAIRMENTS
SICK CARED FOR/OTHER
SICK CARED FOR/TRANSPORTED TO MEDICAL FACILITY
SUICIDAL PERSON
SUICIDE
WALKAWAY
Category: Traffic-related
ACCIDENT PEDESTRIAN W/INJURIES
ACCIDENT W/INJURIES
ACCIDENT W/INJURIES, MEDS NOT NEEDED

ACCIDENT/BICYCLE W/INJURIES
ACCIDENT/MOTORCYCLE W/INJURIES
AUTO ACCIDENT- BLOCKING
AUTO ACCIDENT/ANIMAL
AUTO ACCIDENT/NO INJURY
AUTO ACCIDENT/UNKNOWN
AUTO ACCIDENT-POSSIBLE IMPAIRMENT
CHILD RESTRAINT VIOLATION
DIRECT TRAFFIC
DRUNK DRIVER
DRUNK DRIVER STOPPED
DUI/NON-ACCIDENT
FIRE ASSIST/POINT CONTROL
HIT AND RUN (NO INJURIES)
HIT AND RUN ACCIDENT/INJURY
HIT AND RUN ACCIDENT/NO INJURY
ILLEGAL PARKING
INTOXICATED DRIVER
MOTOR VEHICLE CRASH (EMERGENT)
MOTOR VEHICLE CRASH (NON-EMERGENT)
NON-TRAFFIC ACCIDENT/FATAL-LEAVING THE SCENE
NON-TRAFFIC ACCIDENT/PROPERTY DAMAGE
NON-TRAFFIC ACCIDENT/PRPRTY DMG-LEAVING SCENE
NON-TRAFFIC ACCIDENT/PRSNL INJURY-LEAVING SCENE
OTHER VEHICLE ACCIDENTS/OTHER
POINT CONTROL
PUBLIC ASSIST/MOTORIST
RAILROAD ARMS MALFUNCTIONING
STALLED VEHICLE
TOW TRUCK NEEDED
TRAFFIC & MOTOR VEHC LAWS/ABANDONED VEHICLE
TRAFFIC & MOTOR VEHC LAWS/LICENSE & REGISTRATION
TRAFFIC & MOTOR VEHC LAWS/MOVING VIOLATIONS
TRAFFIC & MOTOR VEHC LAWS/OTHER
TRAFFIC & MOTOR VEHC LAWS/PARKING VIOLATIONS
TRAFFIC & MOTOR VEHC LAWS/ROAD RAGE
TRAFFIC ACCIDENT/FATAL/HIT-AND-RUN/AUTOMOBILE
TRAFFIC ACCIDENT/FATAL/PEDESTRIAN
TRAFFIC ACCIDENT/INJURY/BICYCLE
TRAFFIC ACCIDENT/INJURY/HIT-AND-RUN/OTHER
TRAFFIC ACCIDENT/INJURY/HIT-AND-RUN/OTHER MOTOR VEHC
TRAFFIC ACCIDENT/INJURY/HIT-AND-RUN/PEDESTRIAN
TRAFFIC ACCIDENT/INJURY/OTHER MOTOR VEHC
TRAFFIC ACCIDENT/INJURY/PEDESTRIAN
TRAFFIC ACCIDENT/PRP DMG/BICYCLE
TRAFFIC ACCIDENT/PRP DMG/FIXED OBJECT
TRAFFIC ACCIDENT/PRP DMG/HIT-AND-RUN/FIXED OBJECT
TRAFFIC ACCIDENT/PRP DMG/HIT-AND-RUN/MOTOR VEHC
TRAFFIC ACCIDENT/PRP DMG/HIT-AND-RUN/OTHER
TRAFFIC ACCIDENT/PRP DMG/OTHER MOTOR VEHC
TRAFFIC ACCIDENT/PRP DMG/PEDESTRIAN
TRAFFIC COMPLAINT
TRAFFIC HAZARD
TRAFFIC LIGHT MALFUNCTION
TRAFFIC PURSUIT
TRAFFIC STOP
TRUCK INSPECTION
VEHICLE INTO A BUILDING, INJURIES
VEHICLE INTO A POLE, INJURIES
VEHICLE INTO A TREE, INJURIES
VEHICLE INTO A WALL, INJURIES
Category: Non-criminal incidents
ABANDONED VEHICLE
ADDITIONAL INFORMATION
ALARM AT EPIC
ANIMAL CARCASS
ANIMAL COMPLAINT
ARMORY ALARM
ASSIST OTHER AGENCY/COUNTY CRIMINAL JUSTICE
ASSIST OTHER AGENCY/COUNTY CRIMINAL JUSTICE
ASSIST OTHER AGENCY/FEDERAL CRIMINAL JUSTICE

ASSIST OTHER AGENCY/MUNICIPAL CRIMINAL JUSTICE
ASSIST OTHER AGENCY/OTHER
BARKING DOG
CHECK WELFARE
CIVIL MATTER/COURT ORDER ENFORCE
CIVIL MATTER/PRESERVE THE PEACE
COURT ORDER
COURT ORDER SERVICE
COURT ORDER/OTHER
CPS ASSIST
DEATH
DEATH-HOSPITAL, MORGUE
DELIVER EMERGENCY MESSAGE
DELIVER MESSAGE- NON EMERGENCY
DISTURBANCE/PEACE RESTORED
DISTURBANCE/UNABLE TO LOCATE
DOWNED WIRES
DURESS ALARM
DURESS ALARM-UNK ACTIVATION
ESP Activation
EXPLOSION
FOUND ANIMAL
FOUND BIKE
FOUND GUN
FOUND PROPERTY
FOUND/PROPERTY
GAS LEAK
HAZARD
HAZARDOUS MATERIAL INCIDENT
IMMIGRATION/LAWFUL/NON-ARREST SITUATION
IMPOUND LOT ALARM
IMPROPER CODE - NON BANK
IMPROPER OPENING SIGNAL AT BUSINESS
IMPROPER SIGNAL ALARM
INFORMATION FOR POLICE
INVESTIGATE SMOKE CONDITION
JUNKED MOTOR VEHICLE
LIFELINE ALARM
LOOSE COW
LOOSE DOG- NOT VICIOUS
LOOSE HORSE
LOST PROPERTY
LOST/PROPERTY
MISCELLANEOUS/OFFICER
MISCELLANEOUS/PUBLIC
MISSING PERSON/LOCATED
MISSING PERSON/RETURNED
NON VERIFIED ALARM
OPEN DOOR
OPEN HYDRANT
OPEN WINDOW
OVERDUE PERSON, CAR, ETC.
PANIC ALARM
PANIC ALARM-UNK ACTIVATION
PRESERVE THE PEACE
PUBLIC HAZARD/JUNKED MOTOR VEHICLE
PUBLIC HAZARD/OTHER
SILENT ALARM
SUSPICIOUS ACTIVITY
SUSPICIOUS ACTIVITY/OTHER
SUSPICIOUS ACTIVITY/PERSON
SUSPICIOUS ACTIVITY/STALKING
SUSPICIOUS ACTIVITY/UNABLE TO LOCATE
SUSPICIOUS ACTIVITY/VEHICLE
SUSPICIOUS ITEM
SUSPICIOUS PERSON
SUSPICIOUS PERSON (ADULT)
SUSPICIOUS PERSON (JUVENILE)
SUSPICIOUS PERSON/PROWLER CALL
SUSPICIOUS VEHICLE
SUSPICIOUS VEHICLE (ABANDON)

SUSPICIOUS VEHICLE (OCCUPIED)
SUSPICIOUS VEHICLE (UN-OCCUPIED)
UNFOUNDED/NO BONAFIDE INCIDENT
UNKNOWN/SUSPICIOUS HAZARD
VEHICLE ALARM
VERIFIED ALARM
Category: Police operations
ARREST
ARREST
ARREST FOR OTHER JURISDICTION/FELONY WARRANT
ARREST FOR OTHER JURISDICTION/MISD CRIMINL WARRANT
ASSIST OTHER AGENCY/STATE CRIMINAL JUSTICE
ATTEMPT TO SERVE (CRIMINAL WARRANT)
ATTEMPT TO SERVE (RESTRAINING ORDER)
BACK UP FOR DPS
BACK UP UNIT
BACK UP UNIT FOR TFD
BACKUP FOR PCSO
CRIME CONDITION CHECK
DEPARTMENT OF PUBLIC SAFETY
EMERGENCY CALL FOR HELP FROM POLICE OFFICER
OFFICER NEEDS ASSIST URGENT
OTHER AGENCY ASSIST
PRONET OR LOJACK TRACK
PTS ACTIVATION
PTS RESPONSE
RECORDS INDICATE WANTED OR STOLEN
SUBJECT PURSUIT
TFD REQUEST CODE 99
WANTED PERSON
WARRANT SERVICE
WARRANTS/FELONY
WARRANTS/MISDEMEANOR
Category: Service assignments
15 MINUTE BREAK
30 MINUTE BREAK
ACAD1
ACAD2
ACAD3
ACAD4
ASSIST UNIT
ATTEMPT TO LOCATE
COMPUTER EQUIPMENT FAILURE
CRIME SCENE UNIT EVENT
EVIDENCE
FUEL
LATRINE
MEET COMPLAINANT
MENTOR SESSION
MISCELLANEOUS/PRISONER TRANSPORT - COURT
MISCELLANEOUS/PRISONER TRANSPORT - JAIL
NOTIFICATION
OFF DUTY WORK
OFFICER SAFETY
OTHER AGENCY ATL
OUT OF SERVICE
OUT OF SERVICE - BODY WORN CAMERA
POLICE TEST EVENT TYPE
SECONDARY EMPLOYMENT
SERVICE ASSIGNMENT (CLOTHING REMOVAL)
SERVICE ASSIGNMENT (COURT)
SERVICE ASSIGNMENT (FOUND PROPERTY)
SERVICE ASSIGNMENT (GUARDING PRISONER)
SERVICE ASSIGNMENT (INTERNAL AFFAIRS)
SERVICE ASSIGNMENT (MEETING SUPERVISOR)
SERVICE ASSIGNMENT (OTHER)
SERVICE ASSIGNMENT (PAPERWORK)
SERVICE ASSIGNMENT (TRAINING)
SERVICE ASSIGNMENT (TRANSPORT)
SERVICE ASSIGNMENT (UNION ACTIVITY)
SERVICE ASSIGNMENT (VEHICLE DEFICIENCY)

