Linking Emergency Care and Police Department Data to Strengthen Timely Information on Violence-Related Paediatric Injuries

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ABSTRACT

Background: Combined emergency department (ED) and police department (PD) data has improved violence surveillance in the UK, enabling significantly improved prevention. We sought to determine if the addition of EMS data to ED data would contribute meaningful information on violence-related paediatric injuries beyond PD record data in a US city.

Methods: Cross-sectional data on self-reported violence-related injuries of youth treated in the ED between 1/2015-9/2016 were combined with incidents classified by EMS as intentional interpersonal violence and incidents in which the PD responded to a youth injury from a simple or aggravated assault, robbery, or sexual offense. Nearest neighbour hierarchical spatial clustering detected areas in which 10 or more incidents occurred during this period (hotspots), with the radius of the area being 1000, 1500, 2000 and 3000 feet. Overlap of PD incidents within ED&EMS hotspots (and vice versa) was calculated and Spearman's rho tested statistical associations between the datasets, or ED&EMS contribution to PD violence information.

Results: There were 935 unique EM&EMS records (ED=381; EMS=554). Of these 871 (93%) were not in PD records. In large hotspots >2000 feet, ED&EMS records identified one additional incident for every three in the PD database. ED&EMS provided significant numbers of incidents not reported to PD. Significant correlations of ED&EMS incidents in PD hotspots imply that the ED&EMS incidents are as pervasive across the city as that reported by PD. In addition, ED&EMS provided unique violence information, as ED&EMS hotspots never included a majority (>50%) of PD records. Most (676/871; 78%) incidents unique to ED&EMS records were within 1,000 feet of a school or park.

Conclusions: Many violence locations in ED&EMS data were not present in PD records. A combined PD, ED and EMS database resulted in new knowledge of the geospatial distribution of violence-related paediatric injuries and can be used for data-informed and targeted prevention of violence in which children are injured—especially in and around schools and parks.

WHAT THIS PAPER ADDS

Key Messages
What is already known on this topic
➢ Adding emergency department (ED) information on location of violence-related injuries to PD data in the United Kingdom provided a more comprehensive idea of violence through adoption of the Cardiff Model for Violence Prevention. ➢ Previous studies show that not all community violence that is treated in emergency departments is reported to police (PD). In the U.K., at least half of ED violence hotspots within a studied community were unknown to PD. The extent to which ED contributes violence information is still not known in US cities.
What is study adds
➢ In spatial clustering analyses of combined ED EMS and PD data, involving children in the United States, the great majority (93%) of incident locations of paediatric injuries in the ED and EMS datasets were not in the PD data, especially around schools and parks. Many of the ED & EMS incidents were outside of hotspot areas that were identified by PD data alone.
How this study might affect research, practice or policy
➢ Targeted and comprehensive violence prevention efforts should be based on ED, EMS and PD data and partnership rather than PD data alone. To achieve this the study team is translating the Cardiff Model for Violence Prevention to the United States.

INTRODUCTION

In 2019 there were 173,266 non-fatal injury assaults on individuals aged 1 to 17 treated in emergency departments in the United States, with homicide being the fourth leading cause of death in this group (n=1,348).[1] The World Health Organization has described interpersonal violence as a significant public health problem that is predictable and preventable,[2, 3] and recommends coordinated data collection that helps identify and measure individual and local level factors that are associated with violence.[3]

A comprehensive violence surveillance system and data-supported prevention plan requires knowledge of the locations where interpersonal violence incidents occur. While the principal source of violence information has come traditionally from police (PD), research suggests that emergency departments (EDs)[4-6] and emergency medical services (EMS)[7] are important sources of information about violent incidents that are not reported to PD. In the U.K., at least half of EMS violence hotspots within a studied community were unknown to PD, suggesting the inclusion of EMS data enhances violence surveillance and may represent a strategic violence prevention strategy.[7]

We investigate the paediatric violence location overlap between ED, EMS, and PD data in a city in the United States. While some interpersonal violence surveillance systems link information from PD and other data sources[8] they do not systematically gather information from EMS or ED sources. We sought to investigate the extent to which the ED and EMS data meaningfully contribute information on locations of violence where youth are injured beyond what appears in a corresponding PD database. We hypothesise that the ED and EMS data will provide significant amount of meaningful additional information on violence-related paediatric injuries beyond data from PD records.

