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Huang, Z., Xu, Y., Li, Y. et al. (2025) Where drinks and danger meet: Analyzing the spatial link between Bars and crime in Detroit. *Applied Geography*, 174. 103480. ISSN: 0143-6228

<https://doi.org/10.1016/j.apgeog.2024.103480>

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26 1 Introduction

27 As an entertainment venue that integrates social and leisure functions, an alcohol
28 establishment can meet the social and recreational needs of the public (Martin, 2004).
29 The bar industry has been an important part of the economy in the United States.
30 According to research on Gitnux (*Must-Know Bar Industry Statistics [Recent Analysis]*)
31 and Statista (*Bars and nightclubs in the U.S. - statistics & facts*), the bar industry
32 employed over 4.4 million people in 2019. As of 2021, there were approximately
33 65,000 bars, taverns, and nightclubs across the country, generating about \$23.1 billion
34 in revenue. On average, around 31% of adult consumers visit alcohol establishments at
35 least once a week.

36 The effects of alcohol stimulation may easily result in disputes and conflicts,
37 which can lead to violent crimes in alcohol establishments (McGill et al., 2022; R. Britt
38 et al., 2005; Taylor et al., 2020; Toomey et al., 2012). The classic portrayal of “bar room
39 brawls” in popular culture underscores the commonality of crime in these environments.
40 Alcohol has been found to affect the GABA-benzodiazepine receptor complex in the
41 brain, influencing the physiological, cognitive, affective, or behavioral functioning of
42 the drinker (Miczek et al., 1997; Miczek et al., 1993). The study also reported women
43 were significantly more likely to sustain injuries in assaults by an intimate partner if the
44 partner had been drinking (Lorenz & Ullman, 2016).

45 Research consistently shows that bars are hotspots for violent crime, with murder,
46 aggravated assault, and simple assault being more likely to occur in these
47 establishments based on criminological theories (Hobbs et al., 2020; Savard et al., 2019;
48 Taylor et al., 2020). This risk is further exacerbated by the presence of off-premise
49 alcohol outlets, which are associated with higher rates of violent, property, and disorder
50 crime (Gmel et al., 2016; Haley et al., 2023; Lardier et al., 2020). These findings align
51 with the “routine activities theory, ” suggesting that crime cases increase in areas with
52 more illicit behavior opportunities (Hollis et al., 2013). Therefore, exploring the spatial
53 impact of alcohol establishments on criminal behavior is of great significance (Savard

54 et al., 2019). Spatial data could enable the examination of the multiple spatial scales
55 where bars are related to crimes (Caplan, 2011). Early investigations were plagued by
56 flaws, including statistical weakness and datasets that focused on larger geographic
57 units such as cities, states, or counties (Gmel et al., 2016). Though more recent studies
58 have used census tract data as the geographic unit of analysis by employing spatial
59 analysis techniques - which suggest a positive relationship between alcohol outlet
60 density (AOD) and violent crime (Gmel et al., 2016; Gruenewald et al., 2023; Snowden
61 et al., 2020; Zhu et al., 2004) - few have considered evaluating the risk associated with
62 specific alcohol establishments, typically presented as point features. Additionally,
63 previous studies have highlighted differences between off-licensed, on-licensed, and
64 other types of alcohol establishments (Conrow et al., 2015; Jiang et al., 2017) and
65 attractors for different crimes (Roncek & Bell, 1981; Stoll, 2024). Therefore, dividing
66 crime type and bar type into finer categories is necessary, given association differences.

67 Colocation pattern analysis has been applied in diverse fields, including urban
68 planning (Wang et al., 2017), transportation (Hu et al., 2018), and public health (Chen
69 et al., 2021), proving its versatility in examining spatial relationships among points
70 features. Recent application of colocation patterns in criminology can be classified into
71 three main areas: colocation between different crime types (Shiode et al., 2023),
72 colocation between crime types and facilities (He et al., 2020; Wang et al., 2017), and
73 colocation between crime incident sites and surrounding land use features (Norita et al.,
74 2024; Yue et al., 2017). Given that crime and bar locations both constitute point data,
75 the use of colocation analysis in this study has the potential to address the Modifiable
76 Areal Unit Problem (MAUP) (Dark & Bram, 2007). This statistical issue emerges when
77 aggregating data across various spatial scales, which commonly arises in previous area-
78 level analyses of the social and environmental determinants of crime. Additionally,
79 colocation analysis can be adjusted for different situations by changing the range of
80 data to optimize the analysis results. By examining the temporal variation of crime
81 patterns based on colocation analysis, we can detect the deterioration of security in the

82 area around bars. This can provide evidence supporting the Broken Windows theory
83 (Kelling & Wilson, 1982), which suggests that the presence of crime indicates
84 deterioration of the local community and that these crimes (i.e., a broken window
85 neighborhood) lead to the emergence of increased in more severe crimes in the same
86 area (Hakyemez et al., 2023; Shiode et al., 2023).

87 In this study, we aim to explore crimes potentially related to bars and identify bars
88 that might be under criminal risks. We examined the spatial associations between
89 alcohol establishments and crimes using two colocation quotient models (GCLQ and
90 LCLQ) to identify targeted interventions at different scales. The spatial colocation
91 patterns of five categories of alcohol establishments (bar, hotel bar, live music bar,
92 sports bar, and nightclub) and seven categories of crimes (aggravated assault, burglary,
93 larceny-theft, murder, motor vehicle theft, rape, and robbery) were included. Our
94 study's focus on various subtypes and aspects of crime associated with bars could yield
95 targeted insights for intervention strategies. Our study also uncovers the temporal
96 transition of spatial colocation patterns, theoretically informing the Broken Window
97 theory on the combination of crimes that tend to concentrate in the same region. From
98 an application perspective, our study helps to inform policing strategies and the
99 deployment of police resources in areas close to alcohol establishments. It also makes
100 contributions for bars to optimize their operating hour, enhance security measures, or
101 collaborate with local law enforcement to improve community safety jointly.

102

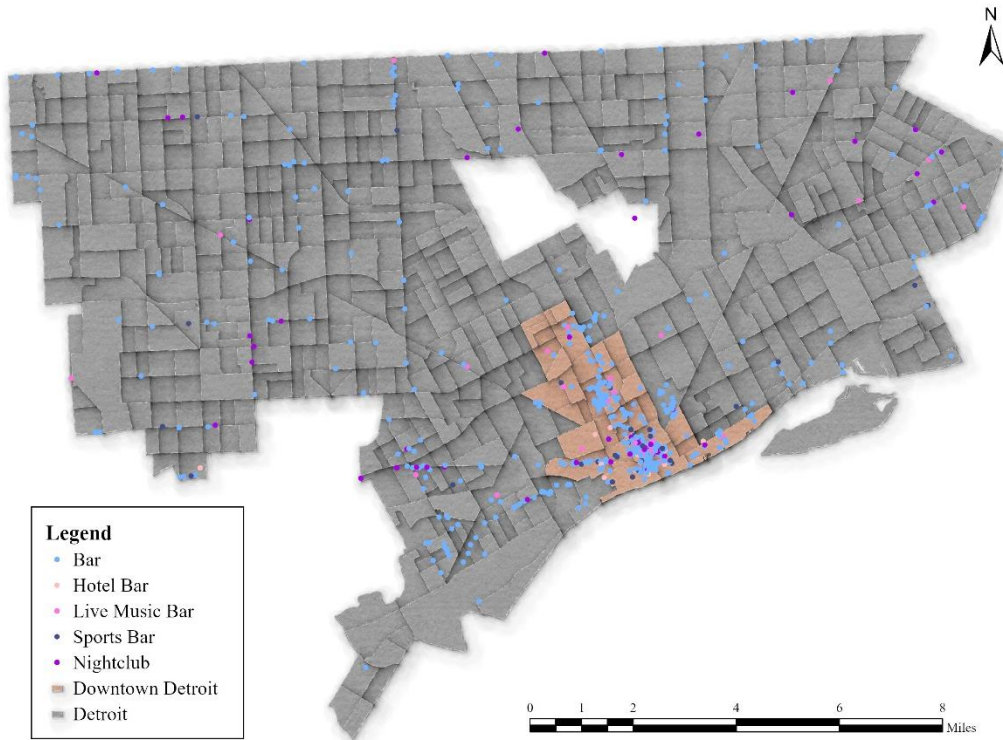
103 2 Material and Methods

104 2.1 Study area and data sources

105 The city of Detroit, known for its high crime rate, serves as the study area for our
106 research. According to local police department detention records, Detroit has been
107 grappling with issues of illegal drugs and sex trafficking, with more than half of the
108 city's murders related to the underground economy. In 2014, Detroit's murder rate was
109 43.4 per 100,000 people, ranking as the second highest in the nation, following St. Louis
110 (McDonald, 2014). In 2022, Detroit had the nation's third-highest homicide rate, at 50.0
111 per 100,000 individuals (Center for Public Safety Initiatives, 2023). Recent trends
112 indicate that crime rates in Downtown Detroit neighborhoods have generally fallen
113 below national and state averages, signifying a notable reduction in crime. At the same
114 time, the majority of the city continues to experience high crime rates, significantly
115 affecting daily life (Regan & Myers, 2020).