SEXUAL ASSAULT KIT
TEST EVENT TYPE
TRANSPORT UNIT EVENT
TRANSPORT/ALL
VEHICLE WASH
Category: Callbacks
ALL OTHER CALLBACK
AUTO ACCIDENT/CALL-BACK
BIKE CALLBACK
BURGLARY CALLBACK
BURGLARY/CALL BACK
CALL BACK OTHER CATEGORY
CITY CODE CALLBACK
COURT ORDER CALLBACK
CUSTODIAL INTERFERENCE/CALL BACK
EMBEZZLED PROPERTY/CALL BACK
EMBEZZLED VEHICLE/CALLBACK
FRAUD CALLBACK
FRAUD CALLBACK9
FRAUD/CALL BACK
FRAUD/CALL BACK
HARASSMENT/CALL BACK
HIT AND RUN CALLBACK
INFO CALLBACK
INFORMATION CALLBACK
LARCENY CALLBACK
LOST PROPERTY/CALLBACK
MISSING PERSON- CALLBACK
OVERDUE VEHICLE/PERSON CALLBACK
PHONE CALLS- CALLBACK
PROPERTY CALLBACK
ROAD RAGE CALLBACK
RUNAWAY JUVENILE/CALL-BACK
SEX OFFENSES CALLBACK
STOLEN LICENSE PLATE/CALL BACK
STOLEN VEHICLE CALLBACK
SUSPICIOUS ACTIVITY/CALL BACK
THREATS- CALL BACK
VANDALISM CALLBACK
VANDALISM/CALL BACK
Category: Hang-ups and deferred calls
911 HANG UP
911 HANG UP CALL
911 HANG UP FROM PSAP
911 HANG UP-NASA
911 OPEN LINE
911 PAYPHONE HANG UP
ABANDONED 911 CALL
DEFERRED CALL

- District: For both Camden and Tucson, researchers constructed a four-level categorical variable based on the sector where police activity occurred. Events in sectors within the 100 series of sectors were coded as district T100/CC100, events in sectors within the 200s were coded as district T200/CC100, and so on.
- Time of day: The sites each provided a time-of-call variable. Based on the hour of the call, researchers constructed a five-level categorical variable that indicates time of day: early morning from 5:00 a.m. until 8:59 a.m., late morning from 9:00 a.m. until 11:59 a.m., afternoon from noon until 4:59 p.m., early evening from 5:00 p.m. until 8:59 p.m., and night from 9:00 p.m. until 4:59 a.m.
- Arrest: Based on linked RMS data, researchers constructed a dichotomous variable (yes/no) that indicates whether there was any arrest associated with a CAD event.

- Total number of charges: Based on linked RMS data, researchers constructed a continuous variable that indicates the total number of charges associated with a CAD event.

RMS arrest data

- Sex of person arrested: female/male.
- Race/ethnicity of person arrested: Researchers constructed a three-level categorical variable to indicate race/ethnicity. Arrests in which a person self-identified or was otherwise identified as Hispanic were coded as Hispanic. For example, both a person who identified as white-Hispanic and someone who identified as nonwhite-Hispanic were coded as Hispanic. People identified as non-Hispanic white were coded as white, and those identified as non-Hispanic Black were coded as Black.
- Age of person arrested: years.
- District where the arrest occurred: A categorical police district variable was provided by each site.
- Majority race/ethnic group of the sector in which the arrest occurred: Researchers constructed this three-level categorical variable (Black/white/Hispanic) from the 2017 American Community Survey data that was used to impute the majority race/ethnic group residing in the sector. Sector is a geographical zone of the city defined by the police department. A sector is smaller in area than a police district—sectors can be aggregated into districts—and it comprises multiple census tracts. Demographic data was available at the census tract level or county level, but not at the sector-level used by the police departments. Therefore, some clipping and overlay mapping was necessary to obtain comprehensive sector-level data for this study. Because the sectors did not map directly onto census tracts or counties, researchers imputed sector-level demographic variables by mapping census tracts to the larger sector using the. The formulas below show the imputation process.

$$X_{Census\ Tract} = Percent\ of\ Census\ Tract\ Within\ the\ Beat$$

$$P_{Census\ Tract} = Population\ of\ Census\ Tract$$

$$Y_{Sector.Beat} = \frac{X_{Census\ Tract} * P_{Census\ Tract}}{\sum (X_{Census\ Tract} * P_{Census\ Tract})}$$

- Poverty level of the sector in which the arrest occurred: Researchers used data from the 2017 American Community Survey to impute the percentage of people living below the poverty line in the sector (see race/ethnicity above). Then, they constructed a three-level categorical poverty variable (low/medium/high).
- Number of charges of the person arrested: Researchers constructed a continuous variable to sum the number of charges accrued by a person in connection with a particular CAD event.

Analytic approach

Taxonomy of arrests

In addition to producing descriptive statistics (means, standard deviations), researchers constructed a typology to organize the multitude of arrests for each site into discrete and manageable categories (clusters). The resulting taxonomy provided initial insights into the many arrests that resulted from the CAD events. This exercise was analogous to the way that botanists organize plants into species to describe meaningful differences among these categories.

The cluster analysis in this study was based on pooled 2016-2017 RMS-CAD data (see data section above). Vera researchers used the K-Proto algorithm to fit mixed data, as opposed to other clustering algorithms that only fit continuous or categorical variables, such as K-Means or K-Modes.[224] The "elbow" test was used to identify the optimal number of clusters for the data.[225] The optimal number of clusters for both Camden and Tucson was seven. The results were presented in tables that display profiles of the seven clusters for each city. Each row in the table describes the representative arrest for that category.

Geographic distribution of arrests

Researchers plotted the geographic distribution of arrests resulting from CAD events on maps using ArcGIS software. The maps display the location of the arrests, overlaid with the race/ethnicity of the person arrested and the sector-level call volume.

Predictors of arrests

Statistical models. Researchers used generalized linear logistic regression models (GLM) to estimate associations between the outcome (arrest) and predictors of interest. A quasi-binomial model was used to address the over-dispersion (clumping) of some variables. All models controlled for covariates.

Stratified analysis. For each city, researchers conducted additional analyses in which the statistical models described above were run on two subsamples of the CAD data based on call type: 1) 911 calls, and 2) officer-initiated events.

[224] Gero Szepannek, "clustMixType: User-Friendly Clustering of Mixed-Type Data in R," *The R Journal* 10, no. 2, December 2018, 200-208, https://journal.r-project.org/archive/2018/RJ-2018-048/RJ-2018-048.pdf.
[225] Purnima Bholowalia and Arvind Kumar, "EBK-Means: A Clustering Technique Based on Elbow Method and K-Means in WSN," *International Journal of Computer Applications (0975 – 8887)* 105, no. 9, November 2014, http://research.ijcaonline.org/volume105/number9/pxc3899674.pdf.

Chapter 7: Applying Natural Language Processing to 911 Narrative Data to Inform Data Collection, Analysis, and Public Safety Response

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The purpose of this chapter is to inform ongoing efforts by police and public safety communications departments to understand the ways in which narrative data that is unstructured (i.e., does not have a discrete category or set of options for data collection purposes) input into computer-aided dispatch (CAD) systems may capture information that is not present in the structured data fields (e.g., set of categories, definitions, and drop-down menus). This examination provides empirical evidence of potential avenues for:

- altering the structure of how narrative data should be stored;
- raising questions about how 911 call for service incident types may be classified improperly or in ways that are counterintuitive or confusing to dispatchers, responding officers, supervisors, and/or researchers; and
- providing recommendations for future research.

The primary aim of this chapter is to discuss the analysis on the narrative text fields found in CAD systems through data science techniques and methods known as Natural Language Processing (NLP). CAD data contains structured and unstructured data derived from 911 calls for service (CFS) as well as police officer-initiated activities. In this analysis, the researchers focused primarily on the narrative fields within the CAD data to examine the research questions and identify areas for future attention and improvement. The researchers also examined data from Records Management Systems (RMS).

To the best of Vera's knowledge, this is the first time that NLP, or any advanced data science practices, have been applied to the 911 call-taking, dispatching, and related police response procedures. Thus, the inquiries presented here are novel, help ground-test the theory of such research, begin to hone a methodology for advancing science and practice in this field, and offer an opportunity for more expansive research in the future.

Research questions

This chapter aims to answer the following research question:

Which, if any, new variables or data systems should be integrated into CAD datasets, to systematically capture information important to 911 call responses? In other words, what, if any, relevant information is routinely captured exclusively in "narrative field" portions of CAD datasets?

To systematically examine this question, the researchers operationalized this research into the following key areas:

- Is there information in the CAD narratives that is not contained in the structured data? Could this information be useful to call-takers, dispatchers, and officers in the field when determining how to respond to a CFS?
  - If so, is that information standard in any way—that is, does it follow a certain structure, or are there common structured elements within the narrative fields?
  - If so, what do the elements of these narratives typically look like, what do they reveal, and what might they indicate about other pieces of information in the narrative field?

In the future, the researchers hope to advance these inquiries to determine if bias that contributes to patterns in the assignment of subjective information within the structured fields can be detected within the narrative field.

Data, methods, techniques, and analytic approach

Though the quantitative structured data produced and provided by both Camden and Tucson capture all of the variables of interest for the preceding analyses, the narrative field may provide a largely untapped source of information on 911 calls and police responses. [226] The researchers find, through a number of different NLP methods, that otherwise uncaptured information exists in the unstructured data and, in some instances, may better inform the structured data. This extracted information sheds light on another element of the data that needs to be explored and analyzed in conjunction with other CAD/RMS variables.

In short, the NLP analysis finds that there is information in the unstructured data that is not present in the structured data. The findings also have implications for how lack of attention to the unstructured data can prevent police departments, public safety communications departments, and communities as a whole from fully understanding the nature of all CFS or the patterns within these calls, which may result in dispatching and response procedures that do not best meet the needs or demands of those affected by the incident.

Data

The data employed in this section comes from the following four datasets:

- Camden County Police Department (Metro) – CAD

[226] The data provided to the researchers is outlined in the preceding chapters of this report.

- Camden County Police Department (Metro) – RMS
- Tucson Police Department – CAD
- Tucson Police Department – RMS

For the purposes of the NLP analyses, the variable of interest in both datasets is the narrative field, which is primarily completed by the 911 call-taker through the course of the conversation and information gleaned from the 911 caller. The CCPD variable is titled "Narrative." The TPD-CAD data includes narrative information under several different "Comms" variables.

Because the narrative fields for both cities can be up to 500 words, and there are more than 1,000,000 observations, they cannot be easily quantified with qualitative processes, such as word coding. As a result, the researchers employed a more innovative method to analyze the text through applied NLP, using statistical language models and machine learning algorithms, which are discussed in the methods section below.

