American Journal of Criminal Justice
https://doi.org/10.1007/s12103-021-09614-z

Measuring Geographic Sentiment toward Police Using Social Media Data

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Received: 11 October 2020 / Accepted: 20 January 2021/Published online: 04 February 2021

Abstract

Using Twitter messages published online from October 2018 to June 2019, and opinion mining (OM) technology, the current study analyzes the geographic sentiments toward police in 82 metropolitan areas within the United States. Building on the frameworks of the neighborhood social contextual models, the construct validity of "sentiment toward the police" is assessed via its relationship with the features of various metropolitan areas. Results of the regression analysis indicate that the violent crime rate, racial heterogeneity, and economic disadvantage significantly affect sentiment toward the police. Our results suggest that opinion mining of social media can be an important instrument to understand public sentiment toward the police.

Keywords Opinion mining · Sentiment analysis · Twitter messages · Attitude towards police

Introduction

With the intense development of information technologies, the ways of communication between people have dramatically changed during the last few decades. Social media became an integrated part of people's lives as personal electronic communication devices, such as smartphones and the PC have become accessible to most of the world. People have gained open access to express their opinion on a diverse set of issues and

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policies through social media, such as Twitter, Facebook, and blogs. Meanwhile, technologies analyzing people's opinions, sentiments, attitudes, or emotions using social media streams, called opinion mining (OM), have also gained significant improvement in recent years (Liu, 2012).

OM, also referred to as sentiment analysis, is a method of identifying the emotional tone—positive or negative—of respondents' attitude towards varying products, organizations, or political issues through evaluating a large body of text (Liu, 2012). With the development of OM techniques, social scientists began to use this new technology to understand public opinions on a variety of phenomena, such as general public mood, sentiment towards U.S. presidential candidates, and sentiment toward different political parties. As OM has been gaining notice in research in a variety of disciplines, rarely has it been used in criminal justice research.

The current study attempts to fill that void by utilizing OM methods (Twitter data) to analyze sentiment toward the police across metropolitan areas in the United States. Specifically, Twitter posts containing the word "police" have been collected in 82 of the largest metropolitan areas from October 2018 to June 2019. Applying an algorithm for Natural Language Processing (NLP), the sentiment of each tweet is evaluated, and then aggregated to construct a geographic index of sentiment toward police for each of the metropolitan area.

Conventional research typically utilizes surveys to collect data and measure attitudes toward the police. This type of method uses structured or semi-structured questionnaires, and targets specific groups (e.g., high school or college students, crime victims). Unfortunately, the sample size may be limited, biases may occur, and the questions may be subjected to interpretation (Davies & Francis, 2018). The development of IT technology, big data, and the emergence of social media provides an alternative, innovative way of collecting data and measuring public opinion. First, the huge volume of text messages posted overcomes the small sample size problem experienced in many conventional surveys. Second, social media, such as Twitter may be less affected by research design problems or the experiment effect. Messages published on social media platforms may be more reliable in expressing opinions toward social issues, and consequently enhance measurement validity (Callegaro & Yang, 2018).

The purpose of this study is to use an alternative data collection method to develop a macro-level index of public attitudes toward the police. Once this index is constructed, its validity is assessed based on neighborhood contextual models. The linkages between geographic sentiment toward the police, sociodemographic characteristics, and crime rates are assessed.

The current study has serious policy implications for police administrators and public officials. At a time when there is an understandable dearth of public trust in the police, especially among young minority members, any innovative way of assessing public opinion is extremely valuable.

Literature Review

Opinion Mining and its Applications

As stated above, OM is a method of analyzing the public opinion or sentiment through the evaluation of a large body of text (Liu, 2012). OM is built upon the structure of artificial intelligence (AI) and its subfield, natural language processing (NLP). As AI technologies have developed, computer engineers and linguists began to train computers to classify texts into positive or negative feelings using machine learning techniques (Dave, Lawrence, & Pennock, 2003), and identify sentiment expressions in texts using natural language processing (NLP) (Nasukawa & Yi, 2003).

