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Research article

The use of emergency medical services (EMS) data to map violence: A case study in Nairobi, Kenya

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Abstract

This study investigates the use of emergency medical services (EMS) data as an alternative source for mapping and understanding violence in Nairobi, Kenya. Given that many crimes go unreported, relying solely on police data can create an incomplete picture of violence hotspots. Using social disorganisation theory as a theoretical framework, this study uses EMS data from fifteen hospitals across three Nairobi sub-counties to map violence and analyse its spatial patterns. A spatial regression model was employed to assess the influence of five social disorganisation variables—unemployment, education, gender, residential mobility and youth demographics—on violence rates, disaggregated by gender. The findings suggest that unemployment is positively correlated with violence, particularly among females, while a higher percentage of youth is unexpectedly associated with lower violence rates. The study demonstrates the value of EMS data for crime mapping in contexts with high levels of unreported crime and offers insights into the spatial distribution of violence in Nairobi, advancing understanding of alternative crime data sources in African urban settings. This approach highlights the utility of EMS data for informing more targeted violence prevention strategies in regions where traditional crime data are limited.

Keywords: Violence; Emergency Medical Services (EMS); Kenya; Spatial Regression.

1. Introduction

It is well established that a large number of crimes that are committed are not reported to the police (Blumstein & Wallman, 2020; Melo *et al.*, 2020; Xie & Baumer, 2019). According to the United States National Victimization Survey (2019), less than 50% of violent crime incidents in the country are reported to the police. The underreporting of crime in Africa is also a significant issue, with roughly 56% of crimes not reported to the police across 32 African countries (O'Regan *et al.*, 2018). Underreporting is most evident in sexual crime, with cases of rape and sexual assaults notoriously under-reported across a variety of contexts (Beecher & Wright, 2023; Spohn, 2020; Thomas-Montford, 2020). There are various reasons why victims of crime do not report to the police, and include fear of repercussion and reprisal (Papp *et al.*, 2019); mistrust and a lack of faith in the police (Graham *et al.*, 2020); lack of evidence (Javdani, 2019), and reporting being viewed as a tiring and long process (Treloar *et al.*, 2021). A number of victims also feel that there is no reason to report crimes to the police if there has been no personal injury or property damage (Tarling & Morris, 2010). Despite this, official police crime data is most often the only source of information used for mapping crime and, concomitantly, used as a basis for managing crime prevention and reduction resources (Desmond *et al.*, 2020). Moreover, the vast majority of the laws and theories in the school of environmental criminology are based on interpretations made from analysis of crime data, most often obtained from official police sources. The school of environmental criminology focuses specifically on understanding how the physical environment and spatial factors influence the occurrence of criminal activities, emphasising the role of location and context in shaping criminal behaviour. One notable example of a well-known law within environmental criminology is the 'law of crime concentration', which posits that a small number of locations are responsible for a disproportionate amount of crime. Many studies have been conducted using the law of crime concentrations as a basis for examining spatial crime patterns in a number of countries, including the Netherlands (Bernasco & Steenbeek, 2017); the United Kingdom (Rosser *et al.*, 2017); Israel (Weisburd & Amram, 2014); Canada (Andresen *et al*, 2017); and South Africa (Breetzke & Edelstein, 2019), among many others. Importantly, the vast majority of these studies rely almost exclusively on official policerecoded crime data to map crime and undertake spatial analyses. While official data offer essential insights into the nature and magnitude of crime in each context, their limitation lies in the fact that, most often, only a limited percentage of crime is actually reported to the police.

