Gunshot Detection Technology Time Savings and Spatial Precision: An Exploratory Analysis in Kansas City

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Abstract:

Gunshot Detection Technology (GDT) is expected to impact gun violence by accelerating the discovery and response to gunfire. GDT should further collect more accurate spatial data, as gunfire is assigned to coordinates measured by acoustic sensors rather than addresses reported via 9-1-1 calls for service (CFS). The current study explores the level to which GDT achieves these benefits over its first five years of operation in Kansas City, Missouri. Data systems are triangulated to determine the time and location gunfire was reported by GDT and CFS. The temporal and spatial distances between GDT and CFS are then calculated. Findings indicate GDT generates time savings and increases spatial precision as compared to CFS. This may facilitate police responses to gunfire events and provide more spatially accurate data to inform policing strategies. Results of generalized linear and multinomial logistic regression models indicate that GDT benefits are influenced by a number of situational factors.

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Introduction

Recent decades have seen an increased reliance on technology in day-to-day police operations. One technology that has recently increased in popularity is gunshot detection technology (GDT). GDT has been adopted by over 200 public safety agencies worldwide according to reports from ShotSpotter, the leading manufacturer of GDT.[1] GDT consists of networks of acoustic sensors that detect and identify the location of gunfire in real time. This can help generate police response to shooting scenes much more quickly than when gunfire is reported by citizens via 9-1-1 calls for service (CFS). GDT should further collect more accurate spatial data, given gunfire locations are assigned to the coordinates measured by acoustic sensors rather than addresses reported second-hand by callers to the 9-1-1 system. The enhanced temporal and spatial precision offered by GDT may support efficient and effective crime prevention activities of police. However, little research has focused specifically on the level to which GDT activations and related CFS differ in terms of exactly when and where they are reported.

The current study is the first to emerge from an applied research partnership between a multi-university academic research team and the Kansas City, Missouri Police Department (KCPD). This partnership aims to inform the future use of GDT by KCPD, specifically through highlighting the benefits and limitations of the agency's current GDT practices. The current study focuses on the time savings and temporal precision offered by GDT over the first five years of the program. Multiple police data systems were triangulated to determine the time and location gunfire events are reported by GDT and CFS. The temporal and spatial distances between GDT and CFS are then calculated. This study provides empirical evidence that GDT

[1] https://www.shotspotter.com/cities/

generates time savings and increases spatial precision as compared to CFS. Results of generalized linear and multinomial logistic regression models indicate that GDT benefits are influenced by a number of situational factors. These findings have important implications for police agencies investing in GDT.

Review of Relevant Literature

Despite being considered a cutting-edge, newly developed technological innovation, research on GDT dates back over 20 years (Mazerolle *et al.* 1998). Most studies have concluded that GDT accurately identifies shots fired incidents relative to reported calls for service (Irvin-Jackson et al., 2017; Mazerolle et al., 1998; 1999; Renda & Zhang, 2019; Watkins et al., 2002; Wheeler et al., 2020), with a few studies raising concerns over identification accuracy (Carr & Doleac 2015, 2016, 2018; Litch & Orrison, 2011) as well as false positive events (Drange, 2016; Ratcliffe et al., 2019). The implications of automated and accurate gunshot event detection for police and medical response to shots fired events has received less scholarly attention.

Put simply, GDT offers the potential to improve the efficiency of first responders to react to shots fired incidents. This potential efficiency hinges on the spatial accuracy of GDT to identify shots fired incidents, which in turn enables a more direct police and emergency medical response. In absence of GDT, shots fired incidents are reported by the public via 9-1-1 emergency calls for service (CFS). Klinger and Bridges (1997) articulate the poor quality of incident information relayed to the police from the public when reporting to 9-1-1, while a multi-city report by Nuesteter and colleagues (2020) provides a robust overview of the challenges CFS present to first responders. In short, their report highlighted the lack of accurate information conveyed from the public when reporting emergency incidents, including the lack of geographic specificity from the public and discretionary interpretations from emergency call dispatchers when identifying emergency incident locations. Although there have been technological improvements to identify the geographic location of 9-1-1 callers via wireless cellular carriers and internet providers, the accuracy of these locations are hindered by inconsistent reporting requirements across cellular carriers, differing levels of technology across public safety answering points (U.S. Department of Transportation, 2017), and geographic caller location data representing the spatial location of the person reporting an incident and not the location of the actual incident. Lastly, shots fired incidents reported by the public are likely to include vague references to location as opposed to a specific location. For example, a caller may report they heard gunfire “somewhere north of me” or “it sounded like it came from around the corner of Main Street and 5th Avenue.” Wheeler and colleagues (2020) found reported addresses for shootings were between 60 feet and 90 feet from the related GDT detection on average, depending on the geocoder used to map the reported address. This distance was larger than the geographic error distances identified by field tests of GDT systems that involved the firing of blank firearm rounds (Aguilar, 2015; Mazerolle et al., 2000).

Studies assessing officer views of GDT indicate perceived response efficiency as a result of GDT compared to CFS (Mazerolle et al., 2000; Selby et al., 2011). Empirical evaluations of GDT versus CFS response times are limited, and have generally observed improved response times resulting from GDT. Mazerolle et al. (1998) observed a 16% decrease in response time to GDT activations. A multi-city study by Urban Institute (Lawrence et al., 2019) operationalized response time as the period between call (or GDT activation) to arrival on scene and observed response times to GDT activations to be between 14% and 28% faster across Denver, Milwaukee, and Richmond. Choi et al. (2014) observed a 33% faster time to dispatch shots fired calls and a 12% increase in officer response times to these same events in Brockton, MA. Interestingly, Mares and Blackburn's (2012) original evaluation of GDT in St. Louis demonstrated improved police response times to shots fired calls for service. However, a more recent evaluation of the same system in St. Louis (Mares and Blackburn, 2021) observed no significant difference. The authors also report an 80% increase in the number of shots fired events, leading to the plausible reality that any potential time efficiency to be gained from GDT activations are negated as a result of increased officer workload on shots fired events — an observation echoed by Ratcliffe et al. (2019).

Potential response time efficiency posited by GDT should not be viewed as an avenue to apprehend offenders (Weisburd & Eck, 2004; Weisburd & Majmundar, 2017). Rather, it holds promise to improve the prehospital emergency response to gunfire events. In short, the sooner police and/or emergency medical services (EMS) can arrive on scene, the sooner a victim can either be transported to trauma care or receive medical attention. It is generally accepted within the public health literature (and more recently the criminology literature) that transport time – as well as transport distance as a function of time – is critical to mortality outcomes of severe trauma (Circo & Wheeler, 2020). Crandall and colleagues (2013) found victims with gunshot wounds had 23% higher mortality risk when located more than five miles from a trauma center in Chicago. Similar findings were observed in Detroit (Circo, 2019) and Philadelphia (Hatten & Wolff, 2020). Relatedly, Tansley and colleagues (2019) found medical transport time more than 30 minutes for patients with penetrating injuries are associated with a 3.4-fold increase of mortality outcome.