Although OM and sentiment analysis did not begin until the early 2000s, (Dave et al., 2003; Nasukawa & Yi, 2003), research on analyzing texts of written documents to predict sentiments toward social phenomena has a much longer history. For example, in 1989, Tims et al. collected economic news stories (Tims, Fan, & Freeman, 1989). Using content analysis, they scored paragraphs as either being favorable or unfavorable toward the economy, and subsequently created a cumulative index of the media's opinion towards the economy. Overall, scores based on the media's opinion accurately predicted the index of consumer sentiment.

Sources of conventional content analysis to explore people's opinion, however, were limited to traditional media prior to 2000. Diverse sources of OM became accessible with the growth of new technology and media since the new century. Meanwhile, with the development of machine learning algorithms, NLP techniques based on AI have dramatically developed during the past two decades. Private corporations forecast sales performance of products using OM. Liu, Huang, An, and Yu (2007) predicted the gross revenue of movies using sentiment analysis of blog posts. Their research established a model to extract latent sentiment factors of each film using OM algorithms, and successfully forecasted sales performance (Liu et al., 2007). In the interim, researchers began to program and analyze web messages and the sentiments reflected in these texts. For example, Othman, Belkaroui, and Faiz (2017) examined the most frequently stated features of certain products on Twitter, and then through sentiment analysis, estimated customers' satisfaction. Hridoy et al. collected millions of Twitter messages containing the phrase of "iPhone 6″ in seven American cities and constructed the geographic sentiment index of each one (Hridoy, Ekram, Islam, Ahmed, & Rahman, 2015).

As OM techniques have grown, social scientists began to use this to understand public opinions on a variety of social phenomena. Using Twitter feeds and sentiment analysis, Bollen et al. constructed a general mood index and used this to predict the Dow Jones Industrial Average over time (Bollen, Mao, & Zeng, 2011). O'Connor et al. analyzed sentiments toward two candidates during the 2008 United States presidential election using Twitter messages. Their study found that support for each candidate correlated with public polls across time (O'Connor, Balasubramanyan, Routledge, & Smith, 2010). OM has also been used to predict political elections outside of the United States. For example, in India, Sharma and Moh (2016) predicted the outcome of general elections based on the result of sentiment analysis for five national political parties using Twitter texts.

While OM has been utilized in a variety of disciplines, its application in criminal justice research is limited. A single study measuring public perceptions of police on Twitter using NLP was found (Oglesby-Neal, Tiry, & Kim, 2019). Oglesby-Neal and her colleagues (2019) classified 65 million tweets mentioning "police" or "cop" into positive, neutral, negative, and unspecified classes using Stanford core NLP, and examined the trends of negative tweets over time. Results of the study revealed public sentiment toward the police became more negative after the death of a man in police custody. This unfortunate event drew the attention of citizens and the media across the USA (Oglesby-Neal et al., 2019). While extant research has employed different methodologies to assess public opinions toward the police, our study uses this innovative technology to evaluate attitudes toward police by assessing online texts.

Attitudes toward Police

Since the middle of the twentieth century, public opinion about the police has been studied by various scholars (see Brandl, Frank, Worden, & Bynum, 1994). For example, researchers have examined the effectiveness of the police (Skogan, 2009), citizen satisfaction with police (Reisig & Parks, 2000; Sampson & Bartusch, 1998; Weitzer & Tuch, 2005), students' trust and respect for the police (Flexon, Lurigio, & Greenleaf, 2009), and confidence in the police (Cao, Frank, & Cullen, 1996; Jang, Joo, & Zhao, 2010). Although each of these taps into unique features, general attitudes toward the police appears to be the most wide-ranging and embraces the continuum from police effectiveness to satisfaction.

To measure attitude toward police (ATP), surveys have typically been utilized. For example, Weitzer and Tuch (2005) asked, "In general, how satisfied or dissatisfied are you with the police department/police officers in your city/neighborhood". Several theoretical frameworks, such as the demographic model, prior contact with the police model, and neighborhood social contextual model (Brown & Benedict, 2002) have been applied in order to guide the literature of ATP.