The acknowledged limitations of using official police-recorded crime data to map and analyse crime patterns has led, in part, to calls for the use of alternative data sources to better understand the spatial patterning of crime. These include victimisation surveys, crowdsourced crime reports, and emergency medical services (EMS) data. These alternative sources of crime data are essential because they offer valuable alternative insights into understanding crime distributions and can be used to inform resource deployment and identify crime hotspots, especially in areas of extensive underreporting or unreporting. A large number of studies have shown how alternative data sources, notably EMS data, can be used as a proxy for crime data (Ariel *et al.*, 2015; Hibdon *et al.*, 2021; Quigg *et al.*, 2017; Sutherland *et al.*, 2017). The vast majority of this work has, however, been exclusively undertaken in the developed world, with much less known about the utility of using alternative crime data sources in less developed contexts. Using social disorganisation theory (Shaw & McKay, 1942) as a framework, this study aims to utilise EMS data to map and examine the causes of vio-lence in Nairobi, Kenya. The well-known social disorganisation theory posits that crime and delinquency are more likely to occur in communities with certain structural and social characteristics, such as high levels of poverty, residential mobility, ethnic diversity, and family disruption. These conditions can weaken the social bonds and informal social controls that typically regulate behaviour and maintain order, leading to the inability of community members to achieve consensus on values and norms. Communities experiencing social disorganisation often have lower levels of community supervision and cohesion, which can create an environment in which criminal behaviour is more likely to flourish. To our knowledge, no study has been conducted in Kenya using EMS data as a proxy for crime data. In fact, the applicability of EMS data in a broader African context has not been empirically assessed.

2. Literature Review

A large number of studies have used alternative sources of data to represent crime incident locations (Ariel *et al.*, 2015; Hibdon *et al.*, 2021; Quigg *et al.*, 2017; Sutherland *et al.*, 2017). The most common type of such sources is the use of EMS data. This type of data refers to the information collected by EMS during their response to emergencies and can include, among others, patient demographics, medical history, vital signs, details of the incident, treatments provided, medications administered, and patient outcomes. Importantly, this kind of data is most often recorded electronically and can be integrated into larger healthcare systems for comprehensive analysis and decision-making. Examples of studies that have employed EMS data to map crime (and violence) include that of Hibdon and Groff (2014), who used EMS data to examine the spatial distribution of illicit drug events in Seattle, Washington, while Quigg *et al.* (2017) mapped violence across North West England using ambulance call-out data. Other examples include Taylor *et al.* (2016) and Hibdon *et al.* (2021). Importantly, these alternative data sources have been found to detect a substantial proportion of violence incidents not recorded by police, potentially improving violent crime surveillance methods. In fact, there is increasing evidence that relying solely on official crime data can lead to law enforcement agencies 'missing' the location of a number of crimes not reported. For example, Sutherland *et al.* (2021) compared ambulance data with police records for violent crimes in the West Midlands of England and found that ap-proximately 90% of cases reported by the ambulance data were not reported to the police. Other studies in-clude that of Wu *et al.* (2019), who found that 83% of violent injuries treated across the Atlanta metropolitan area in the US were not reported to the police. In the UK, Sutherland *et al.* (2017) compared ambulance and police data in the West Midlands and found that between 66% to 90% of the reported ambulance incidents were not recorded in police data, while Simmonds *et al.* (2023) mapped assault hotspots using EMS data in the Thames Valley in the UK, finding that the police were unaware of the location of nearly 8 out of 10 assaults. Outside the US and Europe, Melo *et al.* (2020) examined the geographic distribution of rape cases in Campinas, Brazil using EMS and police data and found that roughly 50% of rape victims who sought treat-ment at the hospital did not alert the police. It is important to also consider that the concentration of police in certain areas can potentially lead to a distortion in the true spatial distribution of crime. That is, if police patrol certain areas more often than others, crime will be recorded disproportionally in those areas. The danger of improperly focused enforcement activities can result in geographic disparities when mapping certain types of crime, with the absence of geographic uniformity in crime data reporting/recording resulting in the inabil-ity of the police to address crime incidents in certain neglected areas, creating a bias when formulating crime prevention and management strategies.