RESEARCH METHODS

Setting

We collected cross-sectional data between January 1, 2015 and September 30, 2016 from the ED at a Level One Paediatric Trauma Centre, a county EMS system and a city-wide PD agency in Milwaukee, Wisconsin, a large, Midwestern, urban community. Milwaukee County has a population of just over 900k residents, with an estimated median household income of $54,790. Approximately 63.2% of the county are White, 27.6% are Black, and 16.4% identify as Hispanic.[9] Descriptive statistics for the three datasets used for this study can be found in the Table 1. All study activities were approved by the institution's IRB.

Data Sources

Emergency Department. All patients who presented to the ED were screened for assault-related injuries by nurses during the triage stage of intake. Prospective collection of this data in the ED was related to a larger overall study to implement a violence prevention model [10, 11]. Youth ages 17 and younger and the parents/guardians of youth with positive screens were asked follow-up questions about the incident and location of the injury. Nurses were trained to capture detailed information about the location of the incident (e.g., street address, intersection, business name) and inputted data into designated fields of the electronic medical record. Additional details regarding data collection in the ED are reported elsewhere.[12] Study staff geocoded the self-reported address information (N=798), which served as incident locations in the ED dataset. For locations with missing address information (e.g., a specific park, school, business), Google Maps was used to determine the street address and intersections remained geocoded as thus in the dataset. All geocoding was completed using the Batch Geocoding Tool in ArcMap 10.3.1 or through Google Map's online batch geocoding tool.[13] Some ED incidents do not have exact injury time. The time for these incidents was set to 0:00:00 for analyses. This arbitrary setting of time will make different incidents that occurred in the same date have the same time and data exploration suggested that this decision did not affect our analytical results.

Emergency Medical Services. Electronic records of assault incidents where there was an EMS response were received from the county's EMS agency. Only the incidents classified by EMS case report variables as intentional injury or assault, where the perpetrator was someone other than the injured child, were included (N=588). The addresses of EMS response were used in the analyses.

Police. Electronic records of violent incidents to which police responded and where a child was injured in a simple or aggravated assault, robbery, or sexual offense with Unified Crime Reporting Codes[14] (13A, 13B, 120, 11A-D) were received from the city PD (N=1,837). The addresses for the child-involved incidents were imputed to the street level by PD, and the Median Centre tool in ArcMap 10.3.1 was used to obtain geocodes for centres of city street blocks for analysis.

The address data from the city's Master Address Index were utilised in for the median location of each street block in the city. Block-level addresses provided by the PD were then matched to the Median Centre tool output (using address ranges; e.g., 10xx Centre Street in the PD dataset was matched to the median centre geocode for 1000 to 1099 Centre Street), and the corresponding geocode was used in the geospatial analysis.

ANALYSES

Spatial Density

Exploratory analysis examined the spatial distribution patterns of violent incidents from the three different sources, using the kernel density method[15]. We mapped the respective spatial patterns of density distribution from each source to compare them.

Spatial-Temporal Filters

As some incidents were recorded in more than one of the datasets and unique identifiers were redacted due to privacy concern, spatial-temporal filters were developed to identify and remove identical incidents. We utilised two strategies for analysing the data to reflect variation in handling of location and time information by the different agencies. For PD and EMS, incidents were considered identical if they were no more than 1,500 feet (ft.) away from one another and occurred within 20 minutes of each other. The 1,500 ft. radius, despite being relatively large compared to other studies,[7] was utilised as incidents reported by the PD were imputed to the street block level rather than the exact address. To find identical records in EMS/ED data and ED/PD data, a spatial-temporal filter with the same geographic distance (i.e., 1,500 ft.) but much longer time difference (24 hours) was adopted. This was required as many records in the ED data did not include exact injury time.

