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Authors
Doucet, Jay J
Godat, Laura N
Berndtson, Allison E
et al.

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Youth violence prevention can be enhanced by geospatial analysis of trauma registry data

AQ1 Joseph Doucet, MD, Laura N. Godat, MD, Allison E. Berndtson, MD, Amy E. Liepert, MD, Jessica L. Weaver, MD, PhD, Alan Smith, PhD, Leslie Kobayashi, MD, Walter L. Biffl, MD, and Todd Costantini, MD, *San Diego, California*

BACKGROUND: Geographic information systems (GIS) have been used to understand relationships between trauma mechanisms, locations, and social determinants for injury prevention. We hypothesized that GIS analysis of trauma center registry data for assault patients aged 14 years to 29 years with census tract data would identify geospatial and structural determinants of youth violence.

METHODS: Admissions to a Level I trauma center from 2010 to 2019 were retrospectively reviewed to identify assaults in those 14 years to 29 years. Prisoners were excluded. Home and injury scene addresses were geocoded. Cluster analysis was performed with the Moran *I* test for spatial autocorrelation. Census tract comparisons were done using American Communities Survey (ACS) data by t-test and linear regression.

RESULTS: There were 1,608 admissions, 1,517 (92.4%) had complete addresses and were included in the analysis. Mean age was 23 ± 3.8 years, mean ISS was 7.5 ± 6.2, there were 11 (0.7%) in-hospital deaths. Clusters in six areas of the trauma catchment were identified with a Moran *I* value of 0.24 (Z score = 17.4, $p < 0.001$). Linear regression of American Communities Survey demographics showed predictors of assault were unemployment (odds ratio, 4.5; 95% confidence interval, 2.7–6.4; $p < 0.001$), Spanish spoken at home (odds ratio, 6.6; 95% confidence interval, 3.4–9.8; $p < 0.001$) and poverty level (odds ratio, 1.9; 95% confidence interval, 1.1–2.7; $p < 0.001$). Education level of less than high school diploma, single parent households and race were not significant predictors.

CONCLUSION: GIS analysis of registry data can identify high-risk areas for youth violence and correlated social and structural determinants. Violence prevention efforts can be better targeted geographically and socioeconomically with better understanding of these risk factors. (*J Trauma Acute Care Surg.* 2022;00: 00–00. Copyright © 2022 Wolters Kluwer Health, Inc. All rights reserved.)

LEVEL OF EVIDENCE: Epidemiological, Level III.

KEY WORDS: GIS; youth violence; trauma; prevention; spatial data analysis.

Violence is a leading cause of death and disability in young people. Trauma is the leading cause of death for those aged 1 year to 44 years, and homicide is the third most common cause of death in those 15 years to 34 years.[1] Youth violence is the intentional use of physical force or power to threaten or harm others by young people.[2] Each day in the United States, about 13 young people are victims of homicide and about 1,100 are treated in emergency departments for nonfatal assault-related injuries. There are strong racial, ethnic, and social disparities for young adults; the homicide rate for non-Hispanic Black youth was 13 times greater than for non-Hispanic White youth in 2013.[3] Youth homicides and assault-related injuries cost more than $20 billion annually in combined medical and lost productivity costs alone, not counting legal, psychological, social, and community costs.[2]

Strategies to prevent youth violence include school and community-based programs to promote family environments, quality education and youth skills, connecting youth to caring adults and activities and creating protective environments.[3] Successful hospital-based violence intervention programs (HVIP) start with the "teachable moment" with the victim and family in the trauma center.[4] Hospital-based violence intervention programs partner with community based organizations to build team alliances and community commitment. Hospital-based violence intervention program surveillance for youth violence prevention can be performed via trauma registry and police records databases to understand the target population. Geographic information systems (GIS) have been used to understand relationships between trauma mechanisms, locations, and social determinants for injury prevention.[5–11] The GIS systems can provide additional community characteristics for crime and social determinants down to individual census tracts. Geographic information system can also identify "hotpots" and clusters of recurrent violence.

We hypothesized that GIS analysis of trauma center registry data for assault victims aged 14 years to 29 years, combined with census tract data, would identify geospatial and structural determinants for youth violence.