2.1. The Cardiff Model

The use of information from health organisations to improve community violence prevention and policing programmes is commonly referred to as the Cardiff Violence Prevention Model. The so-called Cardiff Model is a multi-agency approach to violence prevention that involves collecting and analysing data from both emergency departments and law enforcement to gain a comprehensive understanding of where and when violence occurs. The model encourages the sharing of anonymised information about violent incidents, such as locations and times, between healthcare providers and local authorities. The strength of the Cardiff Model lies in information sharing, with the data collected from EMS departments combined with information from the police to assist communities in mapping places with frequent occurrence of violence. The application and use of the Cardiff Model to identify violence hotspots and trends is relatively widespread in the Global North, however its application in Africa in particular is still in its infancy. In fact, we are aware of only two previous studies that have employed the Cardiff Model in African: that of Faull (2019), who mapped violence in Khayelitsha in the Western Cape of South Africa using various alternative data sources including ambulance and mortuary van trackers, public health facilities, and smartphone applications managed; and Jabar *et al.* (2022), who examined violent crimes reported to the police characterised by violence-related in-juries, presented at various health facilities in Cape Town, South Africa. The researchers found that the overwhelming majority of injuries arising from interpersonal violence presenting at health facilities in Khayelitsha were not reported to the police. Despite these studies, to our knowledge no alternative measures of crime data have been employed in East Africa more generally, and Kenya specifically.

This study therefore aims to explore for the first time the use of alternative urban crime data sources to map violence in eastern Nairobi, Kenya. It uses EMS data collected from various health facilities in three sub-counties in Nairobi (Kasarani, Embakasi Central and Embakasi North) to map and analyse crime patterns and provide tentative explanations for their spatial distribution. All three sub-counties exhibit a mix of resi-dential, commercial and industrial land use, reflecting Nairobi's recent rapidly increasing levels of urbanisation. Kasarani is predominantly residential, featuring a mix of high-rise apartments, gated communities, and informal settlements, with pockets of commercial establishments and recreational spaces.

Embakasi North also has a strong residential presence, with numerous housing estates and informal settlements, alongside light industries and small businesses, while Embakasi Central is more commercially oriented, hosting shop-ping centres, office buildings and industrial zones, particularly in areas along major roads. The land cover in these regions is primarily built-up, with limited green spaces, although some areas have parks and open fields. The selection of the three sub-counties is based on their socio-economic and demographic diversity. That is, all three vary substantially in terms of their socio-economic conditions, population density and crime patterns. These characteristics provide a reasonably representative sample of the violence hotspots through-out the city, ensuring a focused analysis of areas most relevant to the study. Unlike previous studies that have largely employed qualitative methodologies to study violent crimes in Kenya (Baraka & Murimi, 2019; Elfversson & Höglund, 2019), this study utilises EMS data to map the geospatial extent of crime hot spots in Nairobi City.

3. Research Methods

3.1. Emergency medical services (EMS) data

EMS data for the study were obtained from the emergency medical and ambulance departments of 15 hospitals located across Kasarani, Embakasi Central and Embakasi North. The 15 hospitals were selected based on a number of factors, including their geographic representation across the three sub-counties in Nairobi; the availability and reliability of EMS data; and their capacity to provide a diverse range of emergency medical services, ensuring a comprehensive and representative sample for the study. Data obtained included the geographic location of the incident; the date and time of attendance at the health facility; the gender of the individual; and the type of incident reported at each department during the period 2021 to 2022. Incidents captured included attempted murder, sexual offences, assault to cause grievous bodily harm, and common as-sault. It is important to note that the data collection process we employed in the study may be subject to several biases. First, selection bias could arise from the choice of only 15 hospitals in three specific sub-counties, which may not fully represent the broader EMS landscape in Nairobi or Kenya as a whole. Second, reporting bias may exist as certain types of incidents, such as domestic violence, may not be adequately captured in EMS data, leading to an incomplete representation of cases of violence. Finally, geographic bias might be present, as the study is limited to EMS data from hospitals in just three sub-counties, potentially overlooking differences in EMS trends or healthcare access in other areas of the country.