Contemporary views of policing also embrace the role of police officers as public health personnel. Indeed, police officers are now viewed in the context of policing social harms (Carter et al., 2021; Ratcliffe, 2015), responding to co-occurrences of substance abuse and mental health (White & Goldberg, 2018; White & Weisburd, 2018), and embracing public health approaches to gun violence (Cook, 2018). Police officers have also assumed active roles in mitigating on-scene medical incidents by carrying defibrillators to combat cardiac arrest (Krammel et al., 2015) and nasal naloxone to avert opioid overdoses (Fisher et al., 2016; Walley et al., 2013; White et al., 2021). In the context of police response to victims of gun violence, the role of police officer rapid transport to trauma care – known as "scoop and run" – has also positioned the role of first responding police in the prehospital process. Wandling and colleagues (2016) concluded police rapid transport to trauma care holds equally important and effective means of minimizing mortality rate as compared to EMS response. Similarly, Brand and colleagues (2014) observed victims of gunshot wounds and stabbings who were immediately transported by the police to trauma care were more likely to survive than victims awaiting EMS personnel to arrive on scene and then transport to care. Several additional studies have demonstrated police transport of injury victims to trauma care is equivalent in both short- and long-term mortality outcomes as compared to EMS transport (Jacoby et al., 2020; Kaufman et al., 2017; Stratton & Uner, 2014; Winter et al., 2021). These studies suggest that immediate and responsive transport to trauma care should be prioritized over professional medical training for prehospital care of shooting victims (see Winter et al., 2021).

In the case of GDT activations, police may be in a position to "scoop and run" victims to trauma care sooner than if the incident originated from a CFS, as well as call for EMS personnel in a more efficient timeframe. Speaking directly to this potential, Goldenberg and colleagues (2019) examined 627 shooting events in Camden, NJ to quantify differences of transportation to trauma care from both police and EMS across GDT activations and 9-1-1 calls for service. In general, their results showed no significant difference in mortality rates between GDT activations and 9-1-1 calls, however events originating from a GDT activation were accompanied by faster response times by both police and EMS. Interestingly, police transported victims in 36% of events originating from GDT, as compared to just 4% of shooting events reported through 9-1-1.

The present study investigates two research questions that inform the potential for first responders to be more efficient in their response to gun fire incidents. First, what *time savings* is offered by GDT activations, measured as the duration between the GDT activation and the first CFS reporting the gunfire event? Second, what is the *spatial precision* of GDT, operationalized as the distance between the GDT activation and incident address reported via the CFS? These research questions explore key assumptions of GDT systems that are expected to inform police responses to gunfire events. In the current study setting of Kansas City, these insights further help to guide future substantive questions about how KCPD can leverage these potential efficiencies.

Study Setting

Kansas City, Missouri is a large midwestern city with an estimated population of approximately 508,000 living in a land area just shy of 315 square miles. Racial and ethnic minority residents are approximately 28% Black and 11% Latino. Just over 15 percent of residents subsist below the poverty level and nearly 14% of people under 65 years of age do not have health insurance. The Kansas City Police Department (KCPD) is the primary law enforcement agency for the city, complete with a working police force of approximately 1,150 sworn officers and 400 civilian personnel as of time of writing.[2]

Uniform crime report data reveal Kansas City averaged 113 homicides per year from 2012 through 2017 (the years falling within the current study period), which in turn resulted in consistent rankings within the top 20 most violent cities in the U.S. in terms of homicide rate. Firearms were involved in 84% of homicides for the same date range. Kansas City averaged 4,559 aggravated assaults per year from 2010 through 2020, yielding a rate of 897 per 100K residents. Non-fatal shootings show an average of 508 per year from 2012 to 2017.

Kansas City leadership has often sought innovative strategies or technologies to thwart crime, frequently violent crime, over the years. The KCPD has a rich history of such innovation, including being the first law enforcement agency in the United States to share criminal justice information with field officers in the late 1960's[3] to the implementation of ShotSpotter GDT discussed within these pages. Given Kansas City's unfortunate record of high violent crime rates, including for homicide and aggravated assault, local government officials, community stakeholders, and KCPD executive command were seeking any tool possible to help with the city's rising crime rates in the early 2010's.

ShotSpotter's GDT system was brought to Kansas City in 2012 with the goal of enhancing the response to, and prevention of, gunfire-related crime. Congressman Emanuel Cleaver helped secure funding for ShotSpotter through a partnership with the Kansas City Area Transportation Authority (KCATA). The first five years of the ShotSpotter system's funding came from $720,000 made available when a separate KCATA project was completed under budget. The KCATA was the lead agency in both planning and procuring the ShotSpotter system

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[2] https://www.census.gov/quickfacts/kansascitycitymissouri
[3] https://www.ibm.com/ibm/history/exhibits/valueone/valueone_bad.html

for KCPD. KCATA General Manager Mark Huffer described the joint effort as the first such deployment of ShotSpotter in the country, adding "[the KCATA] are pleased to partner with the City of Kansas City and the KCPD to play a role in elevating the level of safety to the community, as well as to our customers and employees."[4] Moreover, ShotSpotter was implemented with the aim to have "KCPD respond faster and more safely to gunfire incidents" while allowing officers "to proactively develop effective problem-oriented, data-driven policing strategies and tactical deployments." It was further expected that the KCPD would be able to gather ballistic evidence, ultimately resulting in increased prosecution for firearm-related crime.[5]

Kansas City's GDT system went live on 9/14/12. KCPD's ShotSpotter system detected 6,967 gunfire events from the "live" date through the end of the study period (5/9/17). The GDT system covers a target area of approximately 3.5 square miles. Despite comprising slightly more than 1% of Kansas City's total geography (~315 square miles), the GDT zone accounted for approximately 10% (1,219 of 12,180) of Part-1 crimes committed with a firearm and approximately 12.5% (15,100 of 40,796) of shots fired CFS over the current study period. The 36 census block groups intersecting the GDT target area have a Black population of nearly 65% with 16.5% of residents living below the poverty level. This compares to a Black population and poverty rate of 28.2% and 16.1%, respectively, city-wide (see Table 1).

[4] https://mptaonline.typepad.com/missouri_public_transit_a/2012/06/kcata-is-first-transit-agency-to-implement-gunshot-detection-system-in-conjunction-with-kc-police-.html

[5] https://cleaver.house.gov/press-release/congressman-cleaver-announces-shotspotter-coming-kansas-city

Table 1. Study setting characteristics

Measures	GDT Target Area	Kansas City
Area	3.5 mi^2	314.95 mi^2
Firearm-related part 1 crime incidents	1,219	12,180
Shots fired calls for service	5,100	40,796
Black population	64.90%	28.20%
Poverty rate	16.50%	16.10%

Notes: Crime and shots fired data cover the period 9/14/12-5/9/17. The sociodemographic data measured at the block group level, with 36 of 518 intersecting the GDT target area. Block group data were collected from the U.S. Census Bureau's American Community Survey 2017 5-year estimates.