The demographic model focuses on individual demographic characteristics. Studies show that females (Cao, 2011; Dai & Jiang, 2016; Taylor, Turner, Esbensen, & Winfree Jr, 2001), Whites (Berthelot, McNeal, & Baldwin, 2018; Dai & Johnson, 2009), and older people (Cao & Stack, 2005; Ren, Cao, Lovrich, & Gaffney, 2005; Wu & Sun, 2009) are more likely to show greater satisfaction with the police and hold higher levels of confidence in the police. Individual experiences of contacting the police also affect attitudes. Results of prior studies reveal that positive experiences enhance public satisfaction (Reisig & Parks, 2000), and confidence in the police (Cao, 2011; Ren et al., 2005).

While demographic characteristics and previous contact with the police may explain individual variances in general attitudes toward police, accountability and city/neighborhood contexts are also important (Taylor et al. (2001). The accountability model suggests that individuals will hold the police responsible when they feel at greater risk due to the high levels of crime or public disorders. According to this model, citizens who feel unsafe and perceive crime or turmoil in their communities will be less likely to hold a positive view of the police (Cao et al., 1996; Luo, Ren, & Zhao, 2017; Ren et al., 2005; Reisig & Parks, 2000; Skogan, 2009; Sprott & Doob, 2014; Zhao, Tsai, Ren, & Lai, 2014).

Several studies support the argument of the accountability model. In research assessing the nexus between police effectiveness and neighborhood crime rates, there was a significant decrease in positive attitudes toward the police when residents observe more criminal activity in their community (Parker, Onyekwuluje, & Murty, 1995; Reisig & Parks, 2000; Sampson & Bartusch, 1998). In a multi-level study by Sampson and Bartusch (1998), satisfaction with the police decreased when neighborhood violent crime increased. Reisig and Parks (2000) also found that residents who reside in neighborhoods with higher rates of homicide are less likely to be satisfied with the police, albeit this disappeared when they controlled for neighborhood disadvantage or poverty rates.

In addition to the rate of crime, prior research has found that neighborhood characteristics and conditions are important (Luo et al., 2017; Maxson, Hennigan, & Sloane, 2003; Van Craen, 2013). One factor that influences ATP is the perception of disorder in the neighborhood. For example, using randomly selected mail surveys, Cao et al. (1996) examined the effect of perceived disorder on confidence in the police. The results of this study revealed that the perceived level of community disorder, including physical and social disorder, decreased confidence in the police net individual demographic information. Oh et al. used telephone surveys in Houston, TX and found that residents who perceive greater social disorder in their community were less likely to have confidence in the police (Oh, Ren, & He, 2019).

Along with perceived community disorder, low social cohesion and disadvantaged neighborhoods also trigger negative attitudes toward the police (Apple & O'Brien, 1983; Reisig & Parks, 2000; Schafer, Huebner, & Bynum, 2003). From social disorganization theory, racial and ethnic heterogeneity, residential mobility, and economic disadvantage reduces social cohesion and collective efficacy, and as a result, trust in the government and police is less likely to be formed (Morenoff, Sampson, & Raudenbush, 2001). For example, earlier research found that the racial component of a neighborhood affected the public's perception of police. As Apple and O'Brien (1983) found, when the proportion of the African Americans is high, negative experiences with the police will increase, which in turn affects overall attitude toward the police. Similar effects are found in a more recent study, which shows that a higher percentage of African Americans reduces satisfaction with the police (Wu, Sun, & Triplett, 2009). Moreover, some studies also reveal the influence of residential instability on perception of police trustworthiness (Lee, Boateng, Kim, & Binning, 2020). However, Sampson and Bartusch (1998) examined three neighborhoods and found concentrated disadvantage and immigrant concentration had a negative effect on satisfaction with the police, whereas residential stability was insignificant. Economic disadvantage is another factor that is linked to the perceptions of the police. Reisig and Parks (2000) found that concentrated economic disadvantage was a determinant of negative perceptions of the police. The authors found that individuals residing in areas experiencing high crime rates and racial segregation evaluated police effectiveness lower (Reisig & Parks, 2000).

In sum, attitudes toward the police are influenced by numerous variables, including individual demographic characteristics, prior experiences with police, and neighborhood contexts (Bolger, Lytle, & Bolger, 2021). Many of these are related to social cohesion and trust in government institutions. Since the current study develops a macro-level index of attitudes toward police, the emphasis is on aggregated social contextual variables. Building upon the framework of the neighborhood-social contextual model, it is anticipated that ATP will be more negative when crime rates and disruptive neighborhood characteristics increase.