Nevertheless, these collective EMS incidents were obtained based on the fact that they involved direct physical interaction between victims and perpetrators, resulting in some form of bodily or psychological distress for which victims sought medical assistance. Importantly, all victims reported to each hospital's triage. Each EMS incident was address-matched to a county (n = 15) and a two-year average was taken (2021-2022) to minimise the impact of annual fluctuations. In Kenya, the county represents the finest spatial level for which associated census data were available from the Kenya National Bureau of Statistics. Three final dependent variables for the study were the overall EMS rate per 1,000 population, the EMS rate per 1,000 male population, and the EMS rate per 1,000 female population. Investigation of violent trends was made separately for overall male and female populations, as this allowed for a more nuanced understanding of how vio-lence impacts different demographics. For instance, males and females may experience different types of violence, have varied injury patterns, or respond to violence in distinct ways. Analysing these separately also helped identify gender-specific risk factors or interventions that can be tailored more effectively to each group, leading to more targeted and impactful public health and safety strategies. Figure 1 shows the overall EMS rate per 1.000 population for the study area while Table 1 shows descriptive statistics for the dependent variables.

Table 1. Descriptive statistics for the dependent variables.

	Min	Mean	Max	SD	Moran's I	p-value
Y1: EMS rate per 1,000 population	1.0	6.3	9.3	2.0	0.1	0.1
Y2: Male EMS rate per 1,000 population	2.0	6.4	18.8	4.1	0.1	0.3
Y3: Female EMS rate per 1,000 population	1.8	6.2	18.5	4.1	0.2	0.1

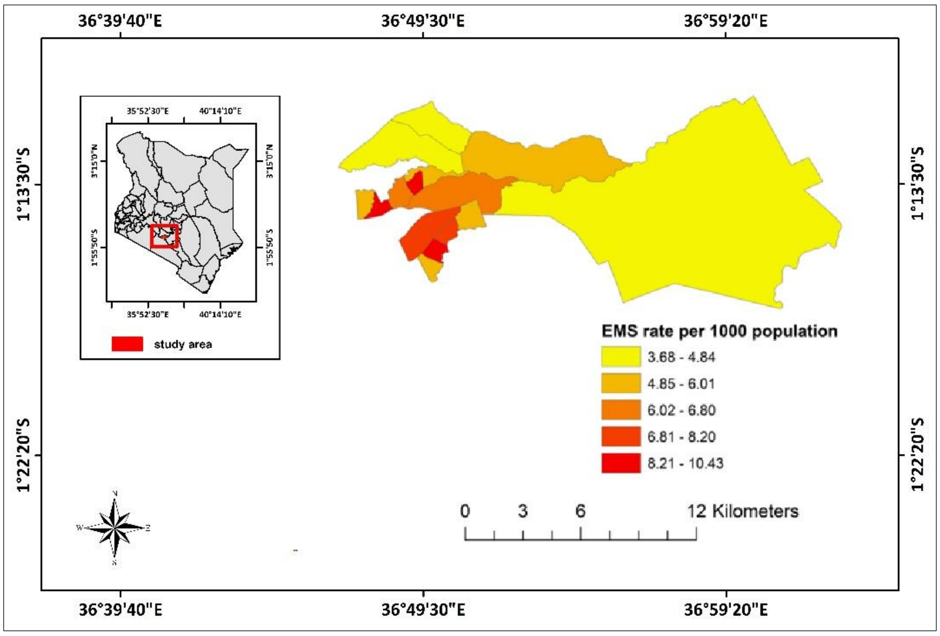

Figure 1. EMS rate per 1000 population.

3.2. Census data

Consistent with previous international research (Andresen, 2006; Breetzke, 2010; Cahill & Mulligan, 2003), a number of independent variables were selected to represent the social disorganisation theory. The five sociodemographic variables used to represent the theory were drawn from the Kenya National Bureau of Statistics (2019) and include the percentage of unemployed, the percentage of residents without high school education, the percentage of males, the percentage of residents renting property, and the percentage of residents aged between 15 and 29. Figure 2 shows the percentage renting for the study area while Table 2 presents the descriptive statistics for the independent variables used in the analysis.