Operationally speaking, internal communication about ShotSpotter accompanied similar externally-focused efforts. KCPD members, particularly those assigned to patrol elements, were notified about the ShotSpotter system's basic functionality, as well as how the Communications Unit would dispatch officers on ShotSpotter system activations deemed to be firearm-related based on live feedback from the Operations Center. Although officers were already routinely dispatched on "Sound of Shots" calls, the information provided via the ShotSpotter system was expected to enhance officer knowledge about the specific location of the reported gunfire. Contrasted to when a citizen may provide a general area or perhaps the citizen's own address, neither of which may be the actual location of where any firearms were fired, the ShotSpotter system records precise geographic coordinates of gunfire. Additional information taken from the ShotSpotter system could be provided to responding officers, such as the number of rounds fired or even if the shots were being fired in a geographic direction (e.g., if a possible vehicle was being driven away as shots were being fired from an occupant). In turn, all of this information allows officers to have increased awareness about not only where a firearm-related incident occurred but also guidance related to the recovery of ballistic evidence, such as the likely number of items.

Methodology

Data

KCPD personnel extracted a variety of data from multiple systems to meet this study's goals and requirements (see Table 2). Data were collected and prepared prior to submission to the research team, and the preparation included a review for errors such as duplicate values, null values, and invalid location information. Data were provided in tabular form, namely in Microsoft Excel format. Overall study data covered the years from 2007 to 2019 in support of a larger evaluation study funded by the National Institute of Justice. The current study focuses on the period from 9/14/12 – 5/9/17, given study objectives and the structure of KCPD databases, as outlined below.

Table 2. KCPD data sources

System/Platform	Data Retrieved
Shotspotter	Activations of the ShotSpotter system, to include date, time, location, and corresponding CAD incident number
Tiburon CAD	Historical data for CAD incidents related to ShotSpotter activations or "Sound of Shots" calls for service; note KCPD stopped using Tiburon as its CAD in May 2017
Hexagon CAD	CAD incident numbers associated with ShotSpotter activations or "Sound of Shots" calls for service
Tiburon RMS	Historical data for crime and other related activity, such as firearm recoveries; note KCPD stopped using Tiburon as its RMS in March 2019

Niche RMS	Data for crime and other related activity, such as firearm recoveries; Niche became the KCPD's RMS in March 2019
Internal KCPD data sources	NIBIN information; non-fatal shooting data; manpower data; information from Annual Reports

The current study seeks to compare GDT activations with the first 9-1-1 call for service (CFS) placed for the same gunfire event. We focused on the post-GDT installation period covered by the legacy Tiburon CAD system (9/14/12 – 5/9/17) in light of the study objectives. GDT activations and CFS were considered separately in the Tiburon system. This resulted in incidents reported through both methods appearing as a GDT detection in the ShotSpotter database and as a CFS in CAD. The upgraded Hexagon CAD system no longer treats GDT and CFS data as mutually exclusive. When a CFS relates to the same event as a GDT detection, it is automatically tagged to that event in CAD, classified as a "ShotSpotter Sound of Shots," and assigned the same location and time of occurrence recorded in the ShotSpotter database. While this upgrade minimizes the risk of double-counting gunfire events reported by both GDT and CFS, it does not allow for the measurement of gunfire event differences reported across the ShotSpotter and CAD systems, which is needed to the explore the current research questions.

GDT activations were extracted from the ShotSpotter system. Longitude and latitude coordinates were provided for each GDT activation, resulting in a 100% match rate. The coordinates record the precise location where sounds of gunfire were detected, and are not editable by the KCPD.[6] GDT activations in the current study reflect the precise location of

[6] One of the anonymous reviewers of this article suggested that ShotSpotter company analysts have the ability to edit certain aspects of the GDT activation data, including the number of gunshots detected and location of the gunfire event. We are unable to determine the level to which GDT activation incidents in the current study were edited in such a manner. While KCPD analysts we have spoken with indicate such editing has likely infrequently occurred with the Kansas City data, we acknowledge there was no way for us to completely rule out the presence of

detection rather an approximation that would result from the anonymizing or general cleaning of the geographic coordinate data. Shots fired CFS were extracted from the CAD system. KCPD received a total of 40,796 shots fired CFS over the study period. CFS data contained longitude and latitude coordinates for all but 114 cases, achieving a match rate of 99.7%. GDT activations were cross-referenced with CFS to identify gunfire events reported by both methods. 2,946 of 6,967 (42.29%) of GDT activations were also reported via CFS and were considered the sample for the current study.

A number of additional datasets from both inside and outside of the KCPD were accessed to collect additional data for this study. The Tiburon RMS provided data on firearm-related part 1 crime incidents, with 12,180 occurring during the study period. Firearm-related crime data were manually geocoded in ArcGIS Pro 2.9.3 through a composite address locator created by KCPD, with a match rate of 98.61% (12,011 of 12,180 matched).[7] The U.S. Census Bureau's American Community Survey was used to measure neighborhood characteristics throughout Kansas City's block groups. All census measures are based on 2017 5-year estimates to reflect the most recent portion of our study period. Land parcel data, denoting the zoned land usage for each parcel in Kansas City, was downloaded from the Kansas City Open Data Portal.[8] The Oak Ridge National Laboratory's LandScan database was used to measure the ambient population—the 24-hour estimate of the expected population present at a spatial scale of about one km2 (Andresen, 2011; Calka & Bielecka, 2019). The National Oceanic and Atmospheric

edited data in our sample. It is within the realm of possibly that such edits could have influenced the accuracy of some measures in the current study.

[7] All geocoding rates achieved in this study are substantially higher than the minimal acceptable geocoding rates identified by past empirical research (see, Andresen et al., 2020; Briz-Redón et al., 2020; Ratcliffe, 2004).

[8] https://data.kcmo.org

Administration's (NOAA) climate database[9] and solar calculator[10] were used to collect daily temperature, weather, and sunrise/sunset data in Kansas City for each day of the study period.

Dependent variables

This study explores three dependent variables. The first dependent variable measures the time savings provided by the GDT system, operationalized as the number of seconds between the GDT detection and CFS. Using date and time functions in Stata version 17, the time of day recorded for GDT and CFS were converted from hh:mm:ss format into integer values. The difference between CFS and GDT report times was then calculated, formatted as a continuous numeric value.