MATERIALS AND METHODS

The trauma registry of the UC San Diego Level I trauma center was used to retrospectively identify admissions with an assault mechanism of injury in those 14 years to 29 years from January 1, 2010, to December 31, 2019. We chose the age 14 years

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From the Division of Trauma, Surgical Critical Care, Burns and Acute Care Surgery, Department of Surgery (J.J.D., L.N.G., A.E.B., A.E.L., J.L.W., A.S., L.K., T.C.), University of California San Diego Health, San Diego; and Trauma Department (W.L.B.), Scripps Memorial Hospital La Jolla, La Jolla, California.

AQ2 Address for reprints: Joseph Doucet, MD, UCSD Medical Center San Diego, CA; email: jdoucet@ucsd.edu.

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TABLE 1. Demographics

	Assault All Victims, 14–29 y	Gunshot Wound Victims, 14–29 y	ACS County Population, 14–29 y
n	1,517	176	731,809
Age (SD), y	23 ± 3.8*	23 ± 3.9*	22.5 ± 0.1**
Male sex	88.6%*†	93.2%*†	53.4%**
Non-White race	77.8%*†	95.8%*†	29.4% ± 0.4**
ISS (SD)	7.5 ± 6.2†	10.0 ± 9.8†	N/A
Length of stay, d	2.2 ± 4.1†	5.2 ± 9†	
ICU days	0.8 ± 9.8†	1.82 ± 9†	
Positive alcohol	52.8%‡	45.8%‡	
Positive drug	32.2%§	34.7%§	

*Significant difference from county, $p < 0.001$.
**Significant difference from assault all victims 14–29 years and gunshot wound victims, $p < 0.001$.
†Significant difference between assault all victims 14–29 years and gunshot wound victims, $p < 0.001$.
‡No significant difference between assault all victims 14–29 years and gunshot wound victims, $p = 0.078$.
§No significant difference between assault all victims 14–29 years and gunshot wound victims, $p = 0.50$.
SD, standard deviation.

as the lower age limit as children that age and younger are admitted to a pediatric center in our county. We chose the age 29 years as the upper limit as that is part of a definition for youth violence used by the World Health Organization. Prisoners were excluded. Data collected included demographics, home and injury location addresses, Injury Severity Scores (ISS), and mortality. Geocoding, mapping, and geospatial analysis of home and injury address locations was done using ArcGIS Pro 2.7 (Esri, Redlands, CA). Geocoded addresses were used to identify the US Census Bureau's American Communities Survey (ACS) data set to provide census tract data. The ACS context for child well-being data set was used to provide the child below poverty level percentage for home census tracts (HCTs), as well as single-parent household percentage, percentage disconnected youth (defined as 16–19 years old and not in school or employed), and percentage of households with children of at least one immigrant parent. The educational attainment level for patient home census tracts was done by selecting the predominant education level (less than grade 9, grades 9–12, high school, some college, bachelor's degree, graduate degree) within the patient's home address census tract from the ACS 2015 to 2019 5-year estimates, Table B15002. The language spoken at home was selected by home address census tract in the ACS 2015 to 2019 5-year estimates, Table B16007.

χ^2 Analysis was done for categorical data, means were compared via analysis of variance. Two-sided p values less than 0.05 were considered significant. Stepwise linear least squares regression was used to analyze HCT characteristics, selecting factors with a p value less than 0.01 from the univariate analysis to identify predictors of the assault rate per 100,000 persons in the HCT. The spatial clustering of assault hotspots were assessed using spatial autocorrelation via the Moran-*I* statistic in ArcGIS Pro 2.7[10] Analyses of descriptive and tabular data were performed with IBM SPSS Statistics 27. The study was exempted from further review by the UC San Diego Human Research Protections Program.

RESULTS

There were 1,608 admissions aged 14 years to 29 years with assault mechanisms of injury from 2010 to 2019 identified, 1,517 (92.4%) had complete home addresses that could be geocoded and were included in the analysis. Mean age was 23 ± 3.8 years, 1,344 (88.6%) were male. Mechanisms of injury included 176 admissions (11.6%) with gunshot wounds, 400 stab wounds (26.4%), and 1,013 (66.8%) had a blunt mechanism. The mean ISS was 7.5 ± 6.2, and there were 11 (0.7%) in-hospital deaths.