The Current Study

The purpose of our study is to measure geographically based public sentiment toward the police utilizing OM, and then examine the construct validity of the measurement based on the neighborhood social contextual models. Specifically, based on the findings of earlier studies, we examine the connection between geographic sentiment toward the police and crime rates, concentrated disadvantage, racial/ethnic diversity, and residential stability. According to the theoretical framework discussed above, general attitudes toward the police are expected to be lower when neighborhoods experience higher levels of crime and disrupting features. If the construct of geographic sentiment toward the police is a valid measure of attitudes toward the police, the following hypotheses should follow:

Hypothesis 1 Higher crime rates negatively affect collective sentiments toward the police in a metropolitan area.

Hypothesis 2 Higher levels of disruptive neighborhood characteristics measured by concentrated disadvantage, racial/ethnic heterogeneity, and residential instability, will have a negative effect on sentiments towards police.

Methods

The Units of Analysis

For the purpose of our study, we utilize metropolitan areas identified by the U.S. Census Core-Based Statistical Areas (CBSA) as the units of analysis. Beginning from 2000, the Census Bureau has identified 922 CBSAs, which comprise 362 metropolitan statistical areas and 560 micropolitan areas in the United States. According to the Census Bureau, a metropolitan statistical area of CBSA, has at least one urbanized area of 50,000 or more population and adjacent territories that share social and economic characteristics with the core area. The present study initially selected the largest 100 metropolitan areas of CBSA based on population sizes; however, 18 CBSAs were dropped due to insufficient amounts of tweets in relevant topics or missing values of index crime in the 2017 Uniform Crime Report (UCR). The final number of metropolitan areas included in the current study is 82. (see Fig. 1).

Data

The data for this research were collected from three sources: (1) tweet messages from Twitter.com; (2) FBI Uniform Crime Reports, and (3) the American Community Survey data.

To collect the text of tweets, XY coordinates (longitude and latitude) of the center point for each metropolitan area were identified, and a radius for each metropolitan area was selected. A circle was then drawn to establish the boundary of the tweet data for each specific metropoplitan area using ArcGIS. Twitter.com claims that their Twitter PowerTrack operators utilize multiple methods to identify the location of users,

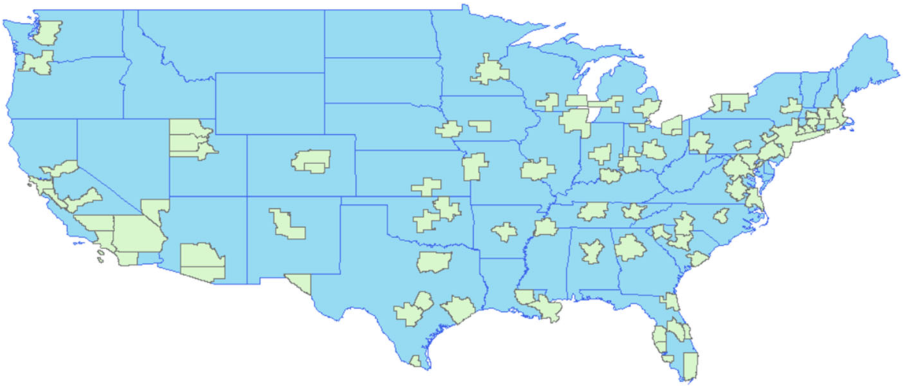

Fig. 1 Map of unit of analysis (CBSA)

although the accuracy of the operator is not realeased to public.[1] In general, the operator identifies the location of users for each tweet by their GPS signal of the device, contextual information in the tweet, and user's home location in their profile. Using *rtweet* package in R 3.5.2., we programmed the PC to randomly collect a maximum of 2000 tweets mentioning *"police"* in each identified metropolitan area per day. According to the policy of Twitter.com, the number of search results is limited to 18,000 every 15 min, therefore, a maximum of 2000 tweets per area was the most optimal limit to finish collecting tweets across 82 areas within 24 h. In smaller areas, the number of tweets with the key word, *"Police"* might not reach 2000 per day. The number of tweets in large areas, however, may reach the maximum limit. From October 2018 to June 2019, 3,917,894 tweet text messages mentioned *"police"* on Twitter.com were collected.