116 Data on alcohol establishments, including bars and nightclubs, was obtained from
117 the Michigan Liquor Control Commission (Michigan Liquor Control Commission,
118 2024b) and verified using Google Maps. Establishments that closed at night or
119 permanently shut down were removed from the dataset. Some representative bars were
120 individually listed based on elements such as price, atmosphere, service, and
121 presentation, including hotel bars, live music bars, and sports bars. Hotel bars are
122 available to guests staying at the hotel and open to the public with more exclusive
123 admittance policies. They are generally permitted to have B-Hotel liquor licenses in
124 Detroit (Michigan Liquor Control Commission, 2024). Live music bars usually have a
125 stage or designated area for a band or DJ to perform and a dance floor for guests to
126 enjoy while drinking. Sports bars tend to be casual and focus more on providing
127 entertainment than serving unique drinks, with games and sporting events displayed on
128 TV screens throughout the bar (Rocklin, 2024). Nightclubs are venues that open at night
129 for drinking, dancing, and other entertainment, typically offering a more vibrant and
130 high-energy atmosphere (Wikipedia Contributors, 2024). Figure 2 displays their spatial

131 distribution after geocoding (Zandbergen, 2009). Most alcohol establishments are in
 132 the downtown districts. Discrepancies in the proportions of different types are shown
 133 in Table 1.



134
 135

Figure 1 Alcohol establishments in Detroit City.

136

Table 1 Numbers and proportions of Alcohol establishments of different types

Category	Count	Proportion
Bar	693	92.03%
Hotel bar	24	3.19%
Live music bar	38	5.05%
Sports bar	37	4.91%
Night club	60	7.97%
Summary	753	100%

137 Crime data was sourced from the official Detroit Open Data Portal’s “RMS Crime
 138 Incidents” dataset, which is compiled from the Detroit Police Department’s records
 139 management system (Detroit's Open Data Portal, 2024). We categorized the cases
 140 according to the FBI’s Uniform Crime Reporting Program (FBI, 2019) into violent
 141 crimes –subdivided into aggravated assault, murder, and rape – and property crimes -
 142 subdivided into burglary, larceny-theft, and motor vehicle theft. This categorization

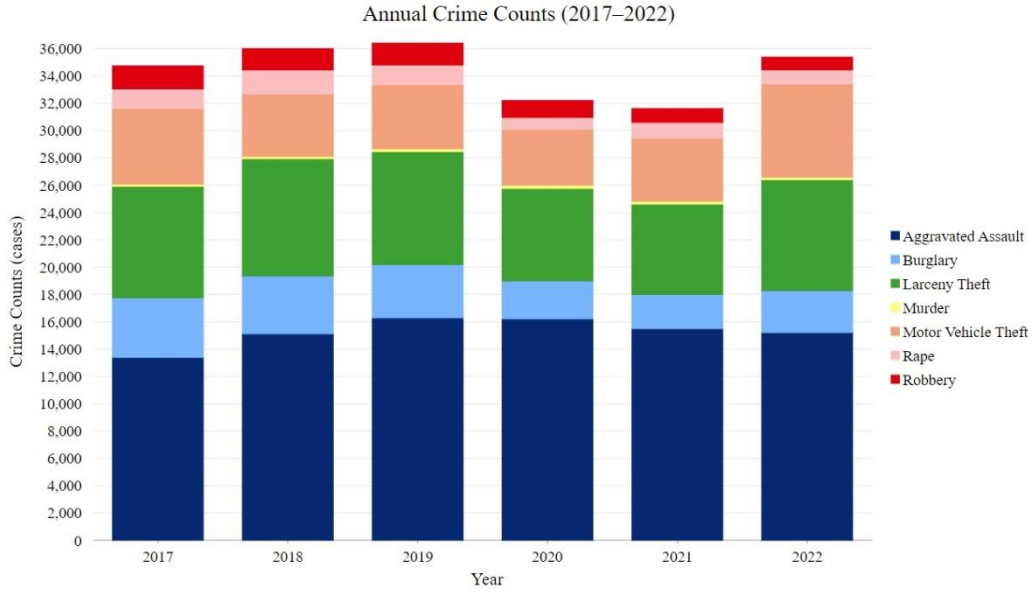
143 enabled the vast majority of types of crime to be covered in order to fully explore the
144 spatial links between bars and various types of crime.

145 We selected the period from 2017 to 2022 as the study timeframe because it
146 encompasses both the pre-COVID-19 and post-COVID-19 lockdown periods, allowing
147 for the examination of temporal variation in bar safety and crime patterns during the
148 pandemic. In our research, crime incidents were recorded during evening hours, from
149 18:00 to 6:00 the following day. This period is characterized by a higher frequency of
150 crimes and a thriving nighttime economy, particularly within the bar industry
151 (Cremeens et al., 2014; Gruenewald et al., 2023; Haleem et al., 2021). The total number
152 of cases during this period amounted to 206,308 cases in total, as illustrated in Table 2.
153 Temporal fluctuations in crime are demonstrated in Figure 2, showing an increase from
154 34,732 incidents in 2017 to 36,401 in 2019. This trend was followed by a reduction
155 during the COVID-19 period, with figures dropping to 32,194 in 2020 and 31,611 in
156 2021. The economic downturn in 2022, a repercussion of the pandemic, has led to a
157 resurgence in crime rates.

158 **Table 2** Statistics of crime in evening hours from 2017 to 2022

Crime Category	Count
Aggravated assault	91,696
Murder	1,178
Rape	7,735
Robbery	8,015
Burglary	20,859
Larceny-theft	46,531
Motor vehicle theft	30,294

159



160

161

Figure 2 Annual crime counts from 2017 to 2022.

162

163 2.2 Global colocation quotient

164 The colocation quotient, as proposed by Leslie and Kronenfeld (Leslie &
 165 Kronenfeld, 2011), comprises the global colocation quotient (GCLQ) and colocation
 166 quotient (LCLQ) models. The GCLQ, diverging from the K function (Peterson, 2009),
 167 utilizes nearest neighbors to measure the overall colocation pattern between two types
 168 of point objects and their joint distribution and is formulated as follows:

$$169 \quad CLQ_{A \rightarrow B} = \frac{\frac{N_{A \rightarrow B}}{N_A}}{\frac{N_B}{N-1}} \quad (1)$$

170 Where N represents the total number of point objects under investigation, N_A and N_B
 171 depict the count of A and B, respectively, and $N_{A \rightarrow B}$ is the number of type A points whose
 172 nearest neighbor belongs to type B points. The numerator calculates the observed
 173 proportions of B, which are the closest neighbors of A, where the denominator estimates
 174 the expected proportion by chance. As a point cannot be the nearest neighbor of itself,
 175 $N-1$ rather than N is used when measuring the expected proportion.

176 A point might have multiple neighbors, while GCLQ allocates equivalent weight
 177 to calculate $N_{A \rightarrow B}$. As formulated in Eq. (2), i denotes each A point, nn_i represents the

178 number of nearest neighbors of i, j depicts each of the nn_i nearest neighbors, and f_{ij} is a
179 binary variable indicating whether the point i 's nearest neighbor j is of B type under
180 investigation or not (1 indicates yes and 0 otherwise).

$$181 \quad N_{A \rightarrow B} = \sum_{i=1}^{N_A} \sum_{j=1}^{nn_i} \frac{f_{ij}}{nn_i} \quad (2)$$

182 GCLQ can differentiate the spatial interactions between A and B in both directions.
183 $GCLQ_{A \rightarrow B}$ informs the extent to which type A points are attracted to type B objects,
184 while $GCLQ_{B \rightarrow A}$ expresses the extent to which type B points are drawn to type A points.
185 $GCLQ_{A \rightarrow B}$ has an expected value of one when all points are allocated randomly given a
186 fixed distribution pattern of points (Leslie & Kronenfeld, 2011). A $GCLQ_{A \rightarrow B}$ value
187 larger than one indicates a possible colocation pattern, and the larger the value is, the
188 stronger the colocation pattern would be. On the contrary, a $GCLQ_{A \rightarrow B}$ value less than
189 one impresses a possible isolation pattern.

190 In our study, $GCLQ_{bars \rightarrow crime}$ and $GCLQ_{crime \rightarrow bars}$ are the two indicators that
191 evaluate the general links between bars and crimes in Detroit City. $GCLQ_{bars \rightarrow crime}$
192 indicates the potential for criminal activity to occur near bars. A $GCLQ_{bars \rightarrow crime}$
193 value of less than one means that the overall likelihood of crime occurring near bars is
194 relatively low compared with other areas, indicating that bars in Detroit are generally
195 safe. Conversely, a $GCLQ_{bars \rightarrow crime}$ value larger than one means that the crime
196 occurring around bars is of high probability, which may indicate a high risk associated
197 with bars in Detroit. A $GCLQ_{crime \rightarrow bars}$ less than one means that crimes are spatially
198 dispersed from bars in general, which may result in a lower likelihood of bars being the
199 cause. A larger $GCLQ_{crime \rightarrow bars}$ than one shows an overarching colocation pattern of
200 crime to bars, revealing that crimes may be more likely induced by bars and alcohol
201 than not.