Complementarity, Overlap and Correlation Analyses

After applying the spatial-temporal filters, we were able to find the duplicative incidents recorded between different databases (i.e., ED/PD; EMS/PD; ED/EMS). The ED and EMS databases were combined (ED&EMS) and incidents that were represented in the PD database were removed. To determine to what extent the ED&EMS dataset added to the PD dataset with regard to identifying hotspots (as opposed to individual incidents), we delineated incident hotspots in one database, and counted how many incidents from the other database fell within those hotspots. The nearest neighbour hierarchical spatial clustering method in CrimeStat[16] was used to detect incident hotspots. The method is a variant of the classical hierarchical clustering but with constraints on the number of nearest neighbours and a threshold distance to the nearest neighbours.

A hotspot was defined as a cluster of at least 10 incidents during the study period[7] in which the maximum distance between incidents in an area was less than defined distance thresholds. As the geographic size and total number of clusters are affected by the distance thresholds, we utilised increasingly larger distance thresholds in our analysis, i.e., 1,000; 1,500; 2,000; 2,500; and 3,000 ft. These thresholds were consistent with the distance between approximately 3 to 9 Midwest city blocks. We hope to examine the relation between ED&EMS and PD datasets in small and large hotspots as place-based violence prevention strategies vary size of targeted areas. The convex polygon surrounding the incidents in a hotspot was used to count the incidents in the other database. First, the hotspots were defined in PD data, and the polygon was used to count the number of additional incidents contributed by ED&EMS incidents. Similarly, hotspots for EMS&ED data were determined and then the number of additional PD incidents in the ED&EMS hotspots. We then computed the hotspots-based correlations using the Spearman's rho correlation coefficient between the two databases (one correlation was based on PD hotspots, and the other was based on ED&EMS hotspots) as a measurement of their complementarity and to determine if there were differences across the two methods.

Proximity to Schools and Parks

Additional analyses investigated the distance of PD and ED&EMS cases to schools and public parks. The school and park data were obtained from the parcel and master property open data records available in the City of Milwaukee Open Data Portal (https://data.milwaukee.gov/). Spatial filters drew radii around each school and park in the city. The overall total incidents and percentage of total incidents that fell within varying radii distance thresholds (i.e., 500, 1,000; 2,000; 3,000; >3,001) were calculated.

Patient and Public Involvement

Patient and public involvement was not sought for this initial exploratory analysis of data that was collected for a larger study to implement a violence prevention model in the County [10, 11].

RESULTS

Spatial Density Patterns

PD and EMS data were able to be geocoded according to their address information. For ED data, 381 incidents (47.7%) were able to be geocoded and included in analyses. Of the 381 incidents, 37 had date but were missing the injury time. Although incidents varied across datasets—from 381 (ED) to 588 (EMS) to 1,837 (PD)— the spatial distributions of the densities showed a similar pattern (Figure 1). The highest densities of incidents are shown in red and were located near the central and north parts of the city. ED data revealed a concentration of violence-related injury which was not represented in PD data in the central west area of the city, which was determined to be at a school. EMS data revealed a large concentration of injuries in the east and south-central areas of the city which was also not apparent in PD data.

Incidents Reported to More Than One Agency

Overall, 53 (9%) incidents in the EMS data were represented in the PD data and 24 (6%) incidents in the ED data were represented in the PD data (Figure 2). The ED&EMS database therefore held 935 unique incidents, in which 64 (7%) of the incidents were also represented in the PD dataset.

Hotspots

As the radius size of the hotspot increased from 1,000 to 3,000 ft, more hotspots were detected in both PD and ED&EMS data sets. Maps of hotspots at the 3,000 ft. distance threshold are presented in Figure 3. Additionally as the size of the hotspot grew, the likelihood of ED&EMS incidents being in a PD hotspot (and vice versa) increased.

As shown at the top of Table 2, there were 3 ED&EMS hotspots with 1,000 ft. radii, these included 51 (6%) of total ED&EMS incidents. Only 20 (1%) of PD incidents were located in these small ED&EMS violence hotspots. The majority 638 (73%) of ED&EMS incidents occurred in hotspots with 3,000 ft. radii. While many ED&EMS incidents were present in hotspots over 2,500 ft., a majority of PD incidents were never present in the ED&EMS hotspots. The ED&EMS and PD incidents became significantly correlated at hotspots identified by radii of 2,000 feet or more ($r=0.60$, $p=0.003$). For hotspots of 1,500 ft. radius or larger, the 1:1 ratio of ED&EMS to PD indicates that the PD database added one incident for every violent incident in the ED&EMS hotspot database.