Table 2. Descriptive statistics for the independent variables.

	Min	Mean	Max	SD
X1: Unemployed, %	48.6	53.4	60.8	3.2
X2: No high school education, %	29.4	42.7	52.4	7.0
X3: Male, %	45.7	48.9	51.4	1.6
X4: Renting, %	63.5	88.3	97.0	9.0
X5: Aged 15-29, %	33.7	36.7	42.6	2.3

The correlations between the dependent (overall EMS rate) and independent variables are shown in Table 3. There are relatively weak correlations across all variables, thereby avoiding the risk of multicollinearity. The highest positive correlation was between the overall EMS rate per 1,000 population and the percentage aged 15-29. This suggests an association between young people and violence. Overall, no single variable was strongly correlated to the overall EMS rate, which initially suggests that other variables not included in the study may have a greater impact on violence than those that were included. The highest positive correlation between the independent variables was between the percentage aged 15-29 and the percentage renting, which suggests that young people are more mobile.

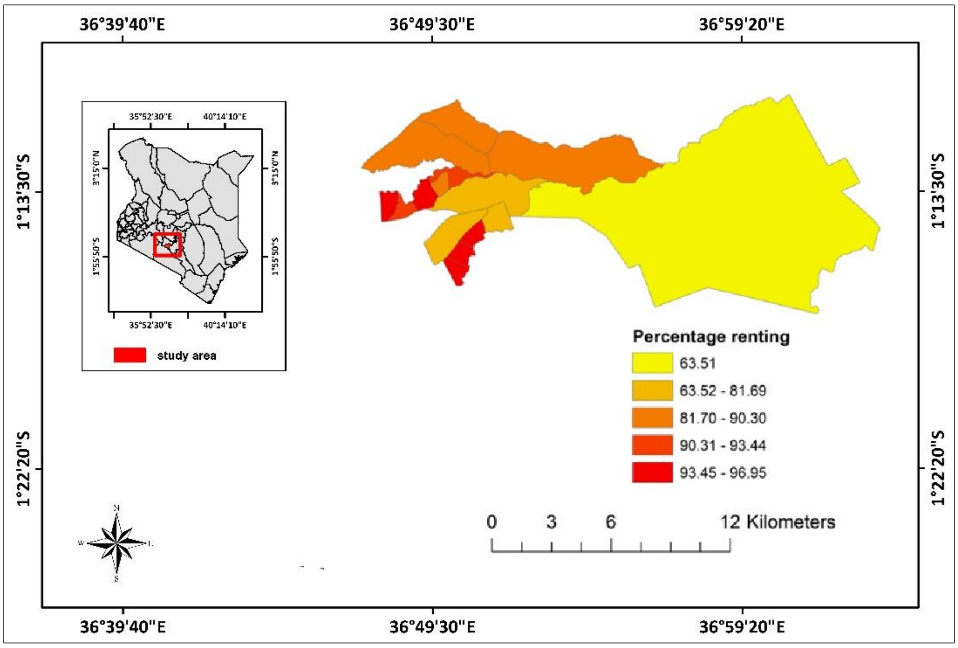

Figure 2. The percentage renting in the study area.

Table 3. Correlations for dependent and independent variables.

Y: EMS rate per 1,000 population	1						
X1 : Unemployed, %	0.123	1					
X2 : No high school education , %	0.047	0.028	1				
X3 : Male, %	0.151	0.116	0.05	1			
X4 : Renting, %	0.03	-0.002	-0.082	0.053	1		
X5 : Aged 15-29, %	0.175	0.056	0.082	0.139	0.16	1	
	Y	X1	X2	X3	X4	X5	1