Methods and techniques

NLP techniques have become increasingly popular as advanced computing is becoming more common. The clear methodological contribution is that it is inherently a mixed-methods approach that combines both qualitative and quantitative elements and provides the "best of both worlds."[227]

The primary aim of the current NLP analysis is to provide an additional perspective on one of the key questions investigated in this report–whether and how information conveyed to call-takers and captured in CAD CFS data influences police response and dispatch. To properly conceptualize this, prior NLP research has established processes for analyzing the natural language and free-form language. Existing research in this area has found how "N-Grams" (connecting text that combines and examines letters, symbols, and numbers) and other NLP methods can be utilized to add structure to unstructured data, to analyze and identify similarities and differences in structured versus unstructured data, including to help to identify bias. For example, one study that examined racist and sexist hate speech online found bias through N-Grams.[228] NLP has also been employed in a range of other contexts and across disciplines, including political science and criminology.[229]

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[227] Jason Seawright, *Multi-Method Social Science: Combining Qualitative and Quantitative Tools*, (Cambridge, UK: Cambridge University Press, 2016).
[228] Zeerak Waseem, "Are You a Racist or Am I Seeing Things? Annotator Influence on Hate Speech Detection on Twitter," Proceedings of 2016 EMNLP Workshop on Natural Language Processing and Computational Social Science, 2016, 138-142, https://www.aclweb.org/anthology/W16-5618.pdf.
[229] See for example Justin Grimmer and Brandon M. Stewart, "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts," Political Analysis, 1-31, 2013, https://web.stanford.edu/~jgrimmer/tad2.pdf; Maarten Van Barneveld, Nhlen-An Le-Khac, and Tahar Kechadi, "A Natural Language Processing Tool for White Collar Crime Investigation," in Transactions on Large-Scale Data- and

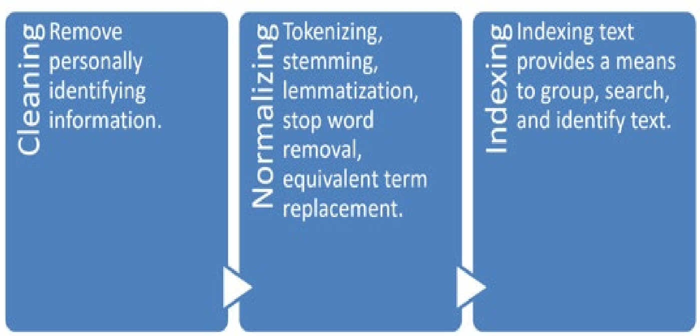
Newly developing research has illustrated both the power and importance of NLP techniques in the social sciences. One study illustrated the accuracy and strength of NLP techniques, in which the generated model scored a 99.8 percent correct classification rate on a set of news group articles written in different languages.[230] This classification technique equated similarly to a necessary grouping approach that could be utilized on our narrative fields, and the extremely high classification rate from the previous study showed promise with the ability to locate key words in the narrative fields.

Approach

The underlying goal of NLP analysis is to establish a form or structure for the full body of text and group these structures into clusters that represent the commonly occurring themes/patterns. These clusters then identify the key characteristics of the bodies of text.

Prior to running any NLP analyses, it is necessary to clean the narrative text to characterize the structured data. Figure 7.1 below demonstrates the steps involved in cleaning, normalizing, and indexing the data to perform NLP analyses.

Figure 7.1: Cleaning, normalizing, and indexing process



First, any and all personally identifying information (PII) is stripped from the data in accordance with IRB guidelines. Next, the text is normalized, which includes tokenizing

Knowledge-Centered Systems XXIII, edited by Abdelkader Hameurlain, Josef Küng, Roland Wagner, et al. (Berlin: Springer, 2016), https://www.researchgate.net/profile/Maarten_Van_Barneveld/publication/281640675_A_Natural_Language_Processing_Tool_for_White_Collar_Crime_Investigation/links/563f0d0a08ae8d65c014ab70/A-Natural-Language-Processing-Tool-for-White-Collar-Crime-Investigation.pdf; and Sumithra Velupillaia, Hanna Suominen, Maria Liakata, et al., "Using clinical Natural Language Processing for Health Outcomes Research: Overview and Actionable Suggestions for Future Advances," Journal of Biomedical Informatics 88 (2018), 11-19, https://www.sciencedirect.com/science/article/pii/S1532046418302016/pdfft?isDTMRedir=true&download=true.

[230] William B. Cavnar and John M. Trenkle, "N-Gram-Based Text Categorization," 2001, http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.21.3248&rep=rep1&type=pdf.

(splitting words from sentences), stemming, lemmatizing, removing "stop words," removing punctuation, and replacing equivalent terms.[231] Each of these foundational processes is required prior to identifying structures and patterns within the narrative text.

Once the cleaning and normalizing procedures are completed, researchers begin identifying data structures, as demonstrated in Figure 7.2. Feature sets are calculated from the normalized collection of words, and the data structure is then determined from these features, which include N-grams, longest-common-subsequence of words, key-phrase extraction, named-entity extraction, and "critical triples."[232] N-Grams are extracted "features" from the list above: longest common subsequences, key-phrases, named entities. Named entities are subject matters housed within sentences, whereas key phrases represent the most statistically significant phrases within a sentence, based on part-of-speech tagging and named entities.[233] It is standard to use these methods when attempting to conduct auto-summarization of a piece text.

Figure 7.2: Creating data providing structure

The next step within the NLP procedures entails combining all of these features to form likely centroids at a document level (or a subset of the document collection) to run a series of different analyses. Centroids are a common set of features that likely relate or correlate multiple CAD entries or observations.[234]

These words or phrases and likely centroids are analyzed to determine the inverse frequency across the entire document collection. In other words, what recurring phrases are

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[231] Stemming is the process of removing derivational affixes (e.g., -ish, -ous, and -ful) to bring a word back to its original root. Lemmatization refers to extracting the lemmas, or word stems, per sentence. A stem (root) is the part of a word that may receive an inflectional (i.e., changing/deriving) affix, such as -ed, -ize, or -s. A lemma is the canonical or dictionary form of a word or set of words, such as connect, which can receive an inflectional affix of -ion to form "connection" or -ed to form "connected." The process of stemming and lemmatization includes identifying and truncating the verb endings and plurals in a sentence. For example, the process includes converting words like "jumped" and "jumping" to "jump" and "cars" to "car." Stop words do not have significance for the document collection and should be removed to avoid skewing the analysis. These terms include examples like "a", "the", "that", or other genres of texts, such as months, days of the week, and even some gender indicators. Additionally, researchers removed words that were an isolated digit (i.e., a number not connected to other information or not prepended or appended by other letters). For more information, see "Stemming and Lemmatization," 2008, https://nlp.stanford.edu/IR-book/html/htmledition/stemming-and-lemmatization-1.html.

[232] Critical triples are semantic triples of subject-predicate-object sequences that are linked to a weighted/repetitive n-gram.

[233] Auto-summarization is a sub-field within NLP that aims to summarize a piece of writing (usually an article, a conversation, or a book). As researchers tackled the problem of identifying key features, they did so with the goal of borrowing from approaches with a similar foundation in the initial steps in case it appeared like auto-summarization tools would improve the results. Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze, *Introduction to Information Retrieval* (New York: Cambridge University Press, 2008).

[234] This is a relation in the true mathematical sense of the word (a centroid marks a set of related observations).

most likely unrelated and creating noise in the dataset as opposed to those that are helpful or unique when identifying or "indexing" some subset of the documents/CAD entries? The result of this analysis is a group of "strong centroids," or the primary centroids employed when analyzing the entire document collection. The final set of analyses included different clustering algorithms (K-Mean), Principal Components Analysis (PCA), and Gaussian Mixture Models (GMM).[235]

Prior to discussing the findings, it is important to highlight why the researchers decided to employ N-Grams and not the subsequent models.

After completing the aforementioned steps, the researchers recognized a challenge—the CAD narratives do not follow a standard/typical English sentence structure. The statistical models for sentence elements like key-phrase identification or named-entities could not recognize the short note-like structure of many of the CAD entries, often resulting in only one key phrase or subject identified, or none at all. Additionally, though stemming and lemmatization were successful, the shorthand language in CAD narratives is nearly reflective of this form. As such, the text entries did not sustain any significant alterations after undergoing these processes. N-Grams are the largest contributing feature and thus have the most influence in determining which centroid a narrative entry will fit. This is primarily because other features do not always produce data during analysis, given the narratives' unnatural sentence structure. This was true in Vera's research to such an extent that, if the researchers focused solely on N-Grams, they would receive promising results in analyzing the text without the computational and time overhead of the other techniques. Moreover, because there was no comparison to a general outcome, something that is not imperative for N-gram analysis, this lack of comparison rendered many other analyses unnecessary.

Therefore, researchers reverted to the N-Gram analysis in the current study because examining the N-Grams (within the inverse frequency across the document collection) allowed them to effectively know if the CAD entries contained structured data that is not captured anywhere else. To reiterate, N-Grams render patterns and phrases that are commonly used together. This technique can be used to identify structured data not captured in a traditionally structured way.

Limitations

NLP is an innovative approach that allows for a more rigorous exploration of unstructured data, which would not otherwise be possible manually due to time and labor constraints. Nevertheless, like any other method, it has limitations. These limitations must be considered in context with the findings. First, it is important to note that models are imperfect; the results

[235] Manning, Raghavan, and Schütze, *Introduction to Information Retrieval*, 2008; Daniel Jurafsky and James H. Martin, *Speech and Language Processing: An Introduction to Natural Language Processing, Speech Recognition, and Computational Linguistics*, 2nd ed. (Upper Saddle, NJ: Prentice-Hall, 2008); and Christopher D. Manning and Hinrich Schütze, *Foundations of Statistical Natural Language Processing* (Cambridge, MA: MIT Press, 1999).

(computed N-Grams and centroids) are only as sound as the data fed into the applied models used for computation. In the current analysis, the tagging and model-based analyses rely on the standard structure of an English sentence. Considering that the narrative information in the CAD entries was either fragmented, coded in shorthand, abbreviated, or misspelled, the data does not always adhere to or strictly follow the English-language standard sentence structure.

In addition to the inherent limitations of NLP, it is important to note that some data imperfections from the two datasets may have further limited researchers' ability to properly examine the narrative texts. For example, the Camden narrative information was one continuous string of text contained within a single field, whereas the Tucson narrative information was split into several different fields, which required merging and resulted in a concatenated variable on which NLP was applied for the purposes of this study.

Findings

The findings presented below demonstrate that information clearly exists in the unstructured data narrative fields that is not present in the other structured CAD data. The researchers found such data in the CAD narrative entries not represented in the structured data at both sites. It was established through two different lenses, one characterized as a *qualitative judgment* made on the part of the 911 call-taker or dispatcher (e.g., frequently occurring CAD narrative entries, such as "possible psych," a reference to a person who may be experiencing a mental health crisis) and the other a *shorthand code* (e.g., "CDS," which is an acronym for controlled dangerous substance). Both patterns appeared regularly across the entire dataset in different frequencies. In some cases, these factors significantly altered the intention of the structured data. For example, a "man with a knife/weapon in public, active on the scene" versus "possible psych" shows how the ambiguity of a call code can mask other underlying information provided to the call-taker, which can better inform officer approaches.

Researchers identified examples like the following in the Camden data, in which the call-taker appears to be issuing a qualitative judgment to course correct to a better outcome. Although some of the calls were demarcated as violent offenses, the call-taker provided additional and critical information relating to mental health/substance use elements of the situation that can better inform police encounters:

> *"apt b, 50 year old female hasn't taken psych meds in 5 days, she is violent throwing glass. county en route" "apt b,,,,caller stated she needs this female out of her house she is going crazy,,,,, throwing things out of the window and she had a knife,,,,female has schizophrenia,,,ems en route"*

> *"[CAD ID number removed] is an assault of a women by an ex-boyfriend, where the current boyfriend is emotionally unstable (reported schizophrenic) is also having an episode.*

These examples illustrate how difficult it is to automatically detect qualitative judgment style patterns, unless the researchers know at the outset of analysis which words, phrases, or incidents to look for and can thus specify the parameters.