ED&EMS Incidents Within PD Hotspots

The bottom of Table 2 shows that there were 34 PD violence hotspots with 1,000 ft. radii; these included 494 (27%) of total PD recorded incidents. Only 83 (10%) of ED&EMS recorded incidents occurred in the smallest PD hotspots. Hotspots 1,500 ft and larger included over half of the PD recorded incidents. Unlike PD records of violent incidents in the hotspot areas identified from ED&EMS data, a majority of ED&EMS incidents was present in PD hotspots over 2,000 ft radius. PD and ED&EMS datasets were significantly correlated at all levels of hotspot radii. Ratios for ED&EMS to PD decreased as the PD hotspots became larger. For hotspots of 2,000 ft. radius or larger, the 1:3 incident ratio shows that the PD database was missing one ED&EMS record for every three PD records.

Proximity to Schools and Parks

Over half of unique ED&EMS incidents (51%) and nearly half of unique PD incidents (42%) occurred within 500 ft of a school or park and 38% of ED&EMS and 32% of PD incidents were near schools (Table 3). In both datasets the majority of incidents near parks occurred between 1,000 and 2,000 ft radii thresholds of the parks.

DISCUSSION

Public health principles dictate that the most complete surveillance data should be used to best understand true incidence and develop comprehensive solutions to salient issues that are identified.[17] Our findings show that there was small overlaps in the data sets, which means that the ED and EMS contribute a significant amount of violence incidents that are not reported to PD. Only a very small number of violent incidents (7%), which resulted in ED or EMS care, were represented in PD records. The low level of overlap of combined ED and EMS and PD incidents was surprising, given that 44.6% of EMS incidents involved penetrating trauma. Our ratio analyses show that ED&EMS data provide information on one additional assault incident for up to every three incidents in PD data. Moreover, the distribution of the ED&EMS incidents highly correlate to that of PD incidents, especially, at violence hotspots. Most (59%) of ED&EMS and 44% of PD incidents were situated in the larger 3,000 ft. hotspots of the other dataset respectively. This shows that (1) ED&EMS contribute important additional violence information that reflects the major pattern of the city's violence landscape, and (2) many incidents occurred in city areas that result in service delivery by the other sector—which calls for the need of collaboration of the health and law enforcement agencies in addressing a city's violence.

ED and EMS contribute unique information about violence in both public and private places. We found that the majority of violence locations identified only in the ED&EMS dataset were near schools or public parks. Furthermore, ED and EMS datasets revealed new hotspots, some including a school. The complementarity of ED&EMS incidents to PD incidents lies not only in the substantial number of incidents not reported to PD, but also to the new concentrations (hotspots) of violence across different areas of the city that were only identified from ED and EMS data. Our data—principally emergency care data—showing the geospatial association between schools and violence-related paediatric injuries is consistent with literature linking school concentration with increased incidence of violence.[18] Schools have also been geospatially linked with other negative paediatric outcomes such as drug crime.[19] Similarly, the ED&EMS database found a large number of incidents not in the PD database near parks.

Under the Cardiff Model for Violence Prevention (Cardiff Model), the use of blended hospital ED violence-related injury data with PD data sources [10, 11] has reduced violence in the United Kingdom, compared to cities where only police data were used to focus prevention.[4, 5] Translation of combined information into practical prevention by a dedicated, city-level violence prevention board led to decreases in violence related ED attendances,[5] assaults and homicides reported to the PD,[4] and significant health care cost savings.[20] Violent incidents affecting youth which were not known to any other agency resulted in recommendations and actions to ensure improved communication between EDs and school nurses–reflecting the in loco parentis roles of schools.[21][27] A translation of the Cardiff Model Atlanta running concurrent with our efforts showed similar high proportions of incidents in public spaces not reported to police [22], with the Centers for Disease Control and Prevention publishing a toolkit on implementation of the Cardiff Model in the United States.[23]