Table 1 shows demographics for all assault admissions, for gunshot admissions, and for the entire San Diego County population from ACS data. Assault victims overall were significantly more likely to be non-White race than the mean for the county, and gunshot wound victims were significantly more likely to be non-White than overall assaults or the county population. Table 2 shows HCT results—assault victims HCT's percentage of population older than 5 years, speaking Spanish at home, percentage single parent households, percentage children of immigrants, percentage unemployment, percentage child poverty level, and percentage of disconnected youth were all significantly higher than the county mean. The HCTs for the subset of assault admissions who were gunshot wound victims had significantly higher percentages of population older than 5 years speaking Spanish at home, percentage of single parent households, percentage with children of immigrants, unemployment rate, percentage

TABLE 2. Home Census Tracts

	Assault All Victims, 14–29 y	Gunshot Wound Victims 14–29 y	ACS County, Mean ± SD
Population age 5+ y who speaks Spanish at home HCT	45.0% ± 24.7*,**	55.3 ± 22.3*,**	23.8% ± 0.9†
Single parent household HCT	32.2% ± 19.1*,**	23.9 ± 11.5*,**	7.6% ± 0.6†
Child of immigrants HCT	41.0% ± 20.4 *,**	55.4 ± 18.7*,**	21.2% ± 8.2†
Unemployment rate HCT	7.8% ± 4.0 *,**	8.4% ± 4.0*,**	5.6% ± 0.4†
Child poverty level HCT	20.4% ± 14.7 *,**	23.6 ± 14.8*,**	10.2% ± 0.5†
Disconnected youth 16–19 y HCT	8.1% ± 16.5 *,**	7.7% ± 16.5*,**	3.5% ± 0.2†
Predominant education level HCT	High school graduate or higher	High school graduate or less *,**	High school graduate or higher

*Significant difference from county, $p < 0.001$.
**Significant difference between assault all victims 14–29 years and Gunshot wound victims, $p < 0.001$.
†Significant difference from assault all victims 14–29 years and gunshot wound victims, $p < 0.001$.

TABLE 3. Linear Regression: Predictors of All Assaults Rate (Per 100 k) HCT

	B	Std. Error	*p*	95% CI, Lower Bound	95% CI, Upper Bound
Constant	40.7	6.2	<0.0001	28.7	52.8
Percent HCT child poverty level	1.9	0.387	0.0001	1.1	2.7
Percent HCT population age 5+ y who speaks Spanish at home	6.6	0.168	0.0003	3.4	9.8
Percent HCT unemployment rate	4.5	0.958	0.0022	2.7	6.4

child poverty level, and percentage of disconnected youth than the overall assault admissions or the county mean. There was no significant difference between overall assault victim's HCT and the county mean for a predominant education level of high school graduate or higher. However, gunshot wound victims were more likely to come from an HCT with a predominant education level of high school graduate or lower than overall assault admissions or the county mean.

T3 Table 3 shows the final results of stepwise linear least squares regression of the ACS HCT predictors for overall assault rate per 100,000 persons. Unemployment rate (odds ratio [OR], 4.5; 95% confidence interval [CI], 2.7–6.4; $p = 0.002$), Spanish spoken at home (OR, 6.6; 95% CI, 3.4–9.8; $p = 0.003$), and poverty level (OR, 1.9; 95% CI, 1.1–2.7; $p = 0.0001$) were significant predictors. Single parent households, children of immigrants, disconnected youth, education level of less than high school T4 diploma, and race were not significant predictors. Table 4 shows the final results of stepwise linear regression of the ACS HCT predictors for overall assault rate per 100,000 persons. Unemployment rate (OR, 7.5; 95% CI, 0.25–28.3; $p = 0.046$) and poverty level (OR, 1.9; 95% CI, 1.1–2.7; $p = 0.004$) were significant predictors. Spanish spoken at home, single parent households, children of immigrants, disconnected youth education level of less than high school diploma, and race were not significant predictors.