In contrast, the shorthand codes are extremely easy to detect, are very prevalent, and follow the same structure throughout the entire dataset. These codes most likely represent the operating behaviors of call-takers, dispatchers, and police officers or are extensions of standard operating procedures of dispatchers.[236] Additionally, it is important to understand relative frequency of terms in relation to each other.

To put N-Grams and NLP in greater context, Figure 7.3 provides a sample table of observations during one month in the study period (mid-April to mid-May 2017) and their respective counts. This is not comprehensive, as items that are likely routine and not revealing (e.g., "blue jeans" and "latrine") have been removed. Through this examination, researchers can establish the relative frequency of terms in relation to each other.

Figure 7.3: Sample N-Grams and relative frequency

N-Grams	Frequency
Male	838
condition check	577
Female	343
Loitering	235
Bc	230
Cds	218
Narcan	179
weapons/gun/shots	161
fighting/assault	131

[236] CAD systems by nature limit what call-takers and dispatchers can record. Additional research is needed to properly explore this dimension.

child/daughter	99
mother	91
loud music	58
Mt. Ephraim grocery	28

Cross-Site Comparison

The two sites (Camden and Tucson) are more different than similar, but this is not surprising given the limitations involving how the Tucson CAD narrative data is structured (i.e., contained across multiple fields), which may be one reason researchers were prevented from computing strong centroids in the current study.

One similarity worth noting is that domestic-related terms are salient across both cities. This is also not surprising due to the high frequency of domestic disputes and domestic violence calls in both cities. Details about domestic relationships ("her boyfriend," "wife," "husband," "child") were common across sites and prevalent enough that they formed centroids in both datasets. The largest domestic-related centroid in Camden (and one of the biggest overall) was "her boyfriend."

Camden

After computing the second set of N-Grams for the Camden narrative fields, researchers successfully identified the centroid occurring with the highest frequency, "juvenile," which requires further exploration in combination with general outcomes (RMS data). Though this is beyond the scope of the current analysis, the current study revealed additional macro-level findings. For instance, it is clear from the analysis that seasonality among centroids exists both across time of day and throughout the year.

The most salient and concerning finding from the Camden narrative field data is the presence of "possible psych." As highlighted above, there are CFS or incident classifications for some observations where "possible psych" is the primary centroid, but the incident is reported as "Man with a knife" or "Violent/disturbed individual" in addition to other incident classifications. Thus, this raises questions and avenues for further conversation when violent offense calls for service receive a more urgent priority coding and the mental health element is overlooked or masked.

Moreover, the lack of clarity in calls that are related to behavioral health is of particular importance due to the fact that, in the 2016 Camden descriptive analysis, researchers found only

1,797 calls related to behavioral health.[237] Through NLP techniques, researchers were able to identify mental health related calls that included the following substrings: "mental," " mi," mhd," "emotion," "disturbed," "edp," "instability," "psych," "pmhc," "csc,", "bipolar," "schiz," and "suicide."

This suggests that there may be a much larger number of mental health/behavioral health calls that do not capture the seriousness of the problem. Instead, they may potentially be masked by an inappropriate incident classification code that does not properly characterize the situation and risks officers making judgment calls based on the primary incident classification, which requires further investigation to confirm the extent of the problem. This has broad policy implications on how systems should allow for an easier way to indicate mental health calls in addition to other elements for the call.

Another dominant centroid identified was “Narcan.” Narcan is a nasal spray that is administered when a person is going through a narcotic overdose.[238] In 2014, CCPD distributed Narcan to all officers to employ in overdose incidents, which has saved and continues to save countless lives.[239] Currently, all CCPD and TPD officers, along with those in many other departments across the country, have been provided Narcan to dispense if/when they encounter someone experiencing an overdose in the community. Furthermore, the high frequency of “Narcan” in the CAD data illuminates the extensive nature of opioid overdose and prevention efforts in Camden and elsewhere. Community members’ concerns raised during focus groups conducted in conjunction with the current study also support this finding.

Tucson

In contrast to Camden’s CAD data, the Tucson narrative fields have almost no dominant centroids. The narrative fields contained high levels of variation, which is likely due to the nature of how the multi-part narrative fields are structured in Tucson.

Because there are multiple narrative fields in Tucson CAD entries, researchers had to concatenate the variables containing the narrative data. This resulted in fragmented sentences that were more difficult to process during NLP analyses. The only element that is common across the TPD dataset is repeat locations mentioned in narrative fields. It is difficult to find the "qualitative"-style coloring/emphasis in the narrative fields because researchers must first identify some of those by hand to find more of them, which was not possible in the course of the current research.

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[237] See Chapter 5, Section 2 on page 133 for Camden descriptive statistics.
[238] NARCAN® is the brand name for the first and only FDA-approved nasal spray form of naloxone to provide emergency treatment in the event of a known or suspected opioid overdose. For more information on this product, see https://www.narcan.com/.
[239] “CCPD Implementing New Tools to Combat Opioid Overdose,” May 01, 2018, KRIS 6 News, https://kristv.com/news/2018/05/01/ccpd-implementing-new-tools-to-combat-opioid-overdose/.

Nevertheless, it is worth highlighting that "drug related" and "her boyfriend" were some of the most salient features, which is not surprising given the domestic violence and substance use challenges that residents of Tucson encounter.

Conclusion

There are several key findings from applying the NLP approach, methods, and techniques to Camden County's and Tucson's 911 data. The high-level results include the following:

- The narrative fields in the CAD entries are essential to making accurate policing decisions;
- Call-takers, dispatcher, and officers inject subjective bias into the narrative fields;[240] and
- Additional research is needed to understand why this detectable difference between the narrative field and structured data exists, how call-takers, dispatchers, and officers use the narrative field, and how much cognitive load is placed on officers when consuming the narrative data compared to the structured data. This endeavor would require researchers to review the data manually and identify another data presentation method prior to employing a computational/algorithmic approach.

In this chapter, the researchers presented evidence from an exploratory analysis and highlighted how the way that data is captured and stored can either help or serve as a barrier to employing NLP techniques for analysis. NLP techniques were more successful with the Camden data as a result of the narrative information being captured in one field. In contrast, NLP techniques were more difficult to apply to the Tucson data. Many of the methods assume that the narrative follows typical English sentence structures, which was more difficult to achieve in the Tucson data, given that it had to be concatenated from a number of different data entry fields.

Three clear recommendations from this research are to (1) contain all narrative data in one field; or (2) clearly specify why and where different text should be captured; and (3) conduct regular quality assurance examinations of such information. Implementing these recommendations would facilitate more natural English language to be analyzed and allow researchers to more easily identify shorthand codes through these techniques.

This analysis also raises areas for future research with more thorough investigation through other data science methods, including the following:

- topological data analysis;
- automated knowledge base construction;

[240] Though the researchers can identify the presence of bias, the degree to which it influences the CAD entries cannot be empirically confirmed. Therefore, further research is needed to examine the extent of call-taker, dispatcher, and officer bias in 911 system data.

- different text indexing techniques;
- self-organizing maps;
- classification; and
- deep outcome analysis.

To summarize, this analysis was primarily for exploratory purposes to better understand if there is data in the narrative field that is not captured by the structured data. The researchers found, through multiple examples in the data, that the incident classification on its own does not provide all of the information that may best inform police response. Furthermore, this analysis sheds light on areas that require further exploration to better understand the extent of certain hypotheses generated from this exploratory analysis. Finally, it provided recommendations for how narrative data should be collected and stored in order to further employ NLP and similar techniques to unlock findings that could better inform 911 call-taking, dispatching, officer decision-making, or alternatives to police response.

Chapter 8: A National Convening to Understand Police Enforcement through 911 Operations and Analysis

S. Rebecca Neusteter and Sarah Scaffidi

After conducting the empirical research tasks discussed in previous chapters, the Vera Institute of Justice (Vera) hosted a national convening of law enforcement leaders and system stakeholders to present research findings, explore alternatives to enforcement, and identify opportunities for reform. This convening was held in partnership with Arnold Ventures and George Mason University's Center for Evidence-Based Crime Policy (CEBCP). Both research teams (Vera and CEBCP) presented their work on 911 call trends, processes, system maps, and outcomes to field experts to elicit feedback and spark innovation regarding next steps, focusing predominantly on alternatives to enforcement. The national convening provided the opportunity to complement research findings with the perspectives of leading practitioners, further informing recommendations for policy and practice.

Participants from 40 organizations across the country were in attendance, including representatives from 10 police departments, five public safety communications agencies, and 10 research organizations. For a complete list of participating organizations, see Appendix 8. In the lead-up to the convening, Vera asked participants what they were hoping to discuss and used responses to inform the convening's agenda. These responses are summarized below.

The convening was broken into three segments, each focusing on a different aspect of the 911 call system. The first segment, defining the landscape of the 911 service, provided an overview of current practice and research findings. Vera researchers began with an overview of the 911 report, explaining why this research was necessary, the different methods used to answer research questions on call-taking processes and outcomes, and preliminary findings. CEBCP researchers then presented findings from their study of Computer Automated Dispatch (CAD) data from 10 different precincts, highlighting the research process and key takeaways. Vera researchers then led a group discussion on findings from both presentations, allowing participants to respond and offer insights from their various perspectives.

The second segment of the convening, led by representatives of the Camden County Police Department (CCPD) and Tucson Public Safety Communications Division (PSCD), spotlighted recent innovations. CCPD's deputy chief presented on his department's alternative processes to reporting, which were implemented to make more efficient use of police resources. PSCD's delegate presented on Criteria Based Dispatching (CBD), a new initiative that his department implemented in the fall of 2019 in the hopes of streamlining the call-taking and dispatching processes. The Vera team then led a convening-wide group discussion of these and other innovations that participants have adopted to improve the 911 systems in their communities.

The third and final segment of the day was a series of group discussions and presentations on future directions of this work. Four groups were created, each with a focus on either (1) call load/dispatch; (2) responding officers/police practitioners; (3) community education/research; or (4) alternatives. During a break-out session, each group was tasked with developing a new policy, program, or idea that stood to improve service quality, organizational efficiency, and community safety in their specific field. Group members then presented to the convening at large, sparking discussion and actionable feedback.

This chapter of the report seeks to highlight practitioner innovations, as well as researcher- and practitioner-informed challenges and opportunities for growth.

Challenges to the 911 call system

Throughout the convening, participants identified the following challenges to their work in the 911 practitioner and research space.

Lack of governance

Police chiefs and emergency public communications practitioners raised the lack of governance and subsequent lack of a national standard as key challenges to improving 911 call-taking and response. There are more than 6,000 public safety answering points (PSAPs) throughout the country, and 36 states have 911 authorities with differing roles within their job responsibilities. Some communities encourage calling 911 for any emergency, no matter the urgency, whereas others encourage the use of 311 or other public information channels, and still others offer online reporting of minor crimes.[241] There is no set of governing standards for PSAPs to follow, so each locality sets its own rules. This results in callers following one community's standards when calling from a neighboring community with different practices, which slows down the call-processing system.