202

203 2.3 Local colocation quotient

204 The GCLQ model is valuable for identifying the overarching colocation patterns
205 across a large area. However, it may not be suitable for every individual part of a region,
206 particularly urban areas with a diverse mix of objects and complex spatial distributions.
207 The spatial layout of urban facilities often results in significant disparities in colocation
208 patterns at the micro-scale. In contrast, the LCLQ model, developed by Cromley et al.
209 (Cromley et al., 2014), is capable of revealing spatial variability in point dataset
210 associations and measuring localized colocation patterns.

211 The LCLQ is formulated as

$$212 \quad LCLQ_{A_i \rightarrow B} = \frac{N_{A_i \rightarrow B}}{\frac{N_b}{N-1}} \quad (3)$$

$$213 \quad N_{A_i \rightarrow B} = \sum_{j=1(j \neq i)}^N \left(\frac{w_{ij} f_{ij} t_{ij}}{\sum_{j=1(j \neq i)}^N w_{ij}} \right) \quad (4)$$

$$214 \quad w_{ij} = \exp \left(-0.5 * \frac{d_{ij}^2}{d_{ib}^2} \right) \quad (5)$$

215 where A_i represents the i th A point, f_{ij} depicts a binary variable showing whether or not
216 point j is a marked B point (1 for yes and 0 otherwise), t_{ij} is also a binary variable
217 judging whether or not point j is temporal related to point i (1 for yes and 0 otherwise),
218 w_{ij} indicates the weight of point j , denoting the significance of point j to the i th A point,
219 d_{ij} shows the distance between point A_i and point j , and d_{ib} is the bandwidth distance
220 around point A_i . The other notations express the same as themselves in Eq. (3) and the
221 denominator in Eq. (3) still calculates the proportion of observed type B objects that
222 are the nearest neighbors of each type A object. Eq. (4) demonstrates how to calculate
223 $N_{A_i \rightarrow B}$, the weighted average counts of type B points that are the nearest neighbors of
224 point A_i . The Gaussian kernel density weighting function is illustrated in Eq. (5), stating
225 that the closer a neighbor is to object A_i , it will be assigned a greater weight.

226 Specifically, we set a series of space-time windows to calculate t_{ij} in Eq. (3),
227 estimating which features are included in the analyzed neighborhood. The features that

228 are near each other in space and time are analyzed together, allowing for the assessment
229 of all feature relationships relative to the location and time stamp of the target feature
230 (Esri, 2020). In our study, space-time windows are applied to calculate $LCLQ_{crime \rightarrow bars}$,
231 given that the time of criminal incidents should be taken into consideration. Crimes
232 committed too temporally far apart should not be counted as each other's spatial
233 neighbors when assessing one's correlation to its nearing bars by $LCLQ_{crime \rightarrow bars}$.
234 However, when evaluating an individual bar's correlation to surrounding crimes by
235 $LCLQ_{bars \rightarrow crime}$, there is no need to use space-time windows because there can be no
236 spatial irrelevance between bars. Therefore, when calculating a bar's $LCLQ_{bars \rightarrow crime}$
237 value, all the neighbors are appointed the same t_{ij} of one.

238 $LCLQ_{bars \rightarrow crime}$ indicates the potential for crime to occur in proximity to a specific
239 bar. If a bar has an $LCLQ_{bars \rightarrow crime}$ value of less than one, there are few crimes in its
240 vicinity, indicating that the bar is relatively safe. If the $LCLQ_{bars \rightarrow crime}$ value is larger
241 than one, multiple crimes are included in its nearest neighbors, suggesting a higher risk.
242 If the $LCLQ_{bars \rightarrow crime}$ value is approximately one, the local bar and crime numbers are
243 nearly equal, showing a potential local balance between the two.

244 $LCLQ_{crime \rightarrow bars}$ indicates the possibility of a crime related to nearing bars. An
245 $LCLQ_{crime \rightarrow bars}$ value of less than one means that there are few bars near the specific
246 crime, indicating a dispersion pattern to bars and a low likelihood of being bar-related.
247 An $LCLQ_{crime \rightarrow bars}$ greater than one for an individual incident shows its great number of
248 bars within the nearest neighbors and the high possibility of being induced by bars and
249 alcohol. An $LCLQ_{crime \rightarrow bars}$ approximately one also reveals a potential local balance.

250 We used Monte Carlo simulation (Hammersley, 2013) to examine whether the
251 LCLQ value is statistically significant, with a simulation trial randomly relabeling the
252 category for each A_i point, following the frequency distribution of each category. Take
253 $LCLQ_{bars \rightarrow crime}$ as an example. Each simulation randomly reassigns the labels of all
254 objects except bar objects. The number of objects in each category will not change after
255 the simulation procedure. By conducting numerous simulations, such as 499 iterations,

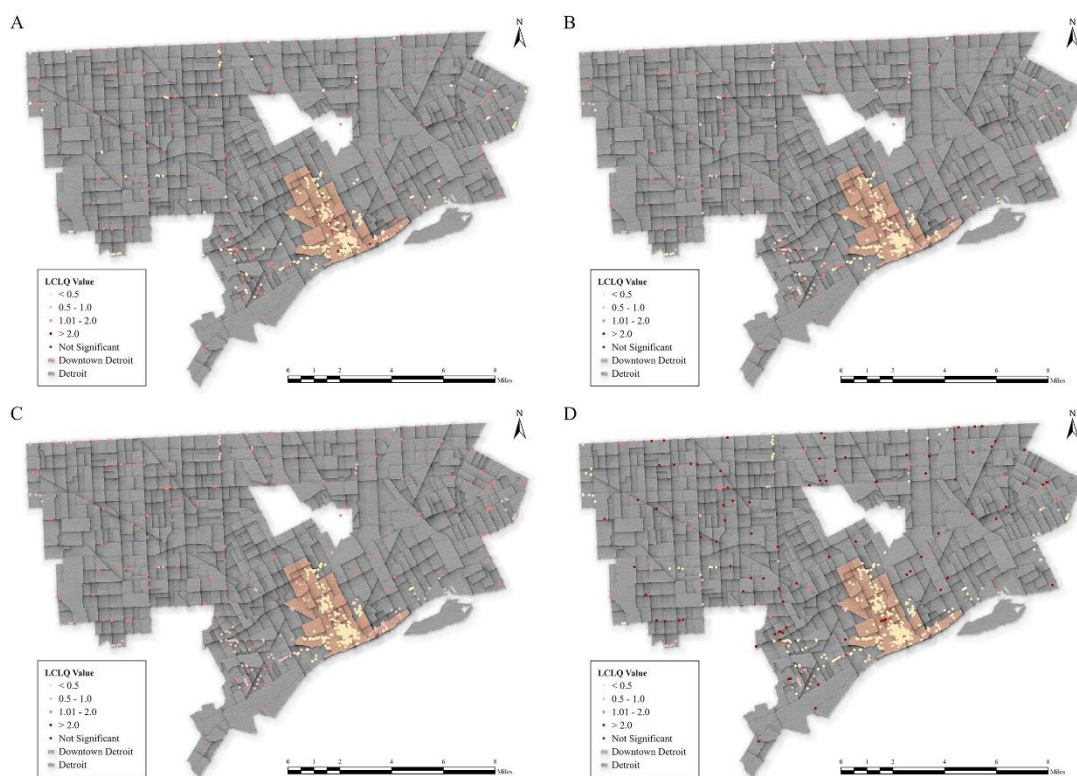
256 a sample distribution for each object using the LCLQ is obtained and subsequently
257 compared with the observed distribution to ascertain the significance level. All results
258 are statistically significant at the 0.05 level.

259 The selection of parameters and metrics can affect the results when constructing
260 an LCLQ model. The smaller the bandwidth, the more clusters with smaller areas and
261 more pronounced variations of LCLQ values are expected. We used the K nearest
262 neighbor method in ArcGIS Pro to determine bandwidth because it is more applicable
263 for classification in colocation analysis compared to the distance band. This method
264 yields more accurate results in measuring spatial impedance, as urban activities are
265 mostly confined to the existing street network.

266 For our sample data, we used alcohol establishments, robbery, and murder in 2017
267 to search for the most appropriate bandwidth, as shown in Figure 3. We set the K nearest
268 neighbors' numbers as 1, 8, 25, and 8 (Figure 3). A 499-time Montes Carlo simulation
269 ran during the whole process. We displayed LCLQ results divided into five categories
270 for subsequent experiments: Significant Colocation ($LCLQ > 2.0$), Colocation ($1.01 <$
271 $LCLQ < 2.0$), Dispersion ($0.5 < LCLQ < 1.0$), Significant Dispersion ($0 < LCLQ < 0.5$)
272 and Not Significant ($LCLQ < 0$). We considered points deemed Not Significant as
273 failures.