The second dataset was drawn from the UCR of the Federal Bureau of Investigation in 2017. UCR provides four types of violent crime (i.e., murder, rape, robbery, aggravated assault), and four types of property crime (i.e., burglary, larceny-theft, motor vehicle theft, and arson) at the agency level. Departments located in each metropolitan area were aggregated to obtain the crime data.

The third dataset was drawn from 2017 American Community Survey of the U.S. Census Bureau. Estimates of the population components for each metropolitan area, such as sex, race/ethnicity, median age, percentage of popoulation living below the poverty rate, percentage of female-headed household, educational attainment, percentage of residents who stay in the same residence over one year, foreign-born, and unemployment, were obtained from the American Community Survey.

Analytical Strategy

To analyze the sentiment of each tweet, we use the sentiment analysis package *syuzhet v1.04* (Jockers, 2017) in *R 3.5.2* since the package contains several lexicons and uses one of the popular NLP, Stanford coreNLP. *Syuzhet* is a

[1] For more information, refer the website https://developer.twitter.com/en/docs/tutorials/filtering-tweets-by-location.html.

sentence-level and lexicon-based sentiment analysis tool, which uses multiple custom sentiment dictionaries, including *bing, afinn, nrc, Stanford, and syuzhet* (Jockers, 2017). In this study, the *syuzhet* lexicon is selected because it comprises the largest number of positive/negative sentiment words, and it can provide scores of sentiments ranging from negative 1.0 to positive 1.0 by one decimal point (Jockers, 2017). Higher sentiment scores indicate a more positive attitude of the text. Individual sentiment scores are then aggregated to the metropolitan area level. The mean of the sentiment scores represent the geographically collective sentiment toward police in each metropolitan area.

To test the construct validity of the measurement, the three datasets are merged using the metropolitan area identification number. Using OLS regression modeling, the relationship between collective sentiment toward police, crime rates and community characteristics are examined based on the theoretical frameworks. *Stata SE 15.0* and *R 3.5.2* are utilized for data merging and statistical analysis.

Measures

Collective Sentiment toward Police

Collective sentiment toward the police for each metropolitan area was measured by averaging scores of sentiment analysis for all tweets including the key word *police* within the study area in the observation period. The sentiment of each twitter post was analyzed using *syuzhet* algorithm developed upon the sentiment extraction tool of the Natural Language Process (NLP) group at Stanford University. The package implemented dictionaries was developed in the Nebraska Literary Lab to extract and analyze sentiment lexicon from texts. The overall sentiment for each tweet was analyzed through *syuzhet* algorithm in R and converted to scores ranging from −1 to 1. The sentiment score over zero indicates that the sentiment of the text is positive, and vice versa. After analyzing the sentiment of 3,917,894 tweets, the average scores of the sentiment analysis for each metropolitan area was calculated. The mathematical equation for this calculation is:

$$y_i = \frac{1}{n}\sum_{k=1}^{n} f(x_{ik})$$

Where y_i	average sentiment scores of area i
Where *xik*	the sentiment score of each *k*th tweet within area i
Where n	the number of total tweets within area i

Crime Rate

Crime rate is measured by two composite measures: property crime rate and violent crime rate in the metropolitan area using 2017 UCR data. The property crime rate includes four types of crime including burglary, larceny-theft, motor vehicle theft, and arson, and violent crime rate includes four types of crime including murder, rape, robbery, and aggravated assault.

Racial Heterogeneity

As mentioned above, prior studies evidenced that race/ethnicity affects the perception of the police (Huang & Vaughn, 1996; Reisig & Parks, 2000; Schafer et al., 2003; Smith, Steadman, Minton, & Townsend, 1999; Worrall, 1999). Our study used the racial heterogeneity index to measure the degree of racial/ethnic minority mixture in the metropolitan area (see Blau, 1977). Racial heterogeneity of metropolitan areas was measured by a generalized heterogeneity formula:

$$Heterogeneity = 1 - \sum_k \left(\frac{n_k}{N}\right)^2$$

where k represents the number of categories of race and ethnicity; n_k means the population size of each racial/ethnic category, and N represents the population size of the metropolitan area. In our study, race and ethnicity were coded into eight categories: non-Hispanic White, Black, Hispanic, Alaska or Native Indian, Asian, Hawaiian, and Other.