The second dependent variable measures the spatial precision of the GDT system, operationalized as the distance between GDT activations and CFS. The linear feet between GDT and CFS points was calculated using the Generate Origin Destination Links tool in ArcGIS Pro. The larger the distance between GDT and CFS points, the more spatial precision we consider to have been provided by the GDT system.[11]

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[9] https://www.ncdc.noaa.gov/cdo-web/datasets

[10] https://gml.noaa.gov/grad/solcalc/

[11] Prior to the statistical analysis, outliers in the time savings and spatial precision variables were transformed using winsorizing techniques via Stata's winsor2 command. Outliers are likely the result of CFS reporting a gunfire event in response to an incident other than the actual gunfire event. For example, a CFS occurring when a gunshot victim is brought to a hospital emergency room by a non-EMS vehicle would be a large spatial and temporal distance away from the GDT detection. In addition, certain cases had CFS times listed a large time interval before the GDT detection. While it is conceivable that a CFS could occur during the time a ShotSpotter analyst reviews an activation (to confirm it as gunfire rather than another loud noise, such as fireworks of a car backfiring), large time intervals may be due to data entry error in such cases. Because we were unable to diagnose the precise causes of outliers—and in consideration of research showing removing outlier cases can bias an analysis (Ch'ng & Mahat, 2014)—we opted for the winsorizing approach over outlier removal. Winsorizing involves re-coding tails of the distribution to fewer extreme values and has been shown to perform as well or better than alternate outlier treatment techniques across a range of datasets (Ch'ng, 2019). The current study re-coded the lowest 5% and highest 10% of time savings values to the 5th and 90th percentile values, respectively, and the highest 10% of spatial precision values to the 90th percentile value. This impacted 308 gunfire events for the spatial precision measure and 440 cases for the time savings measure.

A third dependent variable was calculated to reflect a more nuanced conceptualization of spatial precision as it pertains to police response. In practical terms, raw distances may not matter as much as the exact street segment where police presence is targeted. Crime-and-place researchers have long privileged street segments as a unit of analysis, given they minimize spatial assignment errors, while still being large enough to capture the unique micro-community composition of each unit (Weisburd et al., 2004, 2012). In this context, a distance of 334 feet, the approximate median street segment length in Kansas City, may be negligible if the GDT detection and CFS appear on the same street segment. Conversely, if a distance of 334 feet means incident locations reported by GDT and CFS fall on different street segments, then the implications for police response are heightened as police would be led to different micro-communities. Given this consideration, the third dependent variable measures the contiguity of the street segments associated with GDT and CFS. The street segment contiguity variable is a categorical measure with three potential values: 1) GDT and CFS reported on the same street segment; 2) GDT and CFS reported on different street segments that intersect, and; 3) GDT and CFS reported on different street segments that do not intersect.[12]

Independent variables

Eighteen independent variables measure a range of factors that could theoretically influence the speed at which citizens report gunfire events, as well as the locations where citizens

[12] This variable was generated by first calculating a contiguity table for all Kansas City street segments using the polygon neighbors tool in ArcGIS Pro. As the name suggests, the Polygon Neighbors tool could only be run on polygon features. We converted the street segment line feature to a polygon feature using the buffer tool, with a buffer size of one foot. This small buffer size fulfills the requirement of the Polygon Neighbors tool while maintaining the spatial integrity of the original street segments. The Polygon Neighbors table contains, for each street segment, the unique identifiers for each spatial neighbor (i.e. intersecting street segment). This table was then converted from long into wide format in Stata version 17, resulting in all street segment identifiers being contained within the same row. This converted table was used to create the categorical street segment contiguity variable.

perceive gunshots to be occurring. Any factors influencing citizen reporting behavior in such a manner may impact the time savings and/or spatial precision provided by GDT.

A binary variable measure whether the gunfire event was associated with a shooting (fatal or non-fatal), under the assumption that the presence of shooting victims may influence the speed at which citizens call 9-1-1 as well as the location citizens identify as the crime scene. To identify associated shootings, we calculated whether the gunfire event was close in space and time to a reported shooting. We identified whether any shootings occurred within a quarter-mile of the gunfire event on the date in question (Irvin-Erickson et al., 2017). Gunfire events with a shooting incident occurring within this space-time window are coded as being associated with a shooting victim. A binary variable measures whether the ShotSpotter system detected multiple gunshots (as opposed to a single gunshot) for the gunfire event, which may be more easily detected by citizens than a single gunshot. A binary variable measures whether the gunfire event occurred on a weekend (Friday, Saturday, or Sunday), when more people may be home to witness the incident. Four continuous variables measure crime levels within the street segment encompassing the GDT activation, which may relate to citizen reporting behavior. The variables measure the number of shots fired CFS and firearm-related part-1 crime occurring during the current and prior calendar years. Two variables measure sociodemographic neighborhood characteristics, as reflected in the encompassing census block group. The first measures concentrated disadvantage, a standardized index of the percent residents receiving public assistance, percent families living below the poverty line, percent female headed households, percent Black population, percent unemployed, and percent of population under 18 (Morenoff et al., 2001). This measure reflects the established body of literature indicating residents of disadvantaged communities often do not cooperate in the reporting and investigation of crime, even in serious cases such as gunfire (Baumer & Lauritsen, 2010; Brunson & Wade, 2019; Heubner et al., 2022). The second is a standardized measure of population density (population/total square miles). Ambient population is measured as a standardized value of the expected population in the surrounding one km^2 area over a 24-hour period. Taken together, population density and ambient population reflect the number of people in an area available to detect and report gunfire. The percentage of land parcels on the encompassing street segment zoned for residential use was measured from the land parcel database, under the guise that gunfire in highly residential areas would be more noticeable and disruptive than gunfire in more commercial or industrial areas. A binary variable measures whether the gunfire event occurred during nighttime hours, defined as a time of day outside of the sunrise and sunset times measured in the NOAA solar calculator database, when observing specific details of gunfire events may be more difficult The NOAA climate database was used to measure the daily number of inches of rain or snow as well as the standardized daily maximum temperature, which may influence the amount of people outdoors. A continuous variable measures the year of occurrence (2012 – 2017), to account for any annual local trends in Kansas City. Finally, two binary variables measure if the gunfire event occurred on Independence Day (July 4th) or New Year's Eve (December 31st), days that typically experience unusually high fireworks activity which may challenge the detection and reporting of gunfire.

Multicollinearity amongst the independent variables were tested through a post-hoc calculation of the variance inflation factor (VIF) (see Table 3). For both the time savings and spatial precision models, all tolerance values (1/VIF) were well above 0.1, indicating an absence of multicollinearity among the independent variables (Hamilton, 2013).