274 Figure 3A shows 91 points of Not Significant, revealing that an insufficient
275 number of neighbors substantially increases the likelihood of analysis failure. As the
276 number of neighbors increases, the number of alcohol establishments with LCLQ
277 values approaching one also rises, indicating that the results become smoother. A
278 smaller bandwidth of one nearest neighbor resulted in more spiky spots, while a larger
279 bandwidth of twenty-five nearest neighbors detects a diffused association of less extent.
280 Investigating bars' spatial connection to areas with low crime counts, such as murder,
281 led to larger clusters of Significant Colocation or Significant Dispersion patterns,
282 suggesting that smaller datasets fit smaller bandwidths.

283 Our study showed a wide variation in the annual number of cases by type. For
284 example, murder hovered around 150, while aggravated assaults exceeded 10,000. To
285 reduce the effect of bandwidth differences on LCLQ analysis and ensure that the
286 number of failure objects remained low across different experiments, we settled on
287 setting the bandwidth to 8 nearest neighbors in the follow-up section.



288
289 **Figure 3** LCLQ results between bars and Robbery in 2017 with a bandwidth of (A) one, (B) eight,
290 and (C) twenty-five nearest neighbors. (D) LCLQ between bars and Murder in 2017 with a
291 bandwidth of eight nearest neighbors.

293 3 Results

294 3.1 Global colocation quotient analysis

295 We explored the global colocation patterns between alcohol establishments and
296 different crimes by two different GCLQ models, $GCLQ_{bars \rightarrow crime}$ and $GCLQ_{crime \rightarrow bars}$.
297 The former assessed the vulnerability of bars in Detroit to nearby, while the latter
298 indicated whether crimes in the city collocate with neighboring alcohol establishments.

299 Both models showed spatial dispersion patterns in general, as presented in Tables
 300 3 and 4, with all GCLQ values being less than 1, indicating that Detroit’s alcohol
 301 establishments are not correlated with criminal incidents overall. GCLQ values
 302 fluctuated slightly between different years, peaking during the COVID-19 period,
 303 indicating that crimes were the least dispersed relative to bars during such a period. The
 304 economic downturn caused by the pandemic may account for this trend.

305 $GCLQ_{bars \rightarrow crime}$ values of burglary, rape, and robbery were the lowest, suggesting
 306 that bars were the places where these crimes are less likely to happen. According to
 307 $GCLQ_{crime \rightarrow bars}$ results, burglary and rape were the most spatially isolated types, while
 308 larceny-theft and murder were the least dispersed. This also inferred a degree of
 309 symmetrical dispersed association between bars and crimes. The result of burglary
 310 aligned with its definition (Mawby, 2013). Bars and their surrounding areas tended to
 311 have higher population densities and are usually noisier, making it more challenging to
 312 carry out a burglary. Although several studies have demonstrated an increased incidence
 313 of sexual offenses and robberies in bar environments (Baltieri & de Andrade, 2008;
 314 Feng et al., 2019), our results were contrary to this trend and may indicate the presence
 315 of more effective preventive measures against such crimes in Detroit.

316 GCLQ results demonstrated the overall association between bars and crimes but
 317 remained spatially and temporally stationary, hiding the local association relationship.
 318 LCLQ is more applicable to better account for the spatiotemporal heterogeneity of
 319 different criminal cases and to fit the complex urban environment.

320 **Table 3** $GCLQ_{bars \rightarrow crime}$ from 2017 to 2022

Neighboring Categories	Year					
	2017	2018	2019	2020	2021	2022
Aggravated Assault	0.683	0.685	0.697	0.652	0.696	0.701
Burglary	0.483	0.481	0.468	0.489	0.489	0.499
Larceny Theft	0.822	0.840	0.832	0.743	0.771	0.833
Murder	0.722	0.618	0.646	0.583	0.633	0.646
Motor Vehicle Theft	0.614	0.606	0.584	0.566	0.625	0.693
Rape	0.481	0.478	0.504	0.520	0.501	0.518

Robbery	0.565	0.585	0.559	0.527	0.570	0.539
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321

Table 4 $GCLQ_{crime \rightarrow bars}$ from 2017 to 2022

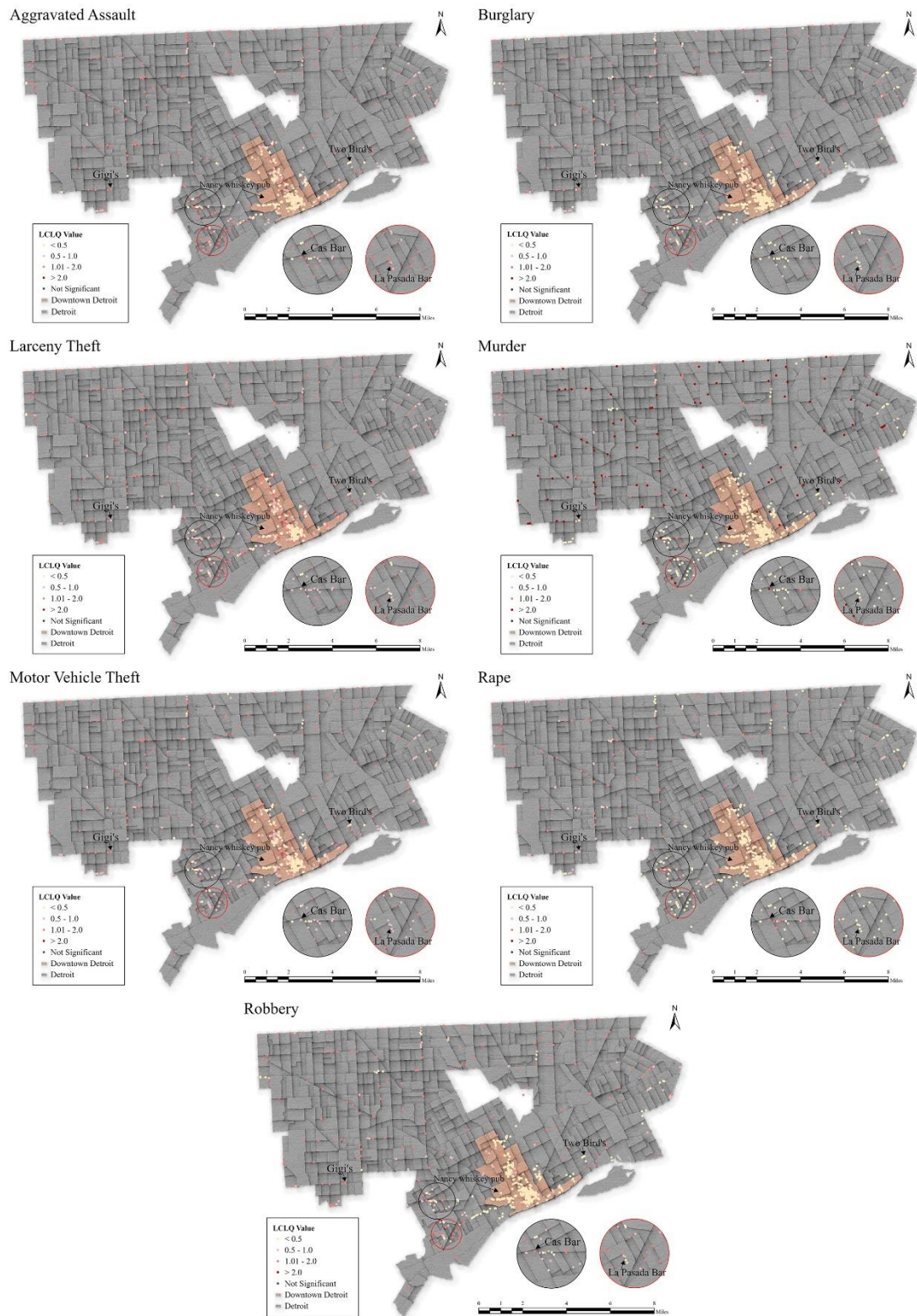
Category of Interest	Year					
	2017	2018	2019	2020	2021	2022
Aggravated Assault	0.587	0.568	0.574	0.559	0.597	0.577
Burglary	0.474	0.475	0.466	0.504	0.485	0.504
Larceny Theft	0.681	0.663	0.711	0.704	0.708	0.684
Murder	0.698	0.662	0.646	0.624	0.686	0.653
Motor Vehicle Theft	0.595	0.599	0.580	0.558	0.600	0.669
Rape	0.450	0.445	0.483	0.511	0.431	0.474
Robbery	0.569	0.587	0.579	0.536	0.578	0.568

322

323 3.2 Local colocation quotient analysis

324 Firstly, we used the LCLQ model to calculate $LCLQ_{bars \rightarrow crimes}$ for each type of
325 crime in 2017-2022, which indicated the extent to which alcohol establishments attract
326 crime incidents. This also reflected alcohol establishments' security level—the lower
327 the value, the safer the establishment is considered to be. Figure 4 shows $LCLQ_{bars \rightarrow}$
328 $crimes$ for different crimes in 2022.