3.3. Empirical analysis

A spatial regression model was used to model the relationship between EMS rates and the various social disorganisation variables because of the problems that arise when using traditional OLS regression with spatial data (Chainey & Ratcliffe, 2005). The general functional form of the spatial regression (lag) model in Equation 1 :

$$y = pWy + X\mathrm{B} + \varepsilon \tag{1}$$

where y represents the EMS rate/s per 1,000 population; Wy is the weighted mean of the local values of y in neighbouring areas; p is the parameter X is the set of violence motivators; B is a vector of coefficients to be estimated; and ε is the error term. Spatial autocorrelation was modelled using first-order rook contiguity, whilst the analysis was performed using the GeoDa spatial statistical freeware package (http://geodacenter.asu.edu/). Using first-order rook contiguity to model data in a spatial regression was justi-fied because this measure captures the relationships occurring between neighbouring spatial units that share a common boundary, which is crucial for understanding spatial dependence. This approach also assumes that spatially-adjacent areas influence each other, making it ideal for modeling phenomena in which proximity plays a significant role, such as in crime (EMS) rates. A total of three spatial regression models were esti-mated.

4. Results and Discussion

4.1. Results

The results of the spatial regression models are presented in Table 4. Model 1 analysed the relationship between the five social disorganisation factors and the overall EMS rate per 1,000 population. The results were very encouraging, with the overall model exhibiting an adjusted R2 of 91 percent. Two measures of social disorganisation were found to be significantly associated with the overall EMS rate: the percentage unemployed (positively), and the percentage aged 15-29 (negatively). Contrary to the expectations of the social disorganisation theory, all other measures (i.e., the percentage of males, the percentage of residents with no high school education, and the percentage renting) were non-significant. Model 2 analysed the relationship between the various social disorganisation factors and the male EMS rate. Again, the results were very encouraging, with the model exhibiting an adjusted R2 of 83 percent. The percentage of the population without a high school education was found to exhibit a positive and significant association with the male EMS rate, while the percentage unemployed was surprisingly found to be negatively associated with this rate, which indicates that higher unemployment is associated with a reduced rate of violence for males. The percentage of young males, the percentage aged between 15 and 29, and the percentage renting were not sta-tistically significant. Finally, Model 3 estimated the impact of social disorganisation factors on the female EMS rate. Approximately 82 percent of the variation in this rate was explained using the five independent variables. Unemployment was again found to exhibit a significant positive association with the female EMS rate, which indicates that higher unemployment rates are associated with an increase in EMS rates for females. This finding again highlights the important role that socioeconomic strain places on the population, leading to potential increases in stress and concomitantly, violence. Educational attainment, measured by the percentage of the population without a high school education, was found to exhibit a significant negative association with the female EMS rate. No other variable was found to be statistically significant.

Table 4. Results of the spatial regression models.

	Model 1	**Model 2**	**Model 3**
	(Overall)	**(Males)**	**(Females)**
Variable	Co-efficient	Co-efficient	Co-efficient
Constant	12.25 (1.59)	3.58 (1.09)	3.56 (1.06)
X1: Unemployed, %	1.56** (0.80)	-0.22*** (0.07)	0.20*** (0.06)
X2: No high school education, %	-0.42 (0.78)	0.24*** (0.06)	-0.23*** (0.06)
X3: Male, %	0.03 (2.08)	-0.04 (0.16)	0.07 (0.16)
X4: Renting, %	0.32 (0.38)	-0.01 (0.03)	0.01 (0.03)
X5: Aged 15-29, %	-2.71* (1.23)	0.05 (0.10)	-0.06 (0.09)
Adjusted R2	0.91	0.83	0.82

NOTE: *p<0.05, **p<0.01, ***p<0.001; standard errors in parentheses.