Table 3. Variance Inflation Factors

	Time savings		Spatial precision	
Independent variable	**VIF**	**1/VIF**	**VIF**	**1/VIF**
Shooting victim	1.01	0.99	1.01	0.99
Multiple gunshots	1.12	0.89	1.12	0.89
Weekend	1.03	0.97	1.04	0.96
Shots Fired CFS (current yr)	1.36	0.74	1.36	0.73
Shots Fired CFS (prior yr)	1.25	0.80	1.26	0.79
Firearm-related crime (current yr)	1.44	0.69	1.45	0.69
Firearm-related crime (prior yr)	1.38	0.72	1.40	0.72
Residential parcel percentage (z)	1.07	0.93	1.08	0.92
Concentrated disadvantage (z)	1.23	0.81	1.25	0.80
Population density (z)	1.54	0.65	1.54	0.65
Ambient population (z)	1.28	0.78	1.28	0.78
Nighttime	1.02	0.98	1.02	0.98
Precipitation total	1.02	0.98	1.03	0.98
Snowfall total	1.09	0.92	1.09	0.92
Maximum temperature (z)	1.11	0.90	1.11	0.90
Year	1.21	0.83	1.20	0.83
July 4th	1.02	0.98	1.02	0.98
December 31st	1.06	0.94	1.07	0.94

Analytical Approach

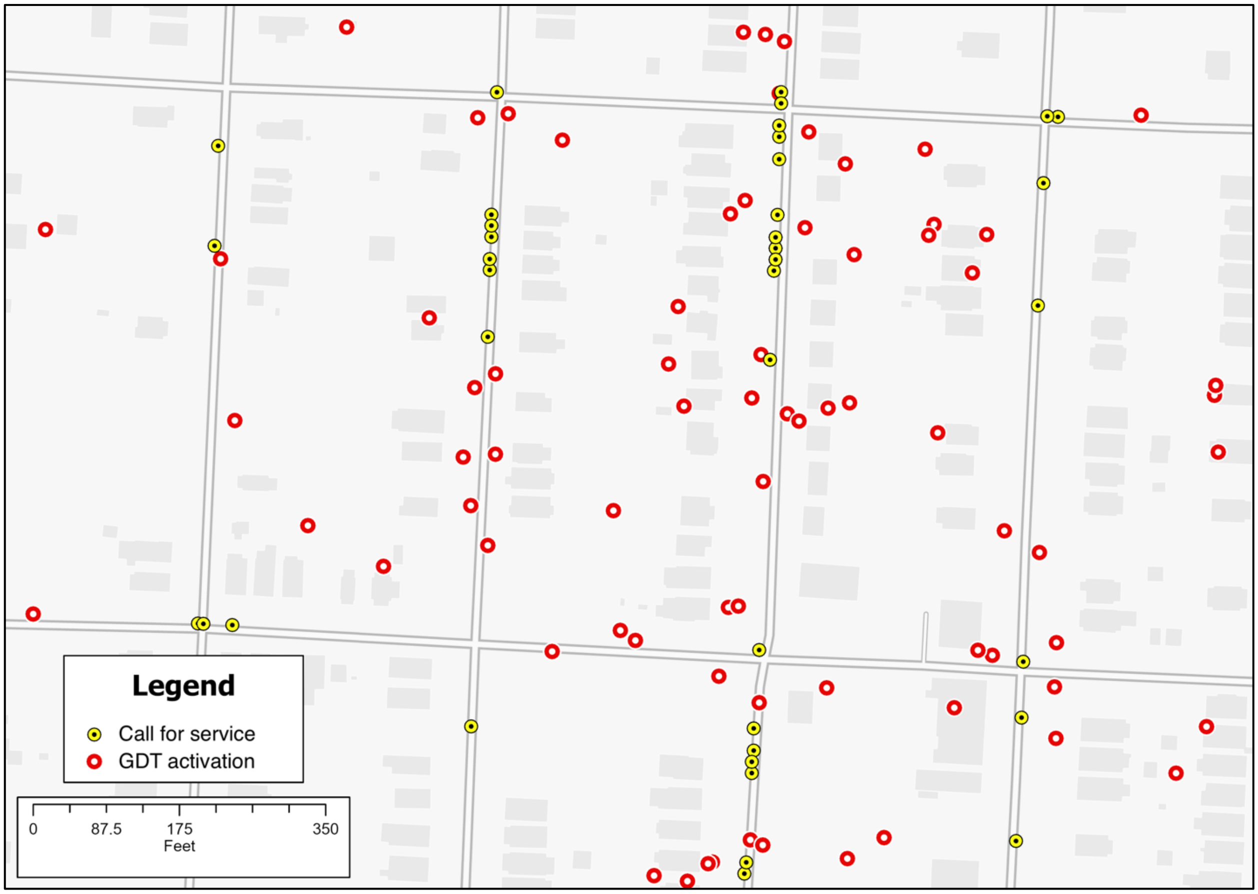
The analysis involves three separate regression models. The unit of analysis in all models is the gunfire event. The effect of covariates on GDT time savings was tested through a generalized linear regression model with Gaussian specification to accommodate the continuous dependent variable. Two separate regression models were used to test the effect of covariates on GDT spatial precision. The linear feet between GDT and CFS was also tested through a generalized linear regression model with Gaussian specification. A multinomial logistic regression model was used to test the effect of covaries on the likelihood that the street segments encompassing the GDT activation and CFS are intersecting or not intersecting. The GDT activation and CFS being recorded on the same street segment was set as the base outcome in the multinomial logistic regression model. All statistical analysis was conducted in Stata version 17.

Results

Descriptive statistics for the dependent and independent variables are presented in Table 4. GDT time savings averaged 125.44 seconds, with a median of 93.00 and a standard deviation of 103.12. GDT spatial precision was 433.91 feet, on average, with a median and standard deviation of 234.91 and 496.66, respectively. GDT and CFS locations were geocoded to the same street segment in 1,383 (46.95%) cases, to intersecting street segments in 763 (25.90%) cases, and to non-intersecting street segments in 763 (25.90%) cases. The street contiguity variable was unable to be calculated for 15 (0.51%) cases due to the CFS location not being successfully geocoded.

Figure 1 allows for visual inspection of the spatial precision offered by GDT. As displayed, CFS locations exhibit a uniform pattern, with calls reported to specific street addresses or intersections. GDT activations spread more widely across the area, given the acoustic sensors measure the precise coordinates of gunfire locations. Such locations do not correspond to precise street addresses of intersections in many instances.