329



330

331

Figure 4 LCLQ_{bars→crimes} results with crimes of various types in 2022.

332

Colocation patterns between alcohol establishments and various crimes were overall

333

homogenous, with most being spatially isolated in 2022. The highest number of bars

334

with an LCLQ value lower than 1 was 625 in relation to rape. At the same time, the

335 lowest number is 495 for larceny theft, which was still higher than 65 % of all bars.
336 However, this did not imply that most bars were adequately safe, as regional differences
337 within Detroit were pronounced.

338 Alcohol establishments in Downtown Detroit were generally dispersed to crimes,
339 with a few notable hotspots of colocation. This pattern may be closely related to the
340 high density of bars in the area - clusters of bars tend to draw crowds during opening
341 hours, and there was a substantial police presence and surveillance around these bars
342 (Doucet & Smit, 2016). Unlike other U.S. cities, Downtown Detroit boasts a middle-
343 class population and tourist attractions, contributing to its relatively safety compared to
344 other neighborhoods (Doucet & Smit, 2016; Mah, 2020). Alcohol establishments in
345 colocation patterns in this region warranted special attention. They were usually found
346 at the edge of the Downtown bar cluster, such as Nancy whiskey pub, which was
347 collocated with aggravated assault, burglary, larceny-theft, motor vehicle theft, and rape
348 in 2022. Crime incidences were more likely to occur in and around bars farther from
349 the center cluster, suggesting a need for enhanced security measures in these locations.

350 Bar clusters located in another part of the city showed different patterns from those
351 in Downtown Detroit. Relationships between bars along Michigan Ave in Claytown
352 (highlighted within the black circle in Figure 4) and crimes were diverse. Half of the
353 bars there showed colocation with aggravated assault and rape, while the majority of
354 bars there exhibit dispersion or significant dispersion to other types of crimes. It is
355 noteworthy that Cas Bar was collocated with most types of crimes and significantly
356 collocated with murder. Colocation patterns between bars in and around Springwell
357 (highlighted within the red circle in Figure 4) and crime were relatively consistent. A
358 number of bars significantly dispersed from murder and rape but collocated to other
359 crimes, with some exceptions like La Pasada Bar, which was dispersed to all crimes. In
360 general, colocation patterns between alcohol establishments in a smaller cluster and
361 crimes were not so accordant. A safer bar might be adjoint to a dangerous one.

362 Alcohol establishments situated away from Downtown Detroit, predominantly at the
363 junctions of blocks, were mostly collocated with all types of crimes. These bars,
364 intended to serve the local community, had security levels that were closely tied to
365 community policing efforts, and the disorder within a neighborhood may influence the
366 crime rates of these venues. Notable exceptions, like Gigi's and Two Birds, were located
367 to the south and not too far from Downtown Detroit. Bars in the suburbs, particularly
368 in the northern area, were more dangerous. The further one went towards the outskirts,
369 the sparser the bars became, often with a few bars within a two-mile radius. More than
370 half of these spots were in significant collocation with murder, and most were in a
371 collocation pattern with other crimes. However, bars along Livernois Ave or Harper Ave
372 were mostly in dispersion. Factors like gangs, black markets, drugs, and other risk
373 factors in Detroit suburbs contribute to this issue.

374

375 3.3 Temporal variation of collocation pattern

376 There was little overall variation in collocation pattern in the time dimension from
377 2017 to 2022, but changes in certain individual bars in localized areas were more
378 pronounced. $LCLQ_{bars-crimes}$ results for rape, shown in Figure 5, were representative
379 even though differences in details did exist compared to other crime types.

380 Alcohol establishments in Downtown Detroit were much safer than other areas as
381 time went by. The farther one went away from Downtown Detroit, the larger its LCLQ
382 value would be, more likely collocated to rape locations. Although the number of
383 incidents decreased in 2020 and 2021, general patterns transformed slightly. Distinctive
384 transformation can be observed in neighborhoods.

385 The vast majority of bars in Downtown Detroit were spread out from areas
386 associated with rape, and those that were collocated had shown a downward trend from
387 2017 to 2019. Prevention measures against rape in these areas had been perfected
388 during that period. Patterns in Downtown Detroit remained stable during and after the
389 COVID-19 period, with less than ten bars exhibiting a collocation pattern in the last

390 three years. It can be inferred that quarantine policy scarcely influenced the security
391 level of Downtown Detroit. However, a portion of the bars, such as Nancy whiskey pub
392 and Tony V's Tavern, located on the outskirts of Downtown Detroit, had consistently
393 collocated to rape cases, with their LCLQ values showing an increase during the
394 pandemic.

395 In contrast, the local collocation pattern of bars around Michigan Ave changed
396 substantially during the six years with diverse results. Alcohol establishments located
397 at the edge of the area, such as Blackhorse Cantina II and The Caribbean Club, were
398 the ones whose LCLQ values were always smaller than one. Those located in the central
399 area with high density exhibited a variability of collocation patterns, with LCLQ values
400 generally exceeding one before 2021. Specifically, more than half of the bars on the
401 street displayed collocation patterns in 2020 or 2021. In 2022, most of these bars became
402 dispersed from rape incidents. The variation of bars in and around Springwells was
403 different. Bars located in the center stayed in a dispersion pattern, while more and more
404 bars located on the edge changed into a collocation pattern in 2020 and 2021. In 2022,
405 almost all bars in the region became significantly dispersed to rape. It can be inferred
406 that these bars were particularly prone to rape cases, and the situation may have
407 worsened during the quarantine time. However, targeted interventions may have been
408 made after the period.

409 Bars located away from Downtown Detroit always served the neighborhood and
410 were mostly collocated to rape during the entire period. Only a small number of notable
411 exceptions situated in the suburb showed dispersion to rape, such as Good Time on The
412 Ave, Ford Patio Bar & Grill and Cornerstone Village Bar & Grill. COVID-19 had little
413 impact on the overall spatial patterns, with few changes in patterns from collocation to
414 dispersion or converse. The number of collocation spots was highest in 2020 and
415 gradually decreased over the subsequent two years.