4.2. Discussion

Overall, the results of the study largely support social disorganisation explanations of violence in Kenya, with all three models performing well. Two of the five measures of social disorganisation in the overall model were found to be significantly associated with violence, but only one was in the expected direction; that is, the percentage unemployed, which was positively associated with violence. This finding is supported by extensive international research, which has similarly found a positive association between unemployment and violence (Ajimotokin *et al.*, 2015; Schleimer *et al.*, 2022). According to social disorganisation theory, high unemployment can result in economic instability and reduced social control, resulting in a potential increased risk of violence. In the Kenyan context, the lack of employment opportunities has previously been found to push individuals to engage in criminal activities as a means to survive (Abdi, 2022; Mbiri, 2017). In contrast, a negative relationship was found between the percentage of those aged 15-29 and violence, with a higher percentage of youth associated with lower violence, which is contrary to the expectations of social disorganisation theory. A strong informal control in the densely populated urban areas can partly explain the inverse relationship between violence and a youthful population. Community-based organisations dealing with socioeconomic initiatives formed by youths in certain parts of Nairobi, including in these sub-counties, could potentially reduce their involvement in certain violent activities. Previous research has found that neighbourhoods with younger populations may not automatically be at an increased risk of violence, but that the relationship between neighbourhood age demographics and risk of violence is complex and context-dependent (Brunton-Smith *et al.*, 2014; Zimmerman, 2013). This is due to a number of factors, including the fact that immigrant communities, for example, are often characterised by younger populations, and these neighbourhoods tend to have lower crime rates (Desmond & Kubrin, 2009). It is therefore feasible that while neighbourhoods with higher youth populations may experience higher crime rates, social control mechanisms could potentially aid in reducing the risk of crime in certain areas. In the Kenyan context, many young people are increasingly involved in small-scale entrepreneurship or informal jobs, which could keep them away from engaging in criminal activities (Omboi, 2020; Osundwa, 2021). The Kenyan government has also recently rolled out several community-based initiatives aimed at promoting cohesion and reducing violence. The programme is relevant in creating safer and cohesive communities, thereby potentially addressing the risks associated with large youth populations. Indeed, the relationship between the youth population and crime has been found to vary in line with community cohesion levels, with more cohesive neighbourhoods generally experiencing less crime, regardless of the youthfulness of the residential population (Gulma, 2018). Regarding this research, it could be that strong social institutions could possibly mitigate the effects of a youthful population on violence.

The percentage of individuals without a high school education was found to be significantly associated with violence on males and females, but in different directions. That is, a positive relationship was found for violence on males and a surprisingly negative relationship found for violence on females. Previous research has shown that socioeconomic pressures caused by lower levels of education are likely to contribute to higher violence among men due to cultural norms and economic strain (Barnett & Maticka-Tyndale, 2023; Farhiya, 2020). On the other hand, women often experience a negative relationship with violence due to the likelihood of cultural expectations and stronger social support networks, which potentially discourage violent be-haviour against them. Unemployment was also found to exhibit differential effects on violence on males compared to violence on females. That is, the percentage unemployed was found to be positively and signifi-cantly associated with violence on females and violence overall, but was negatively associated with violence against males. Most previous research has found a positive effect of unemployment on violence across vastly different contexts (Ayhan & Bursa, 2019; Goulette, 2020). Unemployment could be positively associated with overall violence and violence against females due to weaker support systems and increased economic strain (Abdi, 2022; Mbiri, 2017). Whilst speculative, the inverse relationship with violence against males in this context may be due to different coping mechanisms by males, or varying cultural responses among un-employed men.

Interestingly, we found that the percentage of males was not significantly associated with violence in any of the models. Previous research has found that male-dominated neighbourhoods do not necessarily increase the risk of crime when controlling for other factors such as poverty and unemployment (Agheyisi & Aghedo, 2021). Indeed, the impact of gender composition on crime rates is complex and nuanced, and has been found to be mediated by other socioeconomic factors such as income inequality, employment rates, social norms and educational opportunities (see Brown *et al.*, 2021; Fridel & Fox, 2019). Therefore, while gender composition could potentially play a role in violence, in this study its independent effect was negligible. Finally, the percentage renting property was not found to significantly predict violence in any of the models. This result is somewhat surprising considering the importance of mobility in social disorganisation theory, but is supported by some studies (Danielsson, 2021; Kim & Wo, 2021). Moreover, the effect of renting on crime has been found to vary depending on other economic opportunities and neighbourhood cohesiveness (De-Nadai *et al.*, 2020). In the Kenyan context, this result may be due to the complex relationship and diversity among renters. Unlike in Western countries, renting in Nairobi does not necessarily equate to transience. This is especially so as many tenants reside in the same neighbourhood for longer periods. This has the potential to foster strong local social ties. Renters in the country range from students to professionals, with varying degrees of economic stability and income levels. It could be that the relationship between renting and violence is mediated by community cohesiveness and social networks. Furthermore, modern urban planning such as mixed-use developments fosters diverse communities that may contribute to lower crime rates. It is important to note in this context that local social and cultural factors could also shape violence in Nairobi. Whilst speculative, it is possible that certain gender norms; youth involvement in informal economies; and community cohesion could impact violent rates. The unexpected relationships found between unemployment, education and violence in this study call for context-specific adaptations of social disorganisation theory in Kenyan urban settings. Conversely, the informal economy in Nairobi can create alternative employ-ment opportunities for youths. These opportunities could reduce violence and foster community cohesion. Conversely, an unstable informal economy can contribute to inequality or exploitation, thereby influencing violence.