Concentrated Disadvantage

Similar to earlier studies (Sampson, Raudenbush, & Earls, 1997; Raudenbush & Sampson, 1999; Lee, Zhang, & Hoover, 2013), the degree of concentrated disadvantage was measured by a factor score extracted from indicators of the proportion of citizens with high school diplomas, percentage of the populations below the poverty line, percentage of female-headed households and unemployment (Cronbach's alpha = .83). Results of the confirmatory factor analysis (CFA) show that the model with one factor adequately fits the data (CFI = .98, TLI = .94, SRMR = .02). Each indicator was sufficiently loaded on the extracted factor (> .60) with acceptable eigenvalue (=2.85). The extracted factor score of concentrated disadvantage varies between −1.59 (Madison, WI) and 5.19 (Los Angeles-Long Beach-Anaheim, CA).

Residential Stability

Residential stability was measured by a single variable, the percent of homeownership in the metropolitan area.

Results

During the nine-month study period, a total of 3,917,894 tweets mentioning *police* were collected across 82 CBSAs. Sentiment analysis using *syuzhet* algorithm reports that there are 1,589,555 negative sentiment tweets, 1,653,937 neutral tweets, and 674,402 positive sentiment tweets. Figure 2 presents examples of tweets messages, sentiment scores assigned by *syuzhet,* and distribution of the sentiment scores.

The count of negative tweets are 2.36 times (1,589,555/674,402) higher than the count of the positive ones. About one half of the tweets (1,653,937) did not contain sentiment related words in the text (sentiment score = 0). When aggregating the sentiment scores by the metropolitan area, the average sentiment scores are negative in all areas ranging from −.334 to −.198. In specific, Baltimore-Columbia-Towson in the state of Maryland had the lowest sentiment score (−.334), followed by St. Louis, MO (−.326), Riverside-San Bernardino-Ontario, CA (−.306), Las-Vegas-Henderson-Paradise, NV (−.300), and Dallas-Fort Worth-Arlington, TX (−.299). In contrast, Des Moines-West Des Moines, Iowa had the highest sentiment score (−.183), followed by Greenville–Anderson- Mauldin, SC (−.188), Wichita, KS (−.195), Buffalo – Cheektowaga–Niagara Falls, NY (−.197), and Madison, WI (−.198). Nevertheless, the overall sentiments of tweets mentioning police are negative in every metropolitan area examined in the current study. The mean attitude toward the police measure is −.249 with a standard deviation of .037 (Table 1).

Table 1 shows the description of each indicator variable across 82 metropolitan areas. They closely mirror the nationwide sociodemographic composition of the U.S.A. On average, the property crime rate (mean = 38.34) is higher than the violent crime rate (mean = 8.04). The variation of the racial heterogeneity index for 82 metropolitan areas ranged from .153 to .721. McAllen-Edinburg-Mission, TX area shows the lowest score of racial heterogeneity (.153), while the San Francisco-Oakland-Hayward, CA metro area shows the highest heterogeneity (.721). The factor score of concentrated disadvantage varies between −1.59 (Madison, WI) and 5.19 (Los Angeles-Long Beach-Anaheim, CA). The residential stability variable reports that the mean percentage of homeownership across 82 metropolitan areas is 64.01% with relatively small variance (SD = 4.92).

Table 2 presents the bivariate correlation among the variables. Attitude toward the police, measured by tweet messages, is negatively associated with the violent crime rate, racial heterogeneity, but positively linked to residential stability, whereas property crime rates and concentrated disadvantage are not associated with sentiment toward police in the bivariate model. Neither the violent crime rate nor the property crime rate shows a significant association with racial heterogeneity, concentrated disadvantage, or residential stability.