The study reported here provides further evidence that the data elements of this model can be successfully integrated in the U.S. overall, potentially for the prevention of youth violence and injury in particular. Health systems are uniquely positioned to collect violence location information and engage with multidisciplinary partnerships to address population health burdens

[24] and violence, including violence in educational environments and parks. Paediatric violence surveillance frequently utilises historic data sets to analyse incidents and develop intervention and prevention strategies.[25] Given literature stating that violence underreporting is associated with demographics,[26, 27] location of incident,[26] type of violent offense,[27] and fear of reprisals, believing that police would not or could not do anything to help, and reluctance to have own conduct scrutinised by police, our study shows that additional data from emergency care can fill the substantial gaps in knowledge available from PD records. However, ED has challenges to acquire location and time for all the injuries. In our experience, even though the nurses asked patients the location question in over 90% of cases, around half of the injuries could not be geocoded. Potential reasons can be associated with race, insurance payer, injury type and injury time[9].

Limitations

Data on violent incidents were collected and defined in varying ways across data sets. Additional limitations include the accuracy and precision of location and time of the violence incidents—especially self-reported by patients to nurses in the ED—and the lack of a single identifier for individuals in each database. We employed spatial-temporal filters with varying distance and time thresholds to account for lack of a single identifier and precision of datasets. Locations in PD and EMS databases corresponded to location of services delivered and not necessarily the exact location of the injury event. The low level of overlap between the ED and EMS datasets may reflect that data were collected in only one ED and that only incidents serviced by County EMS were included. However, the ED is the only Paediatric Level One Trauma Centre for the study city and very likely dealt with the majority of paediatric cases requiring hospital visits. Receiving and linking ambulance data that is maintained by multiple EMS organisations (e.g., County, private) can be difficult and was not attempted in the current study.

CONCLUSION

Our hypothesis that ED and EMS data in a U.S. city would provide meaningful information on violence which resulted in paediatric injuries beyond data from PD was supported. The majority incidents recorded in ED and EMS were unknown to PD and a combined database resulted in identification of new hotspots of paediatric violent injuries. For comprehensive targeted prevention, identification of locations where youth are injured—especially in and around schools and parks—is only possible in a U.S. city if location data from ED, EMS and PD records are combined.

Table 1. Demographics and Incident Descriptive Statistics (1/1/2015-9/30/2016)

	Emergency Department Data	Emergency Medical Service Data	Police Data
Number of individuals/victims	381	588	1,837
Age			
Min	0	0	0
Max	17	17	17
Mean	13	12	11
SD	5	6	5
Sex			
Male	208 (54.6%)	371 (63.1%)	940 (51.1%)
Female	173 (45.4%)	212 (36.1%)	897 (48.9%)
Missing	-	5 (0.8%)	-
Race			
White	56 (14.7%)	10 (1.7%)	414 (22.5%)
African American	288 (75.6%)	108 (18.4%)	1391 (75.7%)
Asian	2 (0.5%)	1 (0.2%)	26 (1.4%)
American Indian	-	-	3 (0.2%)
Unknown	35 (9.2%)	469 (79.8%)	3 (0.2%)
Ethnicity			
Hispanic/Latino	44 (11.5%)	17 (2.9%)	235 (12.8%)
Not Hispanic/ Latino	327 (85.8%)	-	1547 (84.2%)
Refused/Unknown	10 (2.7%)	571 (97.1%)	55 (3.0%)
Location			
Public	-	-	896 (48.8%)
Residence	-	-	941 (51.2%)
Injury Type/Means of Attack			
Hands/feet/fist/blunt	263 (69.0%)	315 (53.5.0%)	727 (39.6%)
Penetrating	19 (5.0%)	262 (44.6%)	421 (22.9%)
Other	86 (22.6%)	11 (1.9%)	254 (13.8%)
Missing	13 (3.4%)	0	435 (23.7%)
Assault Type			
Simple Assault	-	-	540 (29.4%)
Aggravated Assault	-	-	554 (30.2%)
Robbery	-	-	400 (21.8%)
Sex offenses	-	-	343 (18.7%)
Domestic Violence			
Yes	-	-	220 (12.0%)
No	-	-	1508 (82.0%)
Escorted to ED by			
Family Member	262 (68.8%)	-	-
Police	13 (3.4%)	-	-
Self	39 (10.2%)	-	-
Other	67 (17.6%)	-	-
Payment type			