Overall assaults within the trauma center catchment are F1 shown in Figure 1. Assaults were strongly clustered in six areas of the trauma catchment, spatial autocorrelation testing had a F2 Global Moran-*I* value of 0.24 (Z score = 17.4; $p < 0.001$; Fig. 2). Gunshot wounds occurred almost exclusively in Hispanic ethnicity predominant HCTs (173, 98.2%), within the trauma catchment, and rarely in White or non-Hispanic predominant HCTs F3 (3, 1.8%) (Fig. 3).

DISCUSSION

We have shown that geospatial analysis of trauma center registry data for assaults on those aged 14 years to 29 years, combined with census tract data, can identify geospatial and structural determinants of youth violence. Surveillance of the trauma catchment for youth violence trends and locations via police records and trauma registry data alone does not reveal the additional community characteristics and location data, such as unemployment and poverty, which is revealed by the addition of ACS data and GIS analysis. With this analysis, our HVIP can focus on the catchment neighborhoods at greatest risk and understand the effects of poverty and unemployment, on youth violence. Geographic information system analysis also indicates the predominant race, ethnicity, language, and educational attainment in high-risk areas, which may not be causal factors, but must be accounted for in tailoring interventions. Geographic information system software also mapped injury mechanisms over census tracts to provide additional insight on what is happening through all parts the catchment for gunshot injury.

In both overall assaults and gunshot injuries, while univariate analysis identified several significant HCT structural determinants—speaking Spanish at home, single parent households, immigrant families, unemployment, child poverty, disconnected youth, and predominant education level. However, only HCT poverty level and unemployment were predictors in multivariate analysis of gunshot wound admissions, while overall assault predictors also included Spanish spoken at home—a common characteristic in the southern half of our catchment. It should be noted that a Hispanic ethnicity predominant HCT is not quite the same thing as a high rate of Spanish spoken at home HCT. In San Diego county, only 24.9% of people speak Spanish at home, but 34.1% identify as Hispanic. Geographic information system mapping vividly demonstrated that youth violence was strongly clustered in six areas in the catchment, predominantly in Hispanic and poorer neighborhoods. Gunshot injury was almost entirely a phenomenon of poor Hispanic neighborhoods and rare in predominantly non-Hispanic White neighborhoods. Our catchment lacks numbers of significant Black neighborhoods, which indicates the need for a larger regional analysis among all San Diego County trauma centers. Not all of these clusters of youth violence were well addressed by our previous violence prevention collaboration, which we are now expanding to all four cities involved.

Existing literature has identified that there are important social determinants of health. These are nonmedical conditions that alter the overall health of individuals, including the risk for intentional injury.[12] Employment, education, income, health care access, social settings, race, culture, and other factors play a large role in determining health.[13] While the established "evidence-based medicine" approach has been important in improving

TABLE 4. Linear Regression: Predictors of Gunshot Wound Victims Rate (Per 100,000) HCT

	B	Std. Error	*p*	95% CI, Lower Bound	95% CI, Upper Bound
Constant	105.3	54.0	0.052	−0.764	211.4
Percent HCT child poverty level	1.9	0.387	0.004	2.3	12.6
Percent HCT unemployment rate	7.5	0.958	0.046	0.25	28.3