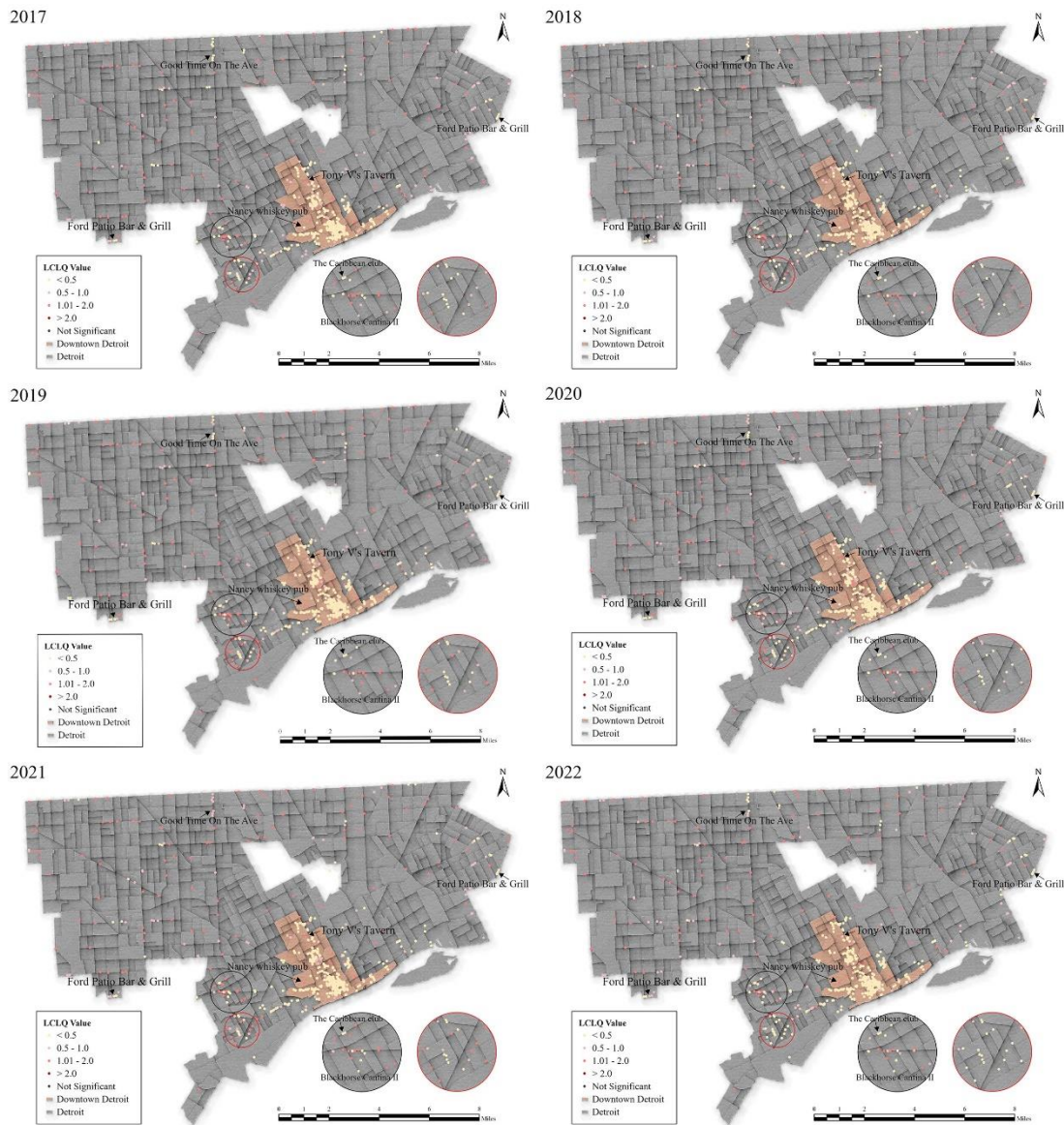


Figure 5 LCLQ_{bars→crimes} results of Rape from 2017 to 2022.

416

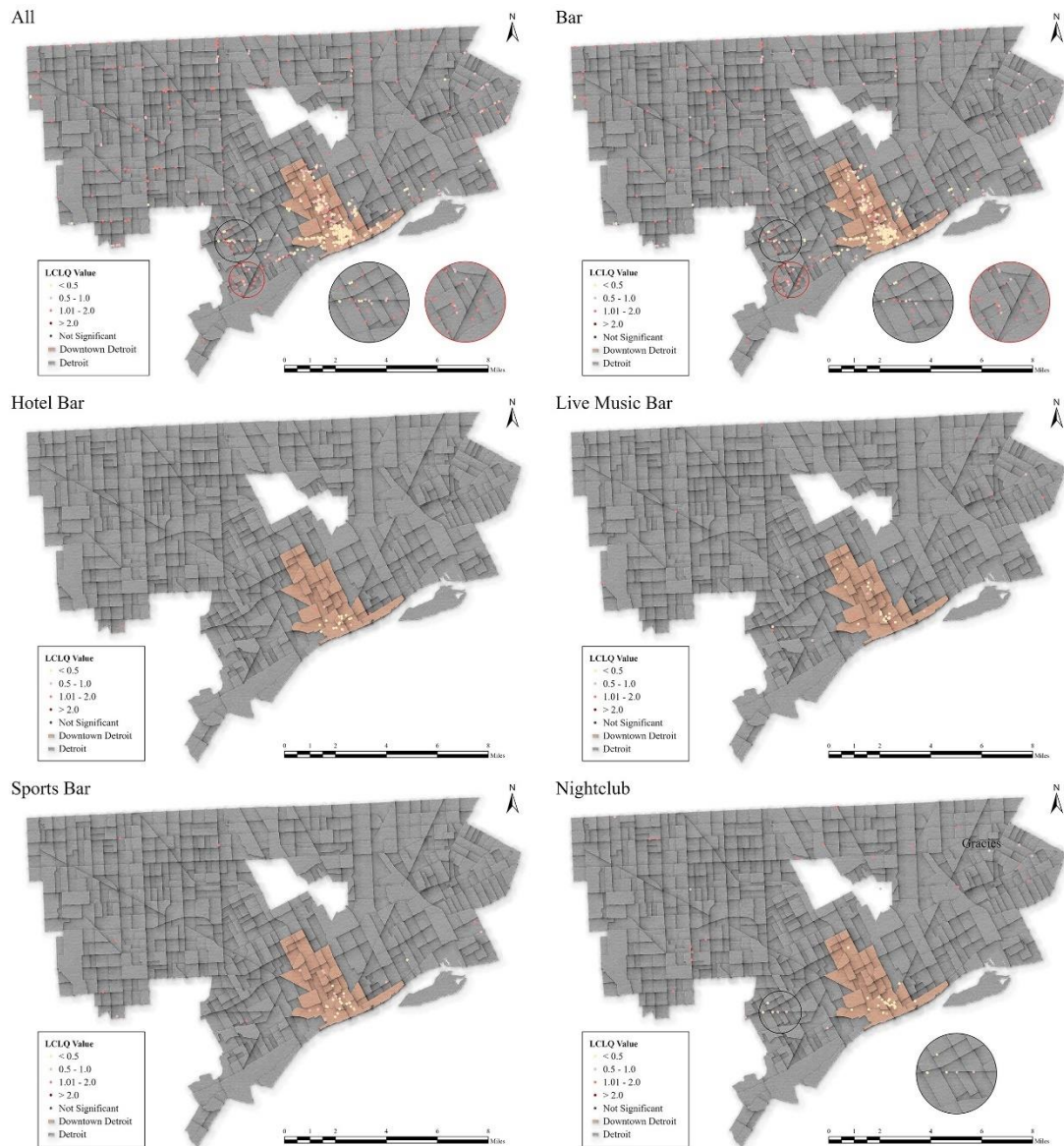
417

418 3.4 Discrepancies in colocation patterns across different types of bars

419 The spatial interplay between alcohol establishments and crimes had wide
 420 differences for different bar types. We chose aggravated assault in 2022 as sample data
 421 to reveal the scenarios in Figure 6. The number of category “Bar” was the largest, with
 422 the most widely distribution. It should be noted that the following establishments,
 423 except the nightclub, were classified under the “Bar” category. In Downtown Detroit,
 424 the southeastern part was much safer than others, where all bars were dispersed from
 425 incidents, with most showing significant dispersion. There were several establishments
 426 located in the middle part, surrounded by bars isolated from crime spots. Given the fact

427 that “Bar” was the main category of alcohol establishments in the two bar clusters in
428 southern Detroit, these spots could mainly represent the characteristics of the two areas.
429 The number of bars collocated with aggravated assault and those dispersed to it was
430 close near Michigan Ave. Bars located in Spingwell were mainly collocated to the crime.
431 Bars located in the neighborhood distant from the downtown area were majorly
432 collocated to aggravated assault incidences. Only bars in the eastern suburbs showed
433 an overall dispersion.

434 The majority of hotel bars, live music bars and sports bars are all located in
435 Downtown Detroit. Hotel bars had the highest portion of collocation pattern while all
436 sports bars were dispersed to aggravated assault there. In blocks away from Downtown
437 Detroit, most sports bars were in collocation pattern, but about half of live music bars
438 were in dispersion. The number of nightclubs in and out of Downtown Detroit was close.
439 Those located in the downtown area or along Michigan Ave were all dispersed from
440 crime spots. In contrast, those located distantly from others in the hood were mostly
441 collocated to aggravated assault. Gracies was the only suburb nightclub showing
442 significant dispersion.



443

444 **Figure 6** $LCLQ_{bars \rightarrow crimes}$ result of Aggravated Assault in 2022, classified by alcohol establishment
 445 types.

446

447 3.5 Impact of bar-related crimes on neighborhoods through colocation analysis

448 $LCLQ_{crimes \rightarrow bars}$ represents how crime spots are attracted to bar locations, partially
 449 judging whether the occurrence of a specific case is related to an alcohol establishment.
 450 In calculating the LCLQ value for individual crime incidents, a seven-day temporal
 451 window was established after parameter selection to filter out unrelated cases and
 452 minimize the influence of incidents occurring far removed in time (Li et al., 2022).

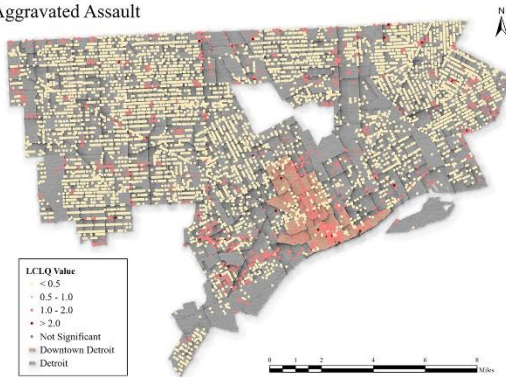
453 Results for different types of crimes in 2022 were demonstrated on the left side of
454 Figure 7. Basically, the closer a crime location was to a bar, the more likely it was
455 collocated to the establishment. Additionally, as bar density increased, both the
456 proportion and number of nearby incidents in the collocation pattern rose. For example,
457 Downtown Detroit had the largest number of collocation spots. LCLQ values of crime
458 spots significantly dispersed to bars were all zero, and the majority of them were located
459 in the middle block groups and suburbs. Proportions of murder, rape and robbery of
460 collocation pattern were the highest, while aggravated assault and three types of property
461 crime were lower.