Figure 1. GDT activation and call for service locations



179 (6.08%) gunfire events are associated with a shooting victim. 1,612 (54.72%) gunfire events occurred on the weekend while 2,354 (79.90%) occurred during nighttime hours. The ShotSpotter system detected multiple gunshots for 1,654 (56.14%) gunfire events. The years 2012 and 2017 accounted for only 6.21% (n=183) and 9.00% (n=265) of gunfire events, respectively, given the study period only partially covered these years. The other years accounted for between 17.14% (n=505 in 2015) and 29.26% (n=862 in 2013) of gunfire events. Street segments experienced averages of 1.40 shots fired CFS during the current calendar year and 0.90 shots fired CFS during the prior calendar year, with standard deviations of 2.56 and 1.83, respectively. Street segments experienced averages of 0.61 firearm-related crime incidents

during the current calendar year and 0.90 firearm-related crime incidents during the prior calendar year, with standard deviations of 1.11 and 0.92, respectively. An average of 60.88% parcels were zoned for residential use on encompassing street segments with a median of 6.04 and standard deviation of 2.19. The concentrated disadvantage index in encompassing census block groups had a mean of 5.75 and median of 6.04, with a standard deviation of 2.19. Population density (persons per square mile) in the block groups was 3,093.94 on average, with a median of 2,706.13 and standard deviation of 2,638.97. Ambient population averaged 974.84 in encompassing LandScan grids with a median of 943.00 and standard deviation of 365.73. Days in the study period had mean and median maximum temperatures of 67.21 degrees and 71.00 degrees, respectively, with a standard deviation of 18.14 degrees. The average daily precipitation was 0.11 inches with a standard deviation of 0.33 inches. The average daily snowfall was 0.06 inches with a standard deviation of 0.49 inches.

Table 4. Descriptive statistics

Dependent Variables	**Mean**	**Median**	**S.D.**	**n**	**%**
Time savings (seconds)	125.44	93.00	103.12	-	-
Spatial precision (feet)	433.91	234.91	496.66	-	-
GDT & CFS street segment contiguity					
same street segment	-	-	-	1,383	46.95
intersecting street segments	-	-	-	763	25.90
non-intersecting street segments	-	-	-	785	26.65
unknown	-	-	-	15	0.51
Independent Variables	**Mean**	**Median**	**S.D.**	**n**	**%**
Shooting victim					
yes	-	-	-	179.00	6.08
no	-	-	-	2767.00	93.92
Multiple gunshots					

yes	-	-	-	1654.00	56.14
no	-	-	-	1292.00	43.86
Weekend					
yes	-	-	-	1612.00	54.72
no	-	-	-	1334.00	45.28
Shots Fired CFS (current yr)	1.40	0.00	2.59	-	-
Shots Fired CFS (prior yr)	0.90	0.00	1.83	-	-
Firearm-related crime (current yr)	0.61	0.00	1.11	-	-
Firearm-related crime (prior yr)	0.47	0.00	0.92	-	-
Residential parcel percentage	60.88	66.67	29.49	-	-
Concentrated disadvantage	5.75	6.04	2.19	-	-
Population density	3093.94	2706.13	2638.97	-	-
Ambient population	974.84	943.00	365.73	-	-
Nighttime					
yes	-	-	-	2354.00	79.90
no	-	-	-	592.00	20.10
Precipitation total	0.11	0.00	0.33	-	-
Snowfall total	0.06	0.00	0.49	-	-
Maximum temperature	67.22	71.00	18.14	-	-
Year					
2012	-	-	-	183.00	6.21
2013	-	-	-	862.00	29.26
2014	-	-	-	536.00	18.19
2015	-	-	-	505.00	17.14
2016	-	-	-	595.00	20.20
2017	-	-	-	265.00	9.00
July 4th					
yes	-	-	-	25.00	0.85
no	-	-	-	2921.00	99.15
December 31st					
yes	-	-	-	41.00	1.39
no	-	-	-	2905.00	98.61

Table 5 reports the findings of the generalized linear model testing covariate effect on time savings. Multiple gunshots detected by the ShotSpotter system was associated with a nearly

9-second reduction in GDT time savings (β= -8.89, *p.*=0.001). Each one-standard deviation increase in the surrounding ambient population reduced time savings by over five seconds (β= -5.66, *p.*=0.012). Gunfire events occurring during nighttime hours experienced a nearly seven-second reduction in GDT time savings (β= -6.90, *p.*=0.022) while each one-inch increase in daily precipitation increased the time savings by 8.5 seconds (β=8.50, *p.*=0.020). Each successive year was associated with an over three-second reduction in GDT time savings (β= -3.33, *p.*<0.001).

Table 5. Generalized linear regression model results, time savings

Independent Variables	**b**	**S.E.**	**z**	***p.***	**[95% C.I.]**	
					Lower	**Upper**
Shooting victim	-0.22	5.07	-0.04	0.965	-10.15	9.71
Multiple gunshots	-8.89	2.57	-3.47	0.001	-13.92	-3.86
Weekend	0.48	2.45	0.20	0.845	-4.32	5.27
Shots Fired CFS (current yr)	0.59	0.53	1.10	0.271	-0.46	1.64
Shots Fired CFS (prior yr)	-1.09	0.73	-1.49	0.135	-2.52	0.34
Firearm-related crime (current yr)	-0.83	1.30	-0.64	0.523	-3.38	1.72
Firearm-related crime (prior yr)	1.88	1.53	1.23	0.219	-1.11	4.87
Residential parcel percentage (z)	2.71	4.20	0.64	0.519	-5.53	10.94
Concentrated disadvantage (z)	1.00	0.61	1.64	0.100	-0.19	2.18
Population density (z)	-1.37	2.37	-0.58	0.563	-6.02	3.28
Ambient population (z)	-5.66	2.24	-2.53	0.012	-10.04	-1.27
Nighttime	-6.90	3.00	-2.30	0.022	-12.77	-1.02
Precipitation total	8.50	3.66	2.32	0.020	1.33	15.67
Snowfall total	0.56	2.47	0.23	0.822	-4.28	5.39
Maximum temperature (z)	2.17	2.22	0.98	0.328	-2.18	6.52
Year	-3.33	0.90	-3.72	0.000	-5.08	-1.57
July 4th	10.78	15.16	0.71	0.477	-18.92	40.49
December 31st	-13.09	10.51	-1.25	0.213	-33.69	7.51

N=2,503
Log likelihood = -13,788.42
(z)= standardized measure

Table 6 reports the findings of the generalized linear model testing covariate effect on GDT spatial precision. Gunfire events having a shooting victim increases spatial precision by approximately 47 feet (β= 47.57, *p.*=0.039). Multiple gunshots detected by the ShotSpotter system was associated with a nearly 50-foot increase in spatial precision (β=49.61, *p.*<0.001). Gunfire events occurring on weekends decreased spatial precision by nearly 23 feet (β= -22.33, *p.*=0.040). Each additional shots fired CFS reported during the prior calendar year and the number of firearm-related crimes during the current calendar year decreased spatial precision by nearly eight feet (β= -7.98, *p.*=0.017) and over 13 feet (β= -13.48, *p.*=0.024), respectively. Each one-unit increase in standardized percentage of residential parcels decreased spatial precision by over 100 feet (β= -101.33, *p.*<0.001). Each one-unit increase in the block group's concentrated disadvantage index increased spatial precision by over 6 feet (β=6.32, *p.*=0.025). Gunfire events occurring during nighttime hours increased spatial precision by over 37 feet (β=37.23, *p.*=0.008). Each successive year was associated with a spatial precision increase of nearly 16 feet (β=15.77, *p.*<0.001). Gunfire events occurring on New Year's Eve were associated with spatial precision reductions of over 129 feet (β= -129.32, *p.*=0.007).