Cell phone prevalence

As discussed in Chapter 2, the 911 call system was set up when landlines were the primary source of calls for service. Each number is registered to a location, which means that call-takers do not have to request this most crucial bit of information. By 2016, more than 80 percent of

[241] See Chapter 2 on page 21.

calls came in from cell phones, which ping off the nearest cell tower and are then routed to a call center. The call center is not always in the same department or precinct that the person is calling from, and when this happens, the call-taker must transfer the caller to the correct area before they can receive assistance, which takes longer and is a drain on resources in both departments. Furthermore, callers may not know the exact location that they are calling from, posing yet another challenge not anticipated by the landline-driven system design.

Disjointed development of technology

Beyond the prevalence of cell phones, the lack of dialogue between technological innovators and 911 practitioners has led to well-intentioned developments that practitioners say are more of a nuisance than a help. One police chief raised the example of 911 alarms on iPhones, which come pre-programmed to dial 911 when a phone user presses the power button three times in quick succession. Though this was designed to improve public safety, practitioners say that the primary outcome of this innovation has been an increase in accidental 911 calls. These calls still must be processed and investigated, further draining limited resources.

Lack of standardization in call-taking

A lack of standardization was raised by call-takers at the convening and was highlighted on an intra-departmental level in the Audio Analysis chapter of this report. There is no national standard for call-taking and coding, which has resulted in practices that vary both within and across call-taking agencies. Initiating a standard would also prove tricky, as each precinct is different. For instance, major violence in a city like Baltimore is likely to mean something very different than major violence in a small rural township. Nevertheless, convening participants argued that a set of adaptable national guidelines is a key resource that is missing from the field.

911 responsibilities have outpaced staffing and funding

The increased demands of the 911 system have outpaced increases in staffing and funding, and practitioners feel the strain of this burden. Participants voiced opinions that call-takers and dispatchers are understaffed, underpaid, and underrepresented in the conversation about reform. Officers want to make the best use of the CAD system, but they lack the internal resources to do so.

Flawed efficacy metrics

Given the available variables in CAD data, the most common metric associated with 911 response efficacy is response time, a measurement that does not reflect the nuances of the response process or its most important aspects. Practitioners explained that timing is only crucial for responding to emergency calls, of which most 911 calls are not, and that it is more important to take time and respond correctly.

Spotlighting new innovations

The presentations on innovations and subsequent discussions highlighted a series of emerging practices. Once evaluated, these innovations may emerge as effective practices in call-taking and policing nationally.

Process innovations

Criteria-based dispatching (CBD) in Tucson

Using a recently implemented CBD system, 911 call-takers will rely on a structured computer-based system of question prompts to guide the information they collect from callers and pass along to emergency responders, with the goal of improving accuracy, efficiency, and service outcomes. Although CBD is commonly used within fire and medical emergency response centers, Tucson will be among the first to employ this technology in a law enforcement context.

Alternative reporting in Camden

By changing the way that community members report certain incidents, the Camden County Police Department sought to free up police resources. Under the new reporting system, incidents including theft and motor vehicle accidents with neither injuries nor drivers under the influence of alcohol or illegal substances must be reported in person. This saves valuable officer time by not requiring them to travel to the scenes of these events when their presence is not necessary to resolve the issue. CCPD plans to next examine disturbance calls, its most frequent call type, to see how the department may alter reporting there.

Community-level innovations

The following are examples of convening members' own innovative practices that deal directly with members of the community by improving outreach and fostering sustainable relationships.

- **Proactive Community Outreach:** Members of Fairfax's Community Response Team proactively go out to meet with people who frequently call 911 to determine what is driving these calls and attempt to solve the callers' fundamental problems in a manner that avoids future unnecessary emergency calls for service. Evaluations have shown this initiative to be successful, but labor and resource intensive.

- **Community Mindfulness Training:** New officers in Houston take field trips into the community to learn about the people they serve, and Washington, DC, officers go through historical training in the National Museum of African American History and Culture.

- **Training the Chronically Underemployed:** Washington, DC, used its LEAP services to train people who are chronically underemployed as 311 call-takers, with the possibility of progressing to 911 call-taking. This starts underemployed community members on a career path that needs recruits.

Technological innovations

The following are examples of convening members' own experiences using technological innovations to improve policing and call-taking practices.

- **Panic Alert Buttons:** Washington, DC, has developed the Rave Panic Alert Button for active shooters and other emergencies. This is now in use in DC schools and government buildings.

- **Texting 911:** Camden, Seattle, Washington, DC, and a number of other jurisdictions allow community members to text 911. Calling is preferable, as in Seattle it takes an average of nine minutes to process and verify a text compared to one minute for audio call-taking, but texting is a useful tool for situations when audio would put the caller in danger.

- **Automated CAD Prioritization:** In Fairfax, calls are automatically prioritized through the CAD system based on the way they are classified by the call-taker. This is helpful in providing a standard and strengthening inter-call-taker reliability, but may pose new challenges, as these matters are often nuanced and difficult to categorize.

- **Critical Incident Response Teams (CIRTs):** In addition to using CIRTs to respond to crises and other traumatic events, some departments also use CIRTs to handle frequent 911 callers. This approach has been effective in jurisdictions that have experimented with it, and users hope that other departments across the country can adapt it to scale.

Opportunities for growth

Throughout the convening, practitioners and researchers identified parts of the 911 system that could be improved by reinvesting resources and adapting practices. These are the most salient opportunities for growth that were raised.

Capitalize on uncommitted police time

Researchers from George Mason University's CEBCP examined 10 police precincts and found that, across the sites, between 40 percent and 45 percent of officer time was unaccounted for in the CAD system. During this time, officers were not responding to 911 calls for service or initiating activity. This presents a unique opportunity to strategically deploy police for crime prevention, which may take the form of an innovation mentioned in the previous section of this chapter, further research, or a new idea altogether.

Invest in call-takers

Call-takers are the first step in the 911 call processing system, making them the effective gatekeepers of public safety. As of this writing, call-takers are classified as secretaries by the U.S. federal government, though the scope of their work is not in line with this description, and the 911 Saves Act will change this if enacted.[242] Call-taking is a poorly paid position with high turnover and levels of PTSD outpacing those of officers. According to the CEBCP study discussed at the convening, call-takers resolve roughly half of all 911 calls. They present the first opportunity to divert police response and the subsequent enforcement that may be applied. Investing in future research and integrating innovative practices for call-taking are cost-effective ways to improve the 911 system.

Invest in dispatchers

Researchers at the convening described dispatchers as patrol managers, as they often know where officers are more frequently than squad captains do. When 911 as a community resource first came into practice more than 50 years ago, dispatchers and officers were in constant communication over the radio. They had strong relationships that facilitated a positive workflow, practitioners at the convening recalled. That practice changed with the inception of CAD, and officers and dispatchers are now engaged with one another in different and sometimes less connected ways. Dispatchers work behind the scenes while officers work on the front lines, but neither has much knowledge of what the other does. Dispatching, like call-taking, is an under-researched field that deserves more attention and innovation.

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[242] The 911 SAVES Act, H.R. 1629, 116th Congress (2019-2020), was introduced by Rep. Norma J. Torres (D-CA) and aims to update the classification of 911 dispatchers from clerical workers to a protective service that better reflect "…the important role of 9-1-1 dispatchers in directing emergency response and providing lifesaving emergency medical instruction." Office of Congresswoman Norma Torres, "Torres, Fitzpatrick Bipartisan Provision to Reclassify 9-1-1 Dispatchers as Protective Service Occupations Passes on House Floor," press release (Washington, DC: Office of Congresswoman Norma Torres, July 19, 2017), https://torres.house.gov/media-center/press-releases/torres-fitzpatrick-bipartisan-provision-reclassify-9-1-1-dispatchers.

Capitalize on technological advancements

The fact that technology has changed so drastically since the inception of 911 certainly poses challenges, but it also provides opportunities for innovation. For example, translation software allowed Seattle to take calls in 43 languages in 2018, and texting 911 allows the texter to update their own location. The Houston Police Department encourages community members to register information with their phone numbers, such as their address and whether they have a child with special needs, with bi-annual emails reminding them to update their profiles. These are just some of the many innovations that technology has enabled.

Divert certain call types

One of the guiding purposes of Vera's 911 report was to determine if sworn officer response is the most appropriate method to answer 911 calls, and practitioners at the convening confirmed that oftentimes it is not. Though communities like Camden have changed reporting practices for certain incident types, there are further opportunities to divert responses to the appropriate agency. Some incidents may be better resolved by mental health professionals, crisis intervention professionals, behavioral specialists, or other public servants. For instance, Tucson has newly dedicated mental health professionals to respond to relevant calls in its call-taking center. It is also worth examining what wraparound services community organizations can reasonably provide to supplement or replace 911 response.

Educate the community

Most Americans have a severely limited understanding of the 911 call system. Children are taught to call 911 no matter what, and that is where education on the call system ends. The average community member does not know that the first point of contact is a call-taker and not an officer, nor that a dispatcher plays a crucial role in determining the service they receive. Re-educating communities on the role and purpose of 911 would lead to increased understanding and perhaps new innovative partnerships like those highlighted in the previous section of this chapter.

Capitalize on the moment

The NG911 Now Coalition has come together to support the 911 Saves Act. This group of police, fire, Emergency Medical Services, National Geospatial-Intelligence Agency, and National Emergency Number Association stakeholders is reinvigorated and should be brought into the conversation around innovative responses to the challenges posed by 911 calls for service.

Conclusion

Vera hoped to have a productive discussion on the landscape of 911 call-taking, dispatch, and officer response, and the national convening exceeded those expectations. Researchers, practitioners, and policymakers may use the ideas highlighted throughout this chapter to inform their work. The following chapter builds on these ideas and provides more comprehensive alternatives to policing and innovative practices to cope with the 911 call load.

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Appendix 8: List of participating organizations

Organization
Arnold Ventures
Bureau of Justice Assistance
California Policy Lab and UCLA Dpt. Of Economics
Camden County Communications Department
Camden County Police Department
Charles Koch Institute
Data Collaborative for Justice
DC Metropolitan Office of Unified Communications
Fairfax County Public Safety Communications
Ford Foundation Gender, Racial and Ethnic Justice Program
George Mason University's Center for Evidence-Based Crime Policy
Global Strategy Group
Houston Police Department
Indianapolis Police Department
John Finn Institute, State University of New York, Albany
Law Enforcement Action Partnership
DC Metropolitan Police Department
National 911 Program (911.gov)
National Organization of Black Law Enforcement Executives
National Police Foundation
New Orleans Police Department
Police Executive Research Forum
Purdue University
RTI International Center for Policing Research Investigation Science
Seattle Police Department.
Tempe Police Department.
Temple University
The Lab at DC
The RedFlash Group
Tucson Public Safety Communications Division
Tucson Police Department
University of Chicago, Crime Lab
University of Cincinnati
University of Michigan
Vera Institute of Justice
Washtenaw County Sheriff's Office
Woodmere Police Department

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Chapter 9: Policy and Practice Recommendations for Improving Policing, 911 Call-Taking, and Dispatching Procedures

S. Rebecca Neusteter, Sarah Scaffidi, Abdul Rad, Frankie Wunschel, Marilyn Sinkewicz, and Daniel Bodah

In this report, the literature review provided a succinct overview of existing research pertaining to the 911 system. The analytic chapters examined different aspects of the 911 call-taking system. The system map and audio analysis chapters offered qualitatively informed insights into the earlier stages of the 911 system—call-taking, dispatching, and early decisions that impact outcomes. The descriptive analysis chapter looked solely at computer-aided dispatch (CAD) data, identifying frequent incident types and providing an overview of how call volume varies by day of the week, time of day, incident type, and geographic location. Lastly, the outcomes chapter traced these CAD entries to their conclusions, focusing on events that ended with an arrest. Each chapter provided insights into challenges and opportunities facing the 911 system.