462 Given that $LCLQ_{\text{crimes} \rightarrow \text{bars}}$ results could not directly reflect the impact of bar-
463 related crimes on neighborhoods, we calculated the crime rate per bar for each block
464 group on the right side of Figure 7 to assess the safety index of neighborhoods near bars.
465 The number of bars within each block group and a 500-meter radius was counted,
466 drawing from routine activity theory (Miró, 2014). To ensure comparability across
467 block groups, this bar-related crime rate was adjusted for every 1,000 residents based
468 on population data obtained from the American Community Survey (ACS, 2018–2022).
469 The lower the bar-related crime rate of a block, the higher the implied safety for
470 neighborhoods near those bars concerning that specific crime type. Notably, this
471 indicator serves as a warning of bar-related security risks rather than a direct count of
472 crimes. For instance, areas with a high number of bars, such as downtown, may report
473 higher overall crime counts but show lower bar-related crime rates per bar, indicating
474 relatively safer conditions for specific crime types.

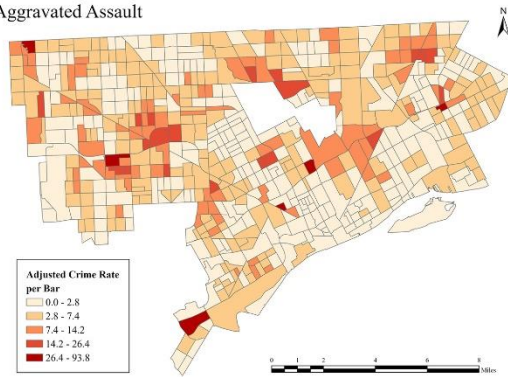
475 Block groups in southern Detroit had lower bar-related crime rates than others,
476 except for Oakwood Heights, which had one of the most dangerous bars collocated to
477 almost all types of crime. Some block groups located in the middle part and along Grand
478 River Ave had high bar-related crime rates, such as Littlefield Community. Suburban
479 regions, particularly in the west, had consistently lower rates. A relatively larger number

480 of block groups had a risk of encountering bar-related aggravated assault, which aligns
 481 with inferences based on $LCLQ_{bars \rightarrow crime}$.

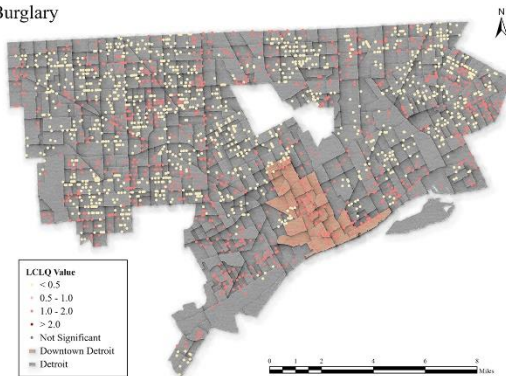
Aggravated Assault



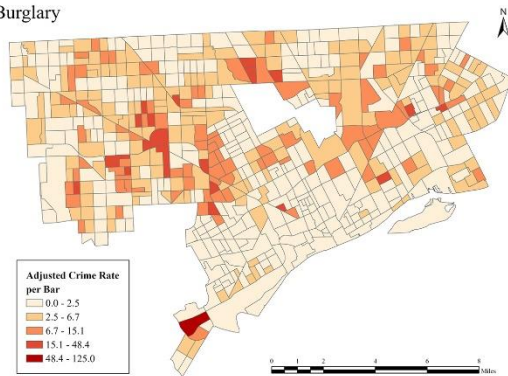
Aggravated Assault



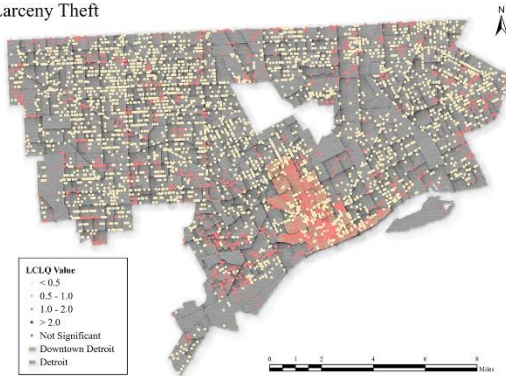
Burglary



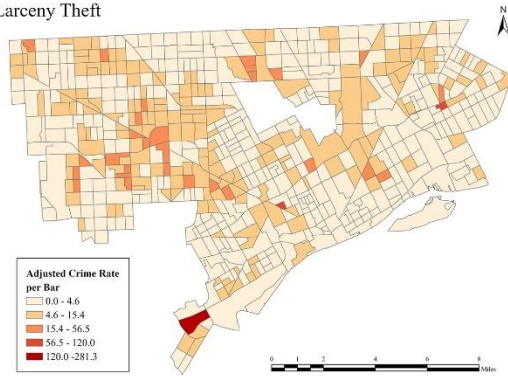
Burglary



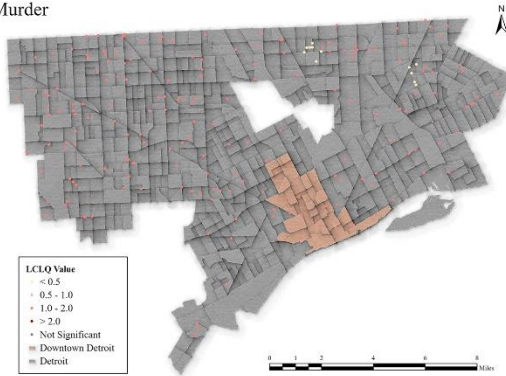
Larceny Theft



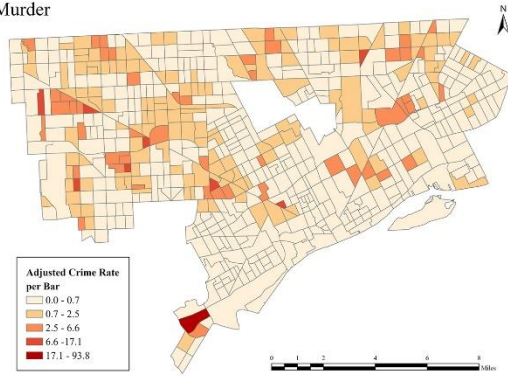
Larceny Theft



Murder



Murder



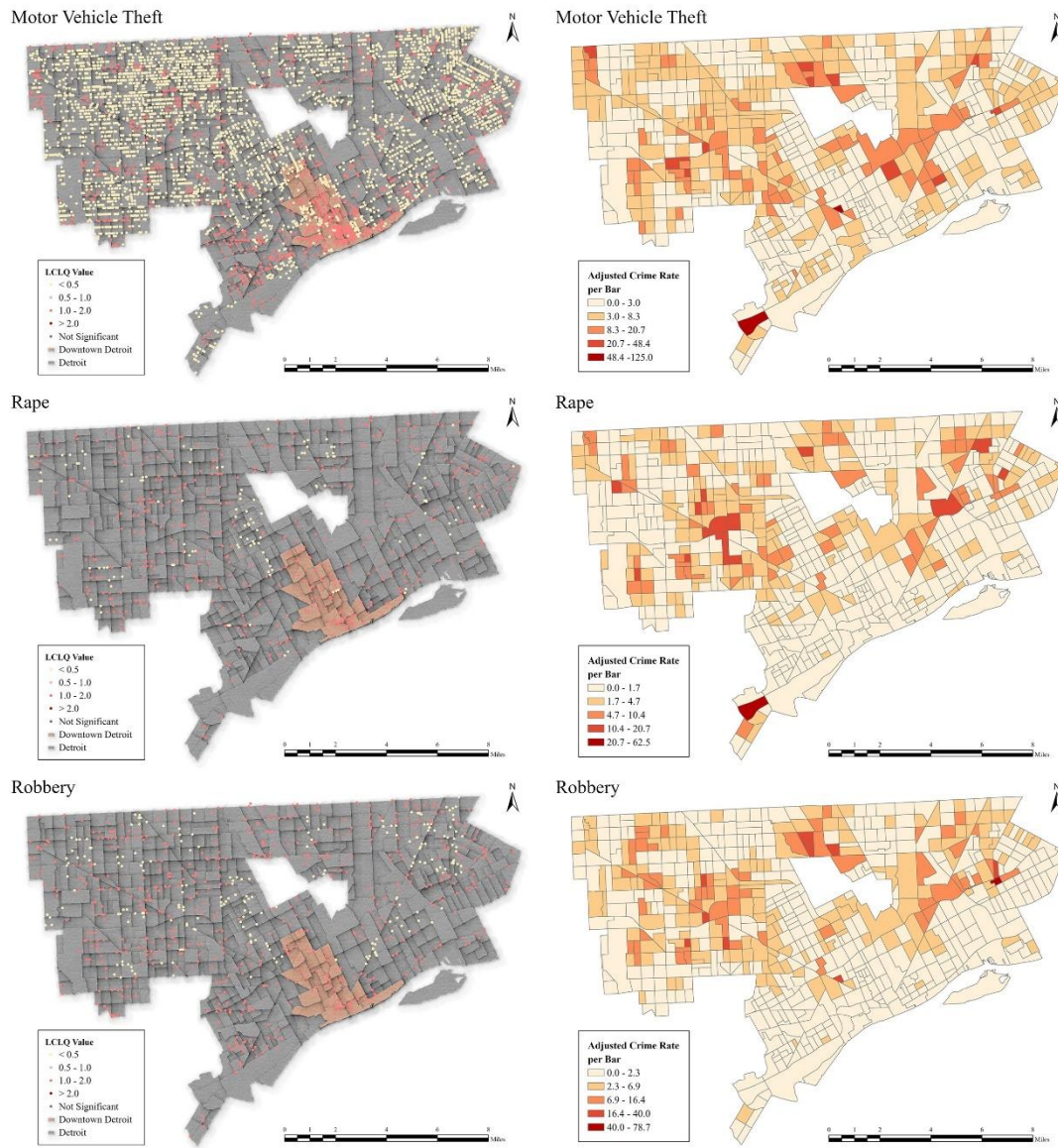


Figure 7 LCLQ_{crimes→bars} results with crimes of various types in 2022.