Table 6. Generalized linear regression model results, spatial precision

Independent Variables	b	S.E.	z	*p.*	[95% C.I.] Lower	Upper
Shooting victim	47.57	23.04	2.06	0.039	2.42	92.73
Multiple gunshots	49.61	11.83	4.20	0.000	26.44	72.79
Weekend	-23.33	11.38	-2.05	0.040	-45.63	-1.03
Shots Fired CFS (current yr)	1.52	2.49	0.61	0.541	-3.37	6.41
Shots Fired CFS (prior yr)	-7.98	3.34	-2.39	0.017	-14.52	-1.43
Firearm-related crime (current yr)	-13.48	5.97	-2.26	0.024	-25.19	-1.77
Firearm-related crime (prior yr)	-1.49	7.15	-0.21	0.835	-15.51	12.53
Residential parcel percentage (z)	-101.33	20.07	-5.05	0.000	-140.67	-61.99
Concentrated disadvantage (z)	6.32	2.82	2.24	0.025	0.80	11.84
Population density (z)	-18.27	11.20	-1.63	0.103	-40.23	3.69
Ambient population (z)	19.91	10.60	1.88	0.060	-0.88	40.69
Nighttime	37.23	13.92	2.67	0.008	9.94	64.52
Precipitation total	2.99	17.20	0.17	0.862	-30.71	36.70
Snowfall total	-13.58	11.29	-1.20	0.229	-35.71	8.55
Maximum temperature (z)	8.76	10.28	0.85	0.394	-11.38	28.90
Year	15.77	4.15	3.80	0.000	7.64	23.90
July 4th	-20.69	61.80	-0.33	0.738	-141.82	100.43
December 31st	-129.32	47.61	-2.72	0.007	-222.63	-36.00

N= 2,638
Log likelihood = -18,652.15
(z)= standardized measure

Table 7 reports the findings of the multinomial logistic regression model testing covariate effect on street segment contiguity. The base outcome is the GDT activation and CFS being reported on the same street segment. Multiple gunshots detected by the ShotSpotter system increased the likelihood of GDT and CFS being reported on intersecting street segments by 23% (RRR=1.23, *p.*=0.034) and on non-intersecting street segments by 66% (RRR=1.66, *p.*<0.001).

Each additional shots fired CFS during the current calendar year reduced the likelihood of GDT and CFS being reported on intersecting street segments by about 13% (RRR=0.87, *p.*<0.001) and reduced the likelihood of occurrence on non-intersecting street segments by about 7% (RRR=0.93, *p.*=0.002). Each additional shots fired CFS during the prior calendar year reduced the likelihood of GDT and CFS being reported on intersecting street segments by about 23% (RRR=0.77, *p.*<0.001) and reduced the likelihood of occurrence on non-intersecting street segments by about 14% (RRR=0.86, *p.*<0.001). Each additional firearm-related crime incident during the current calendar year reduced the likelihood of reporting on non-intersecting street segments by about 13% (RRR=0.87, *p.*=0.006). Each one-standard deviation increase in the percentage of residential parcels on a street segment decreased the likelihood of reporting on intersecting street segments by over 60% (RRR=0.39, *p.*<0.001) and the likelihood of reporting on intersecting street segments by over 80% (RRR=0.18, *p.*<0.001). Gunfire events occurring during nighttime hours were about 28% more likely to have GDT and CFS reported on intersecting (RRR=1.28, *p.*=0.037) and non-intersecting (RRR=1.28, *p.*=0.043) street segments. Each successive year was associated with a 15% increase likelihood of reporting on intersecting street segments (RRR=1.15, *p.*<0.001) and 27% increased likelihood of reporting on non-intersecting street segments (RRR=1.27, *p.*<0.001).

Table 7. Multinomial logistic regression findings, street segment contiguity

Independent Variables	b	S.E.	z	*p.*	[95% C.I.] Lower	Upper
Intersecting street segments						
Shooting victim	0.95	0.19	-0.27	0.785	0.63	1.41
Multiple gunshots	1.23	0.12	2.12	0.034	1.02	1.49
Weekend	1.04	0.10	0.41	0.680	0.86	1.25

Shots Fired CFS (current yr)	0.87	0.02	-5.34	0.000	0.83	0.92
Shots Fired CFS (prior yr)	0.77	0.03	-6.65	0.000	0.71	0.83
Firearm-related crime (current yr)	0.96	0.05	-0.86	0.388	0.87	1.06
Firearm-related crime (prior yr)	1.08	0.07	1.29	0.195	0.96	1.22
Residential parcel percentage (z)	0.39	0.07	-5.53	0.000	0.28	0.54
Concentrated disadvantage (z)	0.98	0.02	-0.90	0.369	0.94	1.03
Population density (z)	1.18	0.11	1.79	0.073	0.98	1.42
Ambient population (z)	0.92	0.08	-0.89	0.374	0.77	1.10
Nighttime	1.28	0.15	2.09	0.037	1.02	1.62
Precipitation total	1.28	0.18	1.79	0.073	0.98	1.69
Snowfall total	0.97	0.09	-0.30	0.767	0.81	1.17
Maximum temperature (z)	0.97	0.08	-0.36	0.719	0.82	1.15
Year	1.15	0.04	3.95	0.000	1.07	1.23
July 4th	1.05	0.51	0.11	0.916	0.41	2.70
December 31st	1.20	0.44	0.51	0.613	0.58	2.48
Non-intersecting street segments						
Shooting victim	1.24	0.24	1.13	0.257	0.85	1.80
Multiple gunshots	1.66	0.17	5.06	0.000	1.37	2.02
Weekend	1.05	0.10	0.51	0.613	0.87	1.27
Shots Fired CFS (current yr)	0.93	0.02	-3.09	0.002	0.89	0.98
Shots Fired CFS (prior yr)	0.86	0.03	-4.43	0.000	0.81	0.92
Firearm-related crime (current yr)	0.87	0.05	-2.74	0.006	0.78	0.96
Firearm-related crime (prior yr)	1.02	0.06	0.28	0.776	0.90	1.15
Residential parcel percentage (z)	0.18	0.03	-10.15	0.000	0.13	0.25
Concentrated disadvantage (z)	1.03	0.02	1.17	0.243	0.98	1.08
Population density (z)	0.88	0.09	-1.29	0.196	0.72	1.07
Ambient population (z)	1.07	0.09	0.71	0.475	0.89	1.27
Nighttime	1.28	0.15	2.02	0.043	1.01	1.61
Precipitation total	0.98	0.15	-0.13	0.896	0.72	1.33