Practitioners and researchers at the Vera Institute of Justice's (Vera's) national convening echoed these insights. The convening offered participants the opportunity to directly discuss innovations they employ to improve use of the 911 system. For more information on the specific challenges, innovations, and opportunities for growth, see Chapter 8.

This chapter provides an overview of challenges related to the current 911 system, after which policy recommendations and alternative practices that can address these challenges will be discussed. The main 911 system problems identified in this report are:

- The 911 system's **lack of governance** has resulted in inconsistent policing and call-taking practices across communities (Chapter 8).
- The **prevalence of cell phones** in a system designed for landlines makes it difficult to locate incidents (Chapters 2 and 8).
- **911 hang-ups** pose a significant strain on resources (Chapter 5, specifically Tucson).
- A **lack of data standardization** in call-taking and classification makes analysis and evaluation across geographic sectors and departments difficult (Chapters 2, 4, 5, 6, 7, and 8).
- **Disjointed innovations in technology** meant to assist practitioners have had the opposite effect (Chapter 8).
- Police departments and communications centers **lack the staff and funding** to meet increased demand and responsibilities (Chapters 2, 3, and 8).
- The **metrics** researchers use to evaluate 911 processes and outcomes, namely the reliance on response time, are **not good indicators of department efficacy** (Chapters 2 and 8).

- **Over-utilization of the 911 call system** for nonemergency incidents taxes limited resources (Chapters 2, 3, 4, 5, 6, and 8).
- **Marginalized groups do not necessarily trust the police enough to call 911,** which calls into question the comprehensiveness of 911 call data and raises larger questions about access to public safety services (Chapters 2, 6, and 8).
- **Requesting police assistance is difficult for** people who speak English as a second language, those who are Deaf or hard of hearing, and **some** other **community members** (Chapters 3 and 8).

This chapter on policy and practitioner alternatives considers the previous research in this report and insights from the convening to provide a broad overview of the landscape of innovation and policy recommendations.

Policy recommendations and practitioner innovations

There is no overarching solution to the challenges outlined above, but police and public safety communications departments might adapt localized, scaled versions of the following innovations.

Alternative police responses

The following recommendations are alternative responses that rely on officers' knowledge of the communities they serve. If wisely implemented, these responses could improve efficiency and enhance the safety of both officers and community members.

- **Responding to alarms:** Officers spend a significant amount of their time responding to alarms (see Chapter 5). Departments may adapt alternative reporting practices to minimize the need for sworn police response, as the Camden County Police Department did (for more on this initiative, refer to Chapter 8). They may also use institutional knowledge and caller location to predict how long an alarm call will take, as well as the likelihood that a given alarm will be false (Chapter 2). The large proportion of time dedicated to alarm response also suggests the need for further research and investigation on whether legislation is needed to regulate alarm companies' standards to prevent unnecessary strains on the 911 system.
- **De-escalation tactics trainings:** Many police departments across the country have implemented de-escalation and crisis intervention tactics and trainings. These approaches can help improve responses and address root causes without the use of force.[243] Some of these trainings, such as Crisis Intervention Team (CIT) co-responder training and related approaches, are also beginning to be adapted and applied to 911 call-taking and dispatching.
- **Community health and social supports**: Investments in community-based physical and mental health services, as well as social supports are a high priority. Appropriate resources are necessary to address homelessness, food insecurity and other social determinants of health and incarceration. A multi-pronged, cross-sectoral response is

[243] Though de-escalation approaches may reduce use of force and subsequent arrest or incarceration of people involved in interactions with crisis intervention officers, they are still reliant on sworn officer presence. Many stakeholders believe the continued use of police to address root causes of community problems inhibits true systematic transformation and alternative supports.

required that aligns with public health and safety approaches to offer prevention, early intervention, and continuity of care.

- **Trauma-informed practice**: Departments should enhance law enforcement response to children exposed to violence and childhood trauma to address their needs and reduce incidents of adverse childhood experiences (ACEs) that can result in heightened risks of subsequent victimization and engagement in criminal activities. An example of this may include the International Association of Chiefs of Police (IACP) project to respond to children exposed to violence and trauma, as well as the associated toolkit for officers.[244]
- **Tracking frequent callers:** It is difficult, if not impossible, to reliably identify frequent callers with most current CAD systems, given the varied origins of calls for service, poor user documentation, and the lack of a reliable master name index. Properly identifying and mitigating frequent callers through improved call-taking practices and police responses will require data management systems that address these deficiencies.

Improving call-taking practice

As discussed in Chapter 8, call-takers are under-examined first responders in the 911 public safety system. As such, ample opportunities exist for innovative policy and practice to improve this part of the system, and by extension, 911 practice as a whole.

- **Integrate mental health clinicians into 911 call-taking and call centers:** One recent innovation that has been adopted by several jurisdictions, including Tucson, is to place specialized certified mental health clinicians in 911 call-taking centers. In Tucson, these clinicians are supported through Medicaid funding and are working to address the needs of 911 callers who are experiencing mental health conditions or crises that can be addressed more effectively by a trained mental health specialist. In many cases, these specialists are reportedly diverting calls from police and enforcement responses by providing support to people in crisis. [245] Non-enforcement practices should be expanded, and programs like those in Tucson would benefit from further evaluation to understand the associated processes and impacts.
- **Invest in call-takers and call-taking practices:** Investing in call-takers and dispatchers is another critical avenue to improve this area of the system. Call-takers and dispatchers are often among the lowest paid and least trained representatives of the public safety system. Properly investing in these crucial personnel as gatekeepers and first responders—and supporting them through the challenging and often traumatic experiences of their work—has been overlooked and undervalued. Prioritizing the pay, training, and working conditions of these critical justice system stakeholders could have long-lasting and far-reaching effects.
    - **Call-taker career ladders:** Some jurisdictions have begun to explore opportunities for call-taking and dispatching career ladders. One such opportunity in Washington, DC, involves partnering with community colleges to

[244] For more information on the International Association of Chiefs of Police (IACP) project, see IACP, "Enhancing Law Enforcement Response to Children Exposed to Violence and Childhood Trauma," https://www.theiacp.org/projects/enhancing-law-enforcement-response-to-children-exposed-to-violence-and-childhood-trauma. The associated officer toolkit is located here: https://www.theiacp.org/resources/enhancing-law-enforcement-response-to-children-exposed-to-violence-toolkit.

[245] Though informal reports suggest some positive outcomes associated with mental health clinician participation in 911 call response, empirical evidence is lacking on these innovative practices, and the full impact of Tucson's initiative is not yet known. Vera supports additional research into non-enforcement responses to 911 calls as more agencies explore similar use of mental health professionals in public safety departments.

train chronically underemployed residents to become 311 call-takers, with the opportunity to move up in responsibility and pay as 911 call-takers and dispatchers (Chapter 8).

- **Improve internal and external procedural justice and customer service outcomes among call-takers:** As a gateway to the justice system, call-takers serve as key customer service agents. However, call-takers are not routinely trained to support the basic tenets of procedural justice: fairness, transparency, impartiality, and voice (the ability to be heard and express concerns). Opportunities to improve and measure procedural justice and customer service have the potential to benefit 911 call center personnel and callers alike.

- **Gather additional data on outcomes of 911 calls:** Rather than relying solely on CAD data collection that ends at officer response, data about other outcomes could be collected and linked to inform call-taker training for a variety of incidents, such as intimate partner and domestic violence calls (Chapter 2).
- **Institute specialized call-taking training, particularly for bias and domestic and intimate partner violence calls:** Though intimate partner and domestic violence calls are frequent and can be stressful and dangerous for community members, call-takers, and officers alike, departments do not universally require specialized training for 911 personnel in this area. This is an under-examined area with little research; however, one study from 2005 found that just half of departments offered such specialized training.[246]
- Call-taker training is limited in most jurisdictions due to scarce training resources and lack of proven practices.
    - Providing call-taker bias training and re-training call-takers to help them consider how stereotypes about people and places may impact their decision-making as key public safety personnel is currently lacking and merits investment.
    - Through the current research, Vera found that domestic violence calls had the highest priority level matches between call-taker categorizations captured in the CAD systems and Vera researcher categorizations, with nine of the 10 calls receiving the same priority type (Chapter 4). These calls appear less ambiguous than other call types.
    - Additional cross-training and education of call-takers, dispatchers, and officers would allow for a greater understanding and appreciation of these respective positions and help highlight needs and opportunities for improvement. For example, few opportunities currently exist nationally for call-takers and dispatchers to experience the operational aspects of officers' jobs and vice versa. When these opportunities do exist, they are typically limited to new recruit training, as opposed to regular in-service training and learning. Supporting regular call-taker and dispatcher ride-alongs and allotted times for officers to shadow call-takers and dispatchers could go a long way towards advancing understanding across these critical justice system stakeholders.

[246] Meg Townsend, Dana Hunt, Sarah Kuck, and Caity Baxter, "Law Enforcement Response to Emergency Domestic Violence Calls for Service," (unpublished report prepared for Bernie Auchter, National Institute of Justice, Washington, DC, February 1, 2005), https://www.ncjrs.gov/pdffiles1/nij/grants/215915.pdf.

  - Motivational Interviewing (MI) is a proven approach that has been implemented in other areas of the justice system, most notably with parole and probation officers, to elicit critical and actionable information. Investing in an exploration of this approach with 911 call-takers offers an opportunity for immediate and transferable insights.

- **Implement and examine alternatives to 911 hotlines:** Chapter 2 revealed that emerging alternatives to 911, such as 211, 311, and crisis hotlines, can offer an alternative to police response when such response is not necessary. However, training appears to be lacking and could benefit from investment to ensure departments do the following:
  - Provide information to call-takers and dispatchers so they are aware of these hotlines, how they work, and which calls may be appropriately rerouted.
  - Cross-train call-takers so, when possible and appropriate, they can resolve calls themselves, as they already do in roughly 50 percent of cases in George Mason University's 10-site study.

- **Explore criteria-based dispatching:** Without national, or even localized, call-taking scripts, 911 calls are handled inconsistently. In some instances, 911 caller concerns may not be properly identified or captured in CAD systems. Criteria-based dispatching (CBD) addresses this problem, including a series of automated questions and prompts to guide information gathering during the initial interaction between call-takers and 911 callers. CBD offers the opportunity to systematize consistency, efficiency, and safety protocols.

- **Improve call categorization**: In many jurisdictions, the largest volume of calls is categorized as "other," which highlights the challenges of gathering relevant information from 911 callers and properly categorizing calls (Chapters 2 and 5). Difficult-to-categorize calls are prevalent and more sophisticated systems for reviewing call data are needed.