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484

485

486 4 Discussion

487 Although multiple studies have examined the relationship between alcohol
 488 establishments and crimes, their results were either unable to provide policy-makers
 489 with detailed information about individual bars or were limited by the MAUP effect,
 490 particularly those studies that utilized GIS algorithms. Moreover, few have delineated
 491 the relationships between bars and all crime types individually. Our research proposed
 492 a novel method, with two indicators, the GCLQ and the LCLQ, to reveal the spatial
 493 interplay between different types of alcohol establishments and various types of crime

494 in Detroit City. Specifically, the GCLQ assesses citywide patterns, while the LCLQ
495 extracts localized patterns at specific sites. We also evaluated different bandwidths of
496 the LCLQ model, utilizing the one of universal applicability across all datasets. Based
497 on the GCLQ results, alcohol establishments and crime spots were dispersed from each
498 other, regardless of category, and were scarcely influenced by the COVID-19 pandemic.
499 In comparison, the LCLQ results revealed the spatial discrepancies of bars' collocation
500 patterns in relation to crimes and assessed bar-related security of neighboring regions.
501 Bars in Downtown Detroit were the most dispersed, those in other smaller clusters
502 showed the greatest variety, bars isolated away from downtown were the most
503 collocated, and some of the bars located in the suburbs were in great dispersion. Given
504 that the factors influencing criminal cases are multifaceted, CLQ analysis is not
505 sufficient to fully deduce the specific causative factors of crime cases. However, the
506 application of CLQ analysis helps us to understand the possible links between pubs and
507 crime and assess the risk level of the areas near alcohol establishments. The discoveries
508 also provide a reference for policymakers and owners on criminality prediction in the
509 subsequent years.

510 Therefore, arrangements should be tailored across different regions, as factors
511 such as location and community culture may influence the impact of bars on crime
512 (Conrow et al., 2015). Although downtown has a high bar density, a stronger dispersion
513 between bars and crime, and a higher neighborhood safety index, the positive
514 relationship between bar density and crime cannot be overlooked. Specifically, bars still
515 collocated with crime in this area should be given special attention. The use of security
516 personnel to protect patrons and staff should be enhanced, and bar managers are
517 expected to circulate regularly throughout the establishments to ensure safety (Savard
518 et al., 2019). Security staff should be adequately trained to intervene promptly before
519 conflicts escalate into violent crimes (Davis et al., 2024). The employee-to-customer
520 ratio can be increased, referred to as the standard of The New York Nightlife
521 Association (Association, 2011). In bar clusters within more collocated establishments,

522 surveillance, lighting, and police patrols might be more efficient in reducing the risk of
523 crime. Bars located in economically and socially disadvantaged communities, which
524 are often collocated with crime, can have a negative impact on residents (Horsefield et
525 al., 2023). To prevent such bars from contributing to the broken window effect on the
526 neighborhood, there should be a restriction on their operating hours, as well as an
527 increase in police presence and supervision. Regular inspections should be carried out,
528 and liquor licenses should be revoked if necessary, depending on the safety situation.

529 Based on the characteristics and motivations of different types of crimes, targeted
530 measures should be implemented in conjunction with spatial distribution patterns for
531 the specific crime. Violent crimes are usually generated by risk factors in alcohol
532 establishments, such as organizational practices and physical characteristics (Franquez
533 et al., 2013). Maintaining law and order in and around pubs should be a priority. For
534 bars collocated to rape, such as La Pasada Bar, managers should consider whether the
535 physical environment and practices facilitate sexual aggression (Davis et al., 2024).
536 Training sober staff who are motivated to intervene as part of their employment duties
537 is also effective (Davis et al., 2024; Leone et al., 2018). In terms of property crimes,
538 which few studies have explored in relation to bars, we also found collocation pattern
539 clusters between alcohol establishments, larceny theft and motor vehicle theft,
540 particularly in the safer block groups in Downtown Detroit. Reduced vigilance while
541 drinking may account for the former, while the lack of parking security could explain
542 the latter. Patrols around parking areas may be the best method for dealing with it.

543 Previous studies have proposed a theory that individual patrons select the contexts
544 in which they drink based on their preferences (Morrison et al., 2016). We emphasized
545 the necessity of evaluating an alcohol establishment's security level in relation to its
546 theme and type in Detroit. Alcohol establishments with overcrowded and noisy
547 environments, such as sports bars and nightclubs, were more frequently collocated with
548 crime. For example, a "hip-hop" or "gangster rap" style live music bar may be more
549 prone to attract crimes than one featuring a "folk singer" (Graham et al., 2006). In sports

550 bars, “highly-identified dysfunctional sports fans” may be loud, obnoxious and
551 aggressive (Wann, 2001). With alcohol stimulation, verbal altercations between them
552 might escalate to violence like aggravated assault. Stylistic differences in alcohol
553 establishments were more pronounced in blocks farther from the city center, resulting
554 in a greater variation in the level of crime risk across bar types. In Downtown Detroit,
555 all types of alcohol establishments mainly showed consistent dispersion. Therefore,
556 location is a more significant factor influencing the level of danger in bars and
557 surrounding neighborhoods, while bar type can be used as a supporting element in
558 governance decisions. Targeted regulations, such as designating a dress code, limiting
559 alcohol availability in nightclubs, and increasing the number of security guards in sports
560 bars during tournaments, can make a difference.

561 Though the crime rate decreased during the COVID-19 period (Halford et al., 2020;
562 Meyer et al., 2022), serious crimes, which were generally not committed with co-
563 offenders, may have been more related to alcohol establishments locally. Several bars
564 in clusters became more collocated with rape, and more isolated bars located in the
565 neighborhoods became collocated with murder. While lockdowns and quarantine
566 clearly impacted group-based offending, they were unlikely to have any bearing on
567 criminal acts that generally occur in situations when peer groups are not present (Boman
568 & Gallupe, 2020). Given the fact that some bars had to suspend business during the
569 period, location and environment account for the occurrence of bar-related criminal
570 cases. Even though we still couldn’t conclude whether COVID-19 lockdowns were
571 positive for improving bar security, the CLQ results can be a reference for policymakers
572 when similar situations arise in the future.

573

574 5 Conclusion

575 This study explores the spatial dynamics between five types of liquor
576 establishments and seven types of crime patterns in Detroit, revealing consistent
577 relationships over time with significant variations based on bar types and locations.

578 Downtown bars were less associated with crime, clustered bars displayed diverse
579 patterns, and isolated bars faced higher risks. A clear link between bar safety and
580 surrounding crime levels highlights the need for targeted prevention strategies in high-
581 risk areas. These findings contribute to urban safety research and offer practical insights
582 for crime prevention and urban planning.

583 Future research should address several limitations to enhance the current study.
584 Expanding the scope to encompass a broader range of entertainment establishments and
585 urban infrastructure would provide a more holistic understanding of the contextual and
586 motivational factors influencing crime patterns. Furthermore, incorporating detailed
587 crime data and comprehensive references could uncover deeper connections between
588 incidents, thereby improving the analytical rigor and reliability of the findings. These
589 advancements would contribute to the formulation of targeted policies designed to
590 promote safer and more sustainable urban environments.

591

592

Crime Type	Definition
Aggravated Assault	An unlawful attack for the purpose of inflicting severe or aggravated bodily injury is frequently witnessed in bars.
Murder	The willful killing of one human being by another.
Rape	Penetration of the vagina or anus with any body part or object, or oral penetration by a sex organ of another person, without the consent of the victim. Bar-related rape has received widespread attention.
Robbery	The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear, which is more common in bars located in chaotic neighborhoods.
Burglary	The unlawful entry of a structure to commit a felony or theft.
Larceny Theft	The unlawful taking of property from the possession or constructive possession of another.
Motor Vehicle Theft	The theft or attempted theft of a motor vehicle.

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