Fig 1 4/C

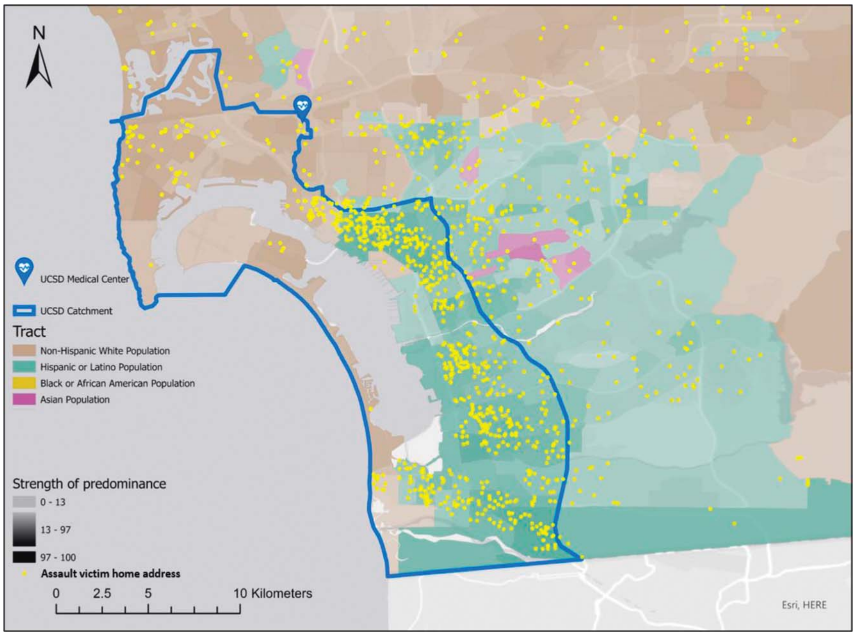

Figure 1. All assaults' home address's locations and the trauma center catchment.

medical therapies, failing to account for these social determinants can mean diagnostic modalities and therapies may not be as successful as when first studied, or even detrimental in some cases.[14] Social determinants have been found to play an important role in prior studies of risks of intentional injury. A study of Mobile, AL trauma registry and census block data demonstrated that unemployment, lack of a high school degree, and single parent households were spatial factors in intentional injury.[6] That study also found that Black or White race alone was not spatially correlated with high-risk areas; however, it did not use Hispanic ethnicity as a risk factor. A study of gunshot injuries in Miami-Dade County demonstrated that Black residents, percentage of single-family households, and median age accounted for 42% of the variation of the GSW incidence rate.[7] AQ3 There was also significant focal clustering of gunshot injury in predominantly poor, Black neighborhoods near downtown Miami. In our study, unemployment and poverty were the significant predictors.

Limitations of our study include the inability to geocode all assault victim's addresses, possibly due to incomplete documentation of address data, reluctance of patients to fully self-identify and homelessness. Another limitation is the grouping

Fig 2 4/C

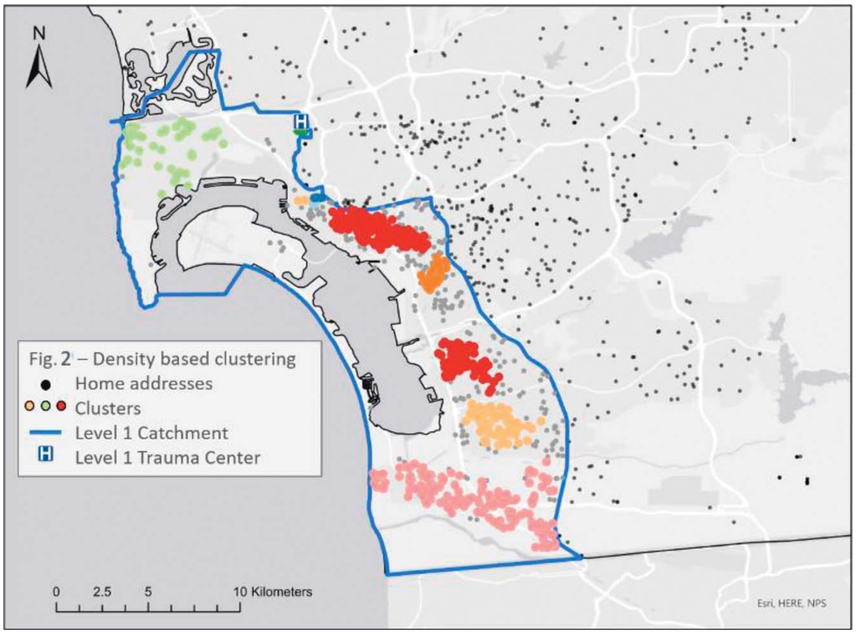

Figure 2. Density-based clustering of all assaults' home addresses and the trauma center catchment.