- **Emerging 911 research:** Scholar and 911 convening participant Jessica Gillooly has identified several additional call-taker recommendations.[247] Her examination of a large 911 call for service administrative dataset revealed that:
  - 911 operators systematically differ in classifying the same type of incident as high priority, meaning that training would be useful in mitigating these discrepancies.
  - Assigning "average" call-takers to train new call-takers can help increase reliability in coding.
  - Reminding call-takers of their connections to the community, their roles as gatekeepers to the criminal justice system, and their potential for building bridges to the police and public safety writ large can help address the cynicism and lack of efficacy that call-takers experience.

Create a national coalition

Currently, 911 call-taking practices lack coherence nationally. Modeled after Vera's convening and the NG911 coalition, there is an opportunity to create a community of 911 organizations to improve communications, increase standardization, and support the ongoing development and

[247] Jessica Gillooly, "'Lights and Sirens': 911 Operators and the Construction of High-Priority Incidents" (unpublished manuscript).

dissemination of promising practices. Such a model could benefit the field and advance thinking.

- **911 roundtables:** These efforts could be modeled on successful roundtable efforts related to reentry, correctional education, and pretrial justice. Roundtables can incorporate multiple perspectives and spark national conversations to identify unmet needs, inform research, and feed into the design of reforms. The goal of the roundtables would be to generate greater investment in 911 police call-taking, dispatching, and response practices, as well as to review existing practices and issue recommendations to centralize different dimensions of public safety communications and highlight opportunities and challenges.
    - Roundtables could provide a seat at the table for community groups and make them critical decision-makers on policy recommendations to the field.
    - Roundtables should adopt a race/equity lens to understand the consequences of 911 implementation for communities of color and other marginalized groups.
    - The roundtables could be structured in a variety of ways to support the inclusion of permanent key stakeholders and rotating participants (e.g., police managers, crime analysts, and public safety communications experts) based on the topic of any given session. The Working Groups convened by the Association of Public-Safety Communications Officials (APCO International), which develop ANSI-accredited technical standards in the public communications area, provide an example (and potential forum) for this kind of engagement.
    - The roundtables could generate much-needed attention and support to 911 systems. Through the development and implementation of this project, researchers learned that few stakeholders, including criminal justice experts, understand the critical role and functionality of 911 operations in the larger context of criminal justice and police reform conversations. Basic operational insights, such as call-takers and dispatchers holding different, necessary, and simultaneous functions, are often conflated, or misunderstood entirely. A public conversation and, ultimately, an information campaign could help reduce unnecessary and harmful overreliance on 911 and police resources.
- **Standardize 911 data and schema:** No nationally standardized 911 data system exists with uniform data elements for state and local 911 or CAD systems. This presents an opportunity to develop a technical schema that reconciles the data collected across different 911 and CAD systems. Such a schema would provide essential information to assist strategic planning, governance, and system improvements.
    - There is an opportunity to develop and execute a robust and actionable research agenda for further internal analysis as well as cross-site collaboration and comparison.
    - Such an approach appears to have been proposed in 2016 but does not appear to have advanced.[248]
- **Produce reliable 911 statistics:** Collecting 911 data, managing it, and sharing it with the right people at the right time is instrumental to this field's success. Creating a system

[248] See National Highway Traffic Safety Administration, "Request for Information: Nationally Uniform 911 Data System," June 30, 2016, https://www.federalregister.gov/documents/2016/06/30/2016-15368/request-for-information-nationally-uniform-911-data-system.

to achieve these goals will depend on stakeholders developing and implementing an accessible technological environment.

- Though the 911 call-taking system is the primary intake point for the entire criminal justice system, reliable information related to total call volume, the type of calls, and their outcomes currently does not exist. Efforts to minimize the size and impact of the criminal justice system require knowledge of what is fueling the system. Without reliable, current data on the 911 system, efforts to systemically understand and shrink the criminal justice footprint, by reducing police involvement and enforcement, are critically limited.
- Relatedly, many police departments have begun to invest in their capacities for internal data analysis, with many departments today having analysts, and in some cases, even entire units, dedicated to these functions. With enhanced in-house analytic capacity, departments can use 911 data as a tool for improving their effectiveness and helping to ensure that policing services are equitable and accessible to underserved communities.

Non-police response/community response

With fewer than 20 percent of calls in the current study resulting from serious crime incidents, and the remainder representing incidents that often do not require an enforcement-based response (Chapters 2 and 5), there is a need to reimagine and triage 911 call-taking, dispatching, and police response. These recommendations examine community-driven solutions that would alleviate officer workload, reduce police response and enforcement, and improve community outcomes.

- **Reimagine and reengineer 911 response:** Nationally, 911 call-taking and dispatch responses are limited to police, fire, and emergency medical services (which are often an extension of fire). With the majority of 911 calls for police service being unrelated to a crime or serious public safety condition, an opportunity exists to reimagine and reengineer responses. A new system could incorporate the following elements:
  - extensive call triaging designed to identify those calls that require an emergency response; and
  - additional services that are deployable for timely response, including:
    - resources for providing assistance in cases of psychiatric crisis;
    - units trained and equipped to provide assistance in cases of drug overdose;
    - conflict resolution efforts to address situations that are unlikely to result in serious injury or harm (e.g., disputes with neighbors over parked cars or blocked driveways);[249]

[249] Organized groups in South Africa apartheid that developed community courts, called *makgotla*, could serve as a model for this. Post-apartheid, such groups were called "People's Courts," and later "Street Committees." For more information on these possible alternatives to enforcement-based conflict resolution, see Rose City Copwatch, "Alternatives to Police," 2008, https://rosecitycopwatch.files.wordpress.com/2010/04/alternatives-to-the-police_-2008_-rose-city-copwatch-_formatted-for-booklet-printing.pdf.

- animal control services to more effectively respond to community conditions that the police are ill-equipped to handle (e.g., loose and aggressive dogs);
- suicide ambulances and ambulatory care akin to the psychiatric nurse response deployed through specialized clinical ambulances in Stockholm, Sweden that have demonstrated promising results; and[250]
- social service and social net services that can reasonably respond to community requests for needs, such as requests for food, when callers have no other alternatives to attend to these basic needs.

- **Crisis Assistance Helping Out on the Street (CAHOOTS):** Through this model, developed in Eugene, Oregon, a mental health worker and medic are paired together and dispatched to calls related to homelessness, mental health, and substance abuse.[251]
  - Several other cities, including Denver, Colorado, have begun piloting this approach to dispatch civilian teams in response to crisis calls that do not involve a weapon or threat to other community members.[252]
- **Alternative responses to crime and violence:** Organizations like Rose City Copwatch in Portland, Oregon through their *Alternatives to Police Toolkit*; the *Creative Interventions Toolkit: A Practical Guide to Stop Interpersonal Violence*; and the *Safe OUTside the System (SOS) Collective* of the Audre Lorde Project's *Safer Party Toolkit* offer specific and practical guidance to community-centric alternatives to calling 911 or seeking a police response.[253] Similar to recommendations outlined above, these programs are designed to help manage and de-escalate conflict through community-based interventions and the involvement of friends and neighbors, as opposed to sworn police response.
  - Numerous other locally led programs have been formed to serve as a resource for people to consult, seek support, and in some instances request help to solve public safety challenges. Among these programs are the following:
    - *The Coalition Against Rape and Abuse (CARA)*: An anti-rape organizing project designed to serve survivors of sexual violence along with their communities.[254]
    - *Sista II Sista*: A collective leadership model consisting of working-class Black and Latina women in Brooklyn, NY designed to achieve personal transformation and social justice. Although this collective is not currently

[250] For an example of this type of alternative response, see Olof Bouveng, Fredrik A. Bengtsson, and Andreas Carlborg, "First-Year Follow-Up of the Psychiatric Emergency Response Team (PAM) in Stockholm County, Sweden: A Descriptive Study," https://www.tandfonline.com/doi/full/10.1080/00207411.2016.1264040
[251] For more information on the CAHOOTS project in Eugene, Oregon, see White Bird Clinic, "CAHOOTS," https://whitebirdclinic.org/cahoots/.
[252] See, for example, Crime and Justice News, "Denver Will Use Civilians to Respond to Some 911 Calls," June 12, 2019, https://thecrimereport.org/2019/06/12/denver-pilot-will-send-civilian-teams-to-respond-to-some-911-calls/.
[253] For more information on the Rose City Copwatch program, see Rose City Copwatch, "Alternatives to Police," 2008. The Creative Interventions Toolkit is available at http://www.creative-interventions.org/tools/toolkit/. For more information about the Safe OUTside the System (SOS) Collective, see Audre Lorde Project, "Programs," https://alp.org/programs/sos.
[254] To learn more about C.A.R.A., see The Coalition Against Rape and Abuse, "Home," http://www.cara-cmc.org.

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operational, several of their existing resources may serve as a model for this work.[255]

- *Safe OUTside the System*: SOS, the Audre Lorde Project's Brooklyn-based Collective described above, has the goal of ending violence against queer people of color through mechanisms that do not involve the police.

- **Restorative justice:** Restorative justice is a practice in place across the world, including the United States. In some rare instances, restorative justice is applied in the United States to crimes of violence.[256] Although these practices may incorporate alternatives to police response, such as community-based conflict resolution efforts involving family, friends, and neighbors, restorative justice practices and principles tend to be applied further downstream—that is, once the police have already been involved and prosecutors have made charging decisions. Opportunities to develop, implement, and evaluate front-end restorative justice programs exist and offer promise. For example, non-sworn responders with restorative justice training could be dispatched, or 911 callers could be referred to restorative justice services in appropriate circumstances.

- **Storytelling, organizing, and narrative development:** Community-based/non-police responses may also involve community-led storytelling, organizing, and narrative development. Technology has advanced some of these practices, with different media currently available, though this is an area that could benefit from greater investment to organize, develop, create, support, and disseminate such messaging. Two existing examples have attempted to fill this gap:

    - *Chain Reaction*: A project focused on participatory research and promoting education with the goal of supporting dialogue toward advancing alternatives to calling police on young people.[257]

    - *Stop Violence Everyday*: An initiative focused on highlighting violence, particularly violence perpetuated by the police, and attempting to address areas in which violence is preventable.[258]

Technological innovations

Technological advancements and the 911 system have a complicated relationship, but the advent of new technology has inarguably created opportunities to improve policing and call-taking. An open dialogue between emergency practitioners and technological innovators could lead to real advances in the field.

- **911 behavioral economics:** CAD and other public safety management systems have been developed and are in operation without key behavioral economics insights. Information such as where and how to display the most critical information could create opportunities to improve information collection, capture, and use.

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[255] To learn more about Sista II Sista and examples of the materials they developed during their operational period, see "Sista II Sista survey," https://web.archive.org/web/20160418200354/http://incite-national.org/sites/default/files/incite_files/resource_docs/3583_siis_survey.pdf; Sista II Sista, "Young Women in Brooklyn Speak Out Against Violence," press release, https://web.archive.org/web/20160418203127/http://incite-national.org/sites/default/files/incite_files/resource_docs/3493_siis_pressrelease_re_breaking_the_silencepg7.pdf
[256] See, for example, Common Justice, https://www.commonjustice.org/.
[257] #ChiCopWatch, "Chain Reaction: Alternatives to Policing," July 27, 2014, http://wechargegenocide.org/category/resources/alternatives/.
[258] StoryTelling & Organizing Project (STOP), http://www.stopviolenceeveryday.org.