It is worth mentioning, however, that the informal economy in Kenya could significantly impact the study results in general by masking true unemployment rates. In areas with high informal employment, individuals may be technically classified as ‘unemployed’ despite engaging in informal work. This could distort the observed positive association between unemployment and EMS rates, particularly for females. Moreover, the role of the informal economy in perpetuating socioeconomic instability, particularly for those with low educational attainment, may contribute to higher levels of stress and violence, influencing EMS rates in ways not fully captured by official employment and education data.

5. Conclusion

The study has demonstrated the significance and value of using EMS data to examine violence in a developing context. We found that several social disorganisation factors predict violence rates in Kenya, with a number of variables found to be statistically significant across all three models, although some were in the opposite direction based on theoretical expectations. To some extent this is to be expected, given that the theory was developed in the specific context of the United States. Previous studies in Africa have also found only marginal support for social disorganisation theory (Breetzke, 2010; Tita *et al.*, 2016). Importantly, this study demonstrates the importance and potential of alternative crime data sources to examine crime trends in Africa. Law enforcement agencies in the country should collaborate with other organisations that capture alterative crime-related information (e.g., emergency medical and ambulance departments) to obtain a more accurate representation of crime risk in the country. Since nearly half of violence-related injuries are not reported to the police, data sharing arrangements between these two entities should be encouraged. These shared data can hopefully enable the police in particular to focus their crime prevention and management resources in cases where violence-related injuries are more prominent. In truth, however, the integration of EMS data into existing crime mapping systems is nuanced and complex. That is mainly because it involves collecting, standardising and geocoding data from two different sources (the police and EMS departments). While this integration can potentially help in violence hotspot identification and inform predictive policing better than a single source could, there are various barriers to data sharing that need to be considered. These include a lack of data standardisation, privacy concerns and legal and ethical challenges, all of which are relevant to the Kenyan context. Privacy concerns in particular could be partially overcome by having secure frameworks in place and establishing clear policies to facilitate collaboration between the police and EMS data providers. Compliance with the national data protection laws would also be necessary to safeguard privacy concerns during the integration of EMS and law enforcement data. While the implementation of such integration is potentially feasible, there are also various other cost implications to also consider, such as system upgrades, software development, data storage, and ongoing maintenance. These would require the alignment of disparate data formats and the development of secure systems to protect sensitive information. Moreover, collaboration between the police, EMS and IT departments would be essential for successful inte-gration, which could incur additional coordination and training expenses. However, the long-term benefits of improved response times and more comprehensive analysis of public safety trends could justify the investment.

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Author Contributions

Conceptualization: Okode, P., & Breetzke, G; **methodology**: Okode, P., & Breetzke, G; **investigation**: Okode, P., & Breetzke, G; **writing—original draft preparation**: Okode, P., & Breetzke, G; **writing—review and editing**: Okode, P., & Breetzke, G; **visualization**: Okode, P., & Breetzke, G. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

All authors declare that they have no conflicts of interest.

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Data is available upon Request.

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