Commercial (private insurance)	40 (10.5%)	-	-
Medicaid (public, non-Managed Care)	128 (33.6%)	-	-
Medicaid Managed Care	196 (51.4%)	-	-
Self-pay	17 (4.5%)	-	-
Assault Perpetrator under Age 18		-	-
Yes No Unknown	183 (48%) 135 (35.4%) 63 (16.6%)	-	-

Note: Some variables were available across all three datasets. Presence of a hyphen indicates that this variable was not available for the given dataset.

Table 2. Overlap of Incidents within Hotspots

Overlap of PD Incidents in ED&EMS Hotspots						
Radius(ft)	Hotspots	PD victims within ED&EMS hotspots No. (%)	ED&EMS victims within ED&EMS hotspots No. (%)	Ratio to PD incidents	Spearmen's rho	p value
1000	3	20 (1%)	51 (6%)	3:1	-0.500	0.667
1500	20	213 (12%)	272 (31%)	1:1	0.384	0.095
2000	22	386 (21%)	382 (44%)	1:1	0.601	0.003
2500	27	589 (32%)	512 (59%)	1:1	0.697	0.000
3000	33	817 (44%)	638 (73%)	1:1	0.651	0.000
Overlap of ED&EMS Incidents in PD Hotspots						
Radius(ft)	Hotspots	PD victims within PD hotspots No. (%)	ED&EMS victims within PD hotspots No. (%)	Ratio to PD incidents	Spearmen's rho	p value
1000	34	494 (27%)	83 (10%)	1:6	0.37	0.030
1500	53	974 (53%)	230 (26%)	1:4	0.60	0.000
2000	61	1,299 (71%)	382 (44%)	1:3	0.73	0.000
2500	54	1,410 (77%)	453 (52%)	1:3	0.83	0.000
3000	51	1,515 (82%)	515 (59%)	1:3	0.80	0.000

Table 3. Distance Distributions of PD and ED& EMS incidents to Schools and Parks.

PD incidents to Park/School, Park only, and School Only						
	Distance to Park/School		Distance to Park only		Distance to School only	
Distance(ft)	Incidents	percent	Incidents	percent	Incidents	percent
0-500	767	42%	239	13%	579	32%
500-1000	574	31%	242	13%	529	29%
1000-2000	452	25%	584	32%	584	32%
2000-3000	43	2%	485	26%	123	7%
>3000	1	0%	287	16%	22	1%
Sum	*1837*	*100*	*1837*	*100*	*1837*	*100*
ED&EMS incidents to Park/School, park only, and school only						
	Distance to Park/School		Distance to Park		Distance to School	
Distance(ft)	Incidents	Percent	Incidents	Percent	Incidents	Percent
0-500	449	51%	153	17%	335	38%
500-1000	227	26%	130	15%	225	26%
1000-2000	182	21%	238	27%	262	30%
2000-3000	19	2%	241	27%	43	5%
>3000	0	0%	115	13%	12	1%
Sum	*877*	*100*	*877*	*100*	*877*	*100*

Figure 1. Spatial Density Patterns of violence in the city of Milwaukee

[Figure 1]

Figure 2. Overlap of Incidents in the ED, EMS and PD Databases

[Figure 2]

Figure 3. Hotspots in the PD and ED&EMS datasets at a 3,000 foot threshold radius across the City of Milwaukee

[Figure 3]

Note: There is full geographic overlap in coverage of the ED, EMS and PD. The City of Milwaukee boundary is shown by the black line in the above maps. The entire city is situated within Milwaukee County. The participating children's hospital is the only Level I Trauma Centre in the entire Southeast part of the state of Wisconsin. Police serve the city of Milwaukee, County EMS serve the city and the entire Milwaukee County and the hospital serves the entire area covered.

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