- **911 public data usability:** Technical tools may be able to address the lack of standardization in 911 data collection by reformatting data after collection. In this regard, Vera researchers have been collaborating with the Two Sigma Data Clinic to explore opportunities to produce clean, standardized datasets for cities that have made their 911 records public.[259]

- **911 applications:** Apps are developing in every corner of contemporary society, with 911 and public safety being no exception. Many of these applications are still young and have yet to be evaluated, but their increasing and rapid development—as well as sometimes short shelf-lives—signals great interest, need, and opportunity. Meaningful study is sorely needed to develop a full understanding of the goals, implications, and potential impact of these apps.[260] This is another aspect of the 911 system that could benefit from an investment to understand the landscape and begin developing standards, procedures, best practices, and guidance. Among these are apps that operate in the following ways:

  - **Alerting peers to emerging incidents:** A number of apps provide users with a means of communicating in real time about situations in which fellow users are in need of emergency assistance. Leveraging social connections among users, these apps may increase safety and resolve emergencies through resources such as video sharing; access to informal networks of peers facing similar issues, such as substance use, mental health crises, or homelessness; or volunteers willing to provide assistance during crises.

  - **Obtaining assistance with animal emergencies:** The current research demonstrated that animal complaints represent a large demand for police response and that police tend to be ill-equipped to effectively manage these situations without applying excessive force. Absent the proper tools and trainings, officers are often put in situations where they resort to ending the life of an animal. It remains questionable whether police should be responding to animal control issues. Apps may provide a means of involving other stakeholders—outside of the 911 system and law enforcement—who may be better able to resolve issues related to animal control.

  - **Providing location services for first responders:** Voice over Internet Protocol (VoIP) technology has offered a solution to the challenge of locating callers on their cell phones. The VoIP E911 system allows community members to subscribe and enter their emergency address information. There are several service providers, and this is a promising avenue for partnerships with police departments.[261] Alternatively, assisted GPS technology can be used to track the location of an E911 call. Although VoIP location is static,

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[259] Two Sigma Data Clinic researchers will be producing the pipeline for open source consumption. This will allow researchers, advocates, and others to better understand 911 data, should it be available publicly, and standardize the variables into a taxonomy that is better suited for analysis. Data Clinic, "What We Do," https://dataclinic.twosigma.com/what-we-do/.
[260] Apps frequently discussed among police practitioners, community members, and researcher include Cell 411, Buoy, CONCRN, Circle of 6, Animal Help Now, Rave Panic Button, and Citizen. These privately developed third-party services are noted for informational purposes, without any endorsement from Vera or any affiliated research sites. Research and analysis on such apps are needed to determine their potential benefits and drawbacks.
[261] To learn more about the service providers who offer 911 access via VoIP systems, see VoIP-info.org, "VOIP 911 Service Providers," https://www.voip-info.org/voip-911-service-providers.

giving only the location at the time of the E911 transmission, it does not fully resolve privacy concerns about tracking community members via cell phones.

- **Contacting and monitoring 911:** Apps may allow users to contact 911 via the push of a button that automatically sends data about the nature of the emergency and perhaps simultaneously alerts peer networks. Such apps may require coordination with public safety entities. Apps also exist to monitor public safety dispatch radio frequencies and provide users with alerts about incidents near their location. These apps may also permit users to share photos, videos, and narratives about relevant observations with other users and/or public safety agents. Although some see such apps as an opportunity for citizen involvement in assisting law enforcement, others have expressed concern about the potential for this technology to incite public fear or biased police response.

Legislative remedies and reforms

Several potential legislative remedies and reforms worthy of consideration emerged through the course of the current research. Though this list should not be assumed to be comprehensive or exhaustive, it represents a set of ideas to inspire further thought.

- **Professionalize and create accurate call-taker and dispatcher occupational titles:** Call-takers and dispatchers have highly specialized professional functions. However, the federal occupational title classifications for these positions are included under generalized administrative and secretarial occupational categories. Legislation providing a unique job classification code for this sector of the public safety workforce is currently making its way through Congress.[262] This is a critical first step in professionalizing call-taking and dispatching, as well as acknowledging the environmental and emotional pressures that call-takers and dispatchers routinely experience.

- **Safeguard 911 revenue streams:** Dedicated funding streams to support 911 call centers and personnel currently exist through surcharges, taxes, and fees assigned to telephone bills. Though the existence of an established revenue stream may suggest that 911 functions are adequately funded, this is not necessarily the case. It appears that, at least in certain jurisdictions, these funds are insufficient to provide adequate capacity. Furthermore, numerous states have reallocated these 911 revenues to other expenses, leaving 911 operations and improvements inadequately funded. The extent of this problem is unclear, but a legislative remedy to prevent and prohibit revenue shifting could provide relief to these underfunded jurisdictions. In some instances, revenues are tied to the volume of 911 calls. This may disincentivize the adoption of alternatives to 911 that seek to improve service by lowering intake volume and call center utilization.

- **Ensure national standards on data collection and produce estimates:** As discussed at multiple points throughout the course of this report, there are no national standards guiding 911 data collection and estimation procedures. Census counts are required in many areas of public service and the criminal justice system to understand critical metrics like crime rates, and arrest and incarceration trends. Without a mandate to produce standardized and regular information, the 911 system operates without

[262] 911 SAVES Act, H.R. 1629, 116th Congress (2019-2020).

oversight. The lack of comparable, cross-jurisdictional information limits the ability to understand how the nation's primary system for responding to public safety concerns operates and where opportunities for improvement exist.

- **Require coordination and public comment on technologies impacting 911:** Technology firms have begun developing and integrating 911 features into their products. For example, many cell phones now have 911 shortcuts. Although such features were designed to enhance public safety, 911 shortcuts and similar innovations have bombarded 911 communications centers with unintended and often burdensome call volumes. Vera researchers hypothesize that this is driving the large uptick in 911 hang-ups (discussed in Chapter 5). Because 911 communications are mandated by Congress, Congress may be best positioned to address these challenges. This could be as simple as requiring board approval or public comment before implementing technology that would directly impact 911 call-taking/dialing. Such a process could also regulate the triggering of 911 activity by residential security alarms. Additional research could also identify best practices for the development of public safety related technologies.

Rigorous evaluation and research

As highlighted by Vera's literature review (Chapter 2), there is a lack of evidence and rigorous evaluation of both orthodox and more innovative 911 systems. Areas that would benefit from further support and research include the following:

- **Data standardization:** This report has highlighted the need for greater data standardization and evaluation. Research in this area is greatly needed.
- **Deeper exploration of existing data:** Though this report summarizes a vast array of findings, many additional insights can be gleaned from the information on hand. Some of this research includes inquiries related to:
    - examining charge data;
    - conducting additional geographic analyses and mapping;
    - examining officer shift times;
    - creating dashboards for service and response identification;
    - developing a statistical distance metric to quantify the differences in call-for-service codes;
    - furthering the quantitative and qualitative understanding of response and processing times;
    - performing qualitative analyses to better understand the challenges in identifying and responding to frequent callers;
    - replicating the methods piloted in this study to conduct additional qualitative 911 call coding; and
    - incorporating the perspectives of community groups and law enforcement practitioners by asking for their feedback on research findings and suggestions for next steps.

- **Site expansion:** The current research was exploratory, including model and theory development and testing. This phase of the work was intensive and involved in-depth work with TPD and CCPD. Now that the methods have been developed and applied in the field, there is an opportunity to expand the research to additional locations.
- **Understanding 911 funding:** 911 call-taking, dispatching, and response continues to be an underfunded enterprise. Though some of the reasons for this underinvestment are known (e.g., 911 user fees being reallocated by states, as discussed above), it is unclear how 911 programs around the country are funded. More research is needed to determine the impact of underfunding, appropriate levels of resource allocation, and best practices for ensuring adequate support.
- **Developing community understandings of safety:** The current research relied primarily on administrative data and qualitative research facilitated by the research site departments (e.g., observing call-taking, dispatching, and police response practices, and administering focus groups with participants organized by the respective departments). This research, therefore, did not examine a crucial aspect of the call-taking, dispatching, and police response continuum: the public perspective, including community perceptions of safety; factors that influence decisions to call 911 across race, gender, geography, and other characteristics; and community assessments of response methods and outcomes. Research on this aspect of 911 usage is needed and would greatly benefit the field.
- **Overarching understanding of available alternatives:** Little is known about the 911 alternatives that exist nationally or the efficacy of different approaches. Investment in this area may provide positive advancements in the field.

Conclusion and next steps

Researchers gained many valuable insights through the course of this research, which have been explored in this report. Although 911 call-taking, dispatching, and police response are core to the public safety mandate, this area of police operations continues to be undervalued and relatively unexplored. The current study helped to map the landscape and demonstrate methodologies for future exploration. As this chapter has documented, there are significant opportunities to improve the 911 system, from triaging calls appropriately upon receipt to ensuring accurate recording by call-takers and dispatchers and providing alternatives to a police response.

Besides identifying opportunities for improvement, this report also identifies areas where further information is needed. The two research sites provided a wealth of quantitative data on the operation of their respective 911 systems. The research team collected additional information from publicly available records, interviews, observations, and focus groups. There is much more to learn from the data compiled as part of this study. Further research could expand the scale and scope of the work, as well as fill the informational gaps that researchers identified in working with this body of data.

Developing a roundtable platform within and across departments could have a significant impact by bringing together key stakeholders and helping them better understand both challenges and opportunities. Such a platform could provide a forum for developing and advancing best practices, conversations around national standards, and coalitions for understanding 911 system practices and moving public safety communications forward. Moreover, these conversations and practices should be developed and examined through a race/equity lens.

The discipline of behavioral economics offers great promise as the practice of 911 call-taking, dispatching, and police response becomes increasingly digitized. To the best of Vera's knowledge, no comprehensive research has been conducted to design CAD and associated response systems in a way that ensures the most important information is being collected in the most logical, intuitive, and understandable ways.

With the current research relying heavily on administrative data and qualitative research facilitated by the access granted by the research sites, a critical gap exists in examining what residents of various neighborhoods and communities think of safety and why they opt into or out of calling 911 when an emergency arises. Fulfilling this research need would greatly benefit the field.

Both the 911 system and public safety field in general are experiencing a surge in mobile application development. Though these technological advancements demonstrate emerging trends in accessing public safety services, basic information about the impact of these apps and related guidelines, protocols, and regulations is lacking.

Additionally, advocacy and lobbying efforts in key areas related to 911 legislation and regulation could help to improve conditions for workers, protect funding streams, and create necessary national standards regarding data collection and estimation procedures.

Finally, as agencies work towards improving the ability to respond to 911 calls, it is essential that they consider the needs of 911 callers, whether a police response is appropriate, and whether 911 systems are serving all members of the community equally. The answers to these questions are not solely within the hands of the police but will require local partnerships to identify alternatives to arrest and community-based responses that can help prevent a default to enforcement and allow for more appropriate responses to calls for police service.