Snowfall total	0.81	0.13	-1.33	0.183	0.59	1.11
Maximum temperature (z)	1.06	0.09	0.69	0.492	0.89	1.27
Year	1.27	0.04	6.72	0.000	1.18	1.36
July 4th	0.86	0.47	-0.27	0.783	0.30	2.50
December 31st	0.43	0.22	-1.63	0.102	0.16	1.18

N=2,931

Log likelihood= -2,897.54

(z)= standardized measure

Base outcome: GDT and CFS on same street segment

Discussion and Conclusion

Findings of the current study suggest that the time savings and spatial precision offered by GDT systems may provide practical benefits to police agencies. GDT generated median time savings of 93 seconds. To contextualize this value, police respond to reported gunfire events in a median time of approximately 223 seconds according to KCPD CAD data. Following arrival on scene, police EMS response times—which typically occur after police arrival on scene and confirmation of gunshot victims—have a median of 78 seconds in Kansas City according to data on the Kansas City open data portal.[13] Street segments in the GDT target area are an average of a 480-second (8-minute) driving distance from the nearest trauma center.[14] The 93-second time savings represents nearly 12% (93 of 781 seconds) of the police response, EMS response, and EMS travel times. Within this context, GDT detections offer nearly 12% "head start" for the victim transport process.

Practical benefits are also evident from the spatial precision figures. The median distance between GDT detections and CFS was 234.91 feet. While this is less than the median street

[13] See https://data.kcmo.org/Safety/KCFD-EMS-Response-Times/rxym-ktqn.

[14] We calculated this variable via the driving time formula of the Google Maps API in Google Spreadsheets. See https://www.labnol.org/google-maps-sheets-200817.

segment length in Kansas City (334 feet, as measured in ArcGIS Pro)[15], the contiguity measure indicates that the respective GDT activation and CFS for gunfire events occur on different street segments in over half of cases. In more than 26% of cases GDT activations and CFS originated from different street segments that do not intersect. In these cases, officers responding to the CFS location would be a meaningful distance away from where the gunshot occurred, as reflected in the GDT-recorded location.

Regression model findings further indicate situational characteristics that may influence GDT performance. The pattern of statistically significant variables suggests time savings decreases in cases that are more conducive to citizen reporting. For example, multiple gunshots detected and ambient population were negatively related to time savings, suggesting that the additional noise generated by multiple gunshots and more people on-street to hear such noises may lead to citizens calling 9-1-1 quicker. Conversely, precipitation was positively associated with time savings, suggesting GDT time savings is heightened when conditions are less favorable to people being outdoors. A similar theme was evident in the spatial precision analysis. Levels of shots-fired CFS and firearm-related crime reported on the street segments were consistently associated with decreased spatial precision. The relative proportion of residential parcels on a street segment was negatively associated with spatial precision across all models. Taken together, this suggests that residents of street segments with high levels of illicit firearm activity may be better positioned to identify the source of gunfire. Conversely, gunfire events having a shooting victim and multiple gunshots increased spatial precision. In considering these findings, perhaps the on-scene tumult that typically follows serious gun violence (e.g. crowds of people fleeing the scene and/or running towards the victim) makes it difficult for citizens to

[15] The median length of street segments in the GDT target area is 335 feet, nearly identical to the city-wide median.

pinpoint to precise origin of the gunfire event. Although, we acknowledge that the shooting victim variable did not achieve significance in the multinomial logistic regression model that measured spatial precision in terms of street segment contiguity rather than linear distance between GDT and CFS.

This study has implications for researcher-practitioner partnerships. The KCPD has a history of working closely with researchers, playing a prominent role in a number of action research projects in recent years (see e.g., Caplan et al, 2021; Fox & Novak, 2018; Kennedy et al., 2018). KCPD's role in the current study differed from these prior efforts, as they were involved more in the front-end process of the current research project. Given the large amount of data needed for the overall project, the grant allotted funding directly to KCPD to assist their efforts in collecting and cleaning data from numerous departmental sources. Data collection was made more challenging due to the recent CAD and RMS system upgrades, meaning data tables often had to be re-formatted to account for different variable names and formats across the contemporary and legacy systems. Having KCPD take the lead in this effort was beneficial, as it allowed the research team to focus more on triangulating KCPD datasets with outside sources (e.g., Census Bureau, NOAA, and LandScan data) and building databases needed for the statistical analysis as opposed to data cleaning and manipulation. KCPD also provided data codebooks for the research team, helping to ensure understanding of the conceptual and operationalization definitions of all variables.

Despite these benefits, some limitations should be noted. In short, data collection proved taxing for KCPD, despite the availability of funding to assist these efforts. KCPD policy prohibits sworn officers from earning overtime on projects not directly related to police operations. This precluded the KCPD liaison to the research team from directly participating in data preparations or tasking officers under his direct command with data collection duties. Instead, civilian crime analysts, who were situated in a unit outside of the KCPD liaison's command, primarily led data collection and cleaning efforts. This meant the crime analysts had to find time to work on data preparation in between their other duties. As observed elsewhere (e.g. Green & Rossler, 2019; Piza & Feng, 2017), crime analysts at KCPD are directly involved in a range of agency functions, which often precludes them from working on additional projects, even on an overtime basis. This was all further complicated by the COVID-19 pandemic, which brought research project activities to a pause for the majority of 2020.

In hindsight, KCPD could have planned on including the crime analysis unit at the outset of the project. Having crime analysts as integral members of the project would have likely provided a number of benefits. In addition to facilitating the data collection and cleaning, crime analysts may have provided important insight into the problem analysis functions of the research team given analysts work with data to analyze crime problems on a daily basis (Braga & Tucker, 2019). Police agencies may also support applied research projects by having on-site personnel dedicated entirely to research support services, such as data collection and cleaning. This can come in the form of research and planning units (Bond & Gabriele, 2018), providing necessary training for officers to serve as pracademics, or partnering with universities to house embedded criminologists on-site at the agency (Braga & Davis, 2014; Douglas & Braga, 2021; Huey & Mitchell, 2016). We acknowledge that many police agencies likely lack sufficient resources to support these types of activities at scale. This makes the tighter integration of crime analysts into research the more prudent solution, given a large proportion of police agencies report employing crime analysts across the United States (Hyland & Davis, 2021), Canada (Sanders & Condon, 2017), and the United Kingdom (Belur & Johnson, 2018; Keay & Kirby, 2018). Positioning crime analysts as core members of researcher-practitioner partnerships supports recent calls to better integrate crime analysis within the evidence-based policing paradigm (see Keay & Kirby, 2018; Lum & Koper, 2017; Piza & Feng, 2017; Santos & Santos, 2019), and can help bolster future partnerships between police agencies and academic institutions.

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