Fig 3 4/C

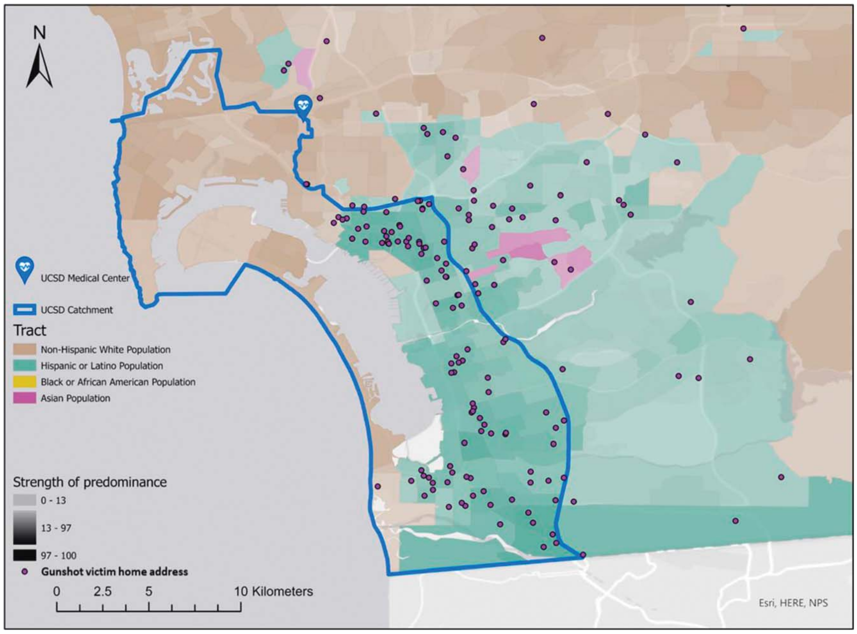

Figure 3. Gunshot wound victims' home address's locations and the trauma center catchment.

of home addresses into census tract groups. Ideally, the predictive factors should be characterized using shapes more specific to the clusters of injury addresses. However, the smallest areas available for use ACS data are census tracts and the clusters found crossed multiple census tracts. Smaller areas, such as block groups, defined to contain between 600 and 3,000 people would be preferable, but not yet available for most variables in our county. The risk factors used were those currently available in ACS, and previously shown to be possible factors for intentional injury and that could be analyzed within the GIS application. There are very likely other factors not yet available within GIS data sets that may be predictive for youth violence, such as availability of firearms or gang activities. Also, the use of demographic data for HCT is most valid when looking at large numbers of individuals for future prevention activities; however, individual patients may be outliers from the HCT demographic means. Further studies of combination of GIS-based databases and trauma center registries are needed to validate our approach.

Geographic information system analysis of injury is becoming an increasingly important tool in studying risk factors and social determinants of injury. Many other GIS applications are possible in trauma, for instance the Multi-Institutional Multidisciplinary Injury Mortality Investigation in the Civilian Pre-Hospital Environment study examining prehospital deaths will use GIS as an important component. Geographic information system has great potential to identify promising areas for research and development in prehospital medical care, injury prevention, and trauma systems. Future work will include expansion of the study area to include all county trauma catchments, as well as examining ways to improve the trauma registry by integrating GIS analysis prospectively. Future trauma registries and national trauma databases should be constructed to include readily geocoded address data and can be readily made to incorporate links to census tract data. Real-time dashboards of GIS data could provide rapid surveillance of injury locations for better targeted injury prevention activities.

CONCLUSION

Geographic information systems analysis of registry data can identify high-risk areas for youth violence and correlated social and structural determinants. The addition of census tract demographic data can provide supplemental variables useful for injury prevention efforts. Trauma center registries and national trauma registries should be constructed to allow for these types of GIS analyses. Thus, facilitating equitable dispersion of violence prevention efforts and resources based on an improved understanding of the geographic, social, and structural risk factors.

AUTHORSHIP

J.J.D. designed the study. J.J.D. performed the literature search. J.J.D. and A.S. did the data collection. J.J.D. and A.S. did data analysis. Critical review was done by L.N.G., A.E.B., A.E.L., L.K., J.L.W., W.L.B., T.C. All authors contributed to data interpretation and article preparation.

DISCLOSURE

The authors declare no funding or conflicts of interest.

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