In the final step, the multivariate linear regression analysis was conducted to examine the relationship between attitudes toward police and crime rates and

Tweet Examples	Sentiment Score
NYPD Police Officer Channels 'Inner Spider-Man' to Rescue Cat From Fence. I have never seen a cat skeleton on top of a fence or in a tree ...but good job anyway.	+1.0
@T00DEEPHERRON i love you too police	+.8
Louisiana army veteran is tasered in her EYE and loses sight in it after 'police brutally attacked her'	-.6
What the fxxk are the police going to "investigate?" Literally just a group of 16yo's joking around and a bunch of bored middle aged white people are trying to ruin their lives forever.	-1.0

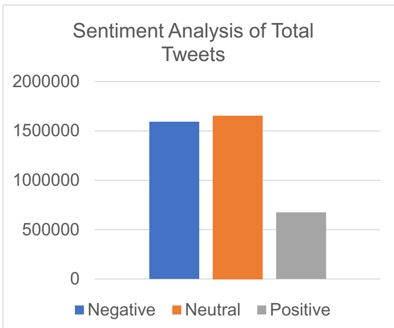

Fig. 2 Example and distribution of sentiment scores of tweets

Table 1 Descriptive statistics of variables

Variable	Mean	SD	Min	Max
Attitude toward Police	−.25	.04	−.33	−.18
Property Crime (per 1000 capita)	38.34	13.34	14.49	80.50
Violent Crime (per 1000 capita)	8.04	4.31	1.00	20.82
Racial Heterogeneity	.50	.13	.15	.72
Disadvantage				
Highschool diploma %	89.06	4.56	65.3	95.7
Below poverty %	8.99	3.25	4.7	26.1
Female headed household %	6.74	1.50	3.8	13.4
Unemployment %	5.07	1.32	2.3	9.9
Stability (Home owner rate)	64.01	4.92	48.4	75.3

$N = 82$

neighborhood contextual characteristics. Although some of the independent variables are correlated, multicollinearity was not found. The VIFs of the variable range from 1.07 to 1.76 (Table 3). Table 3 presents the results of the linear regression model on attitudes toward police as measured by the sentiment scores toward police using twitter messages. While the property crime rate is not significantly related to sentiment scores toward police, the violent crime rate is ($\beta = -.313$). As the rate of violent crime increases, the sentiment score decreases in that area. The results lead to partial support for hypothesis 1 which states higher crime rates will negatively affect collective sentiments toward the police. Moreover, sentiment toward police is negatively influenced by the racial heterogeneity index ($\beta = -.368$), while economic disadvantage and residential stability have no influence on the measurement. The results indicate Twitter users in the areas of greater racial heterogeneity are more likely to post negative tweets pertaining to the police. However, levels of economic disadvantage and residential stability had no influence on Twitter users' evaluation of the police. These results provide partial support for hypothesis 2, which suggests higher levels of disruptive neighborhood characteristics measured by concentrated disadvantage, racial/ethnic heterogeneity, and residential instability, will have a negative effect on sentiments towards police.

Table 2 Zero-order bivariate correlation

	Sentiment	Property crime	Violent crime	Racial heterogeneity	Disadvantage
Sentiment	–				
Property crime	−.053	–			
Violent crime	−.242*	.582***	–		
Racial heterogeneity	−.492***	.072	.072	–	
Disadvantage factor	.009	−.005	−.029	.1052	–
Residential stability	.368***	.103	.101	−.616***	−.232*

$N = 82$, *$p < .05$; ** $p < .01$; *** $p < .001$

Discussion and Conclusion

The emergence of big data and machine learning algorithms have inspired social scientists to locate new methodologies to better understand social phenomena. Although a substantial amount of research in marketing and business have utilized big data to predict consumer satisfaction, few efforts have been made to use big data in criminal justice. The present study focuses on OM techniques to measure general attitudes towards the police using Twitter posts. It is hypothesized that sentiment towards the police is negatively related to crime rates and the degree of disruptive neighborhood characteristics if the newly created measurement accurately captures citizens' view of the police.

The results of the multivariate model found the violent crime, and racial heterogeneity of the area was associated with less favorable attitudes toward police. However, the property crime rate, concentrated economic disadvantage, and residential stability failed to show a significant relationship with attitudes toward the police. These results are consistent with earlier studies. Several studies have previously concluded that the violent crime rate significantly lowers confidence in the police (Reisig & Parks, 2000; Sampson & Bartusch, 1998; Weitzer & Tuch, 2002).

When it comes to neighborhood social contexts, particularly disruptive characteristics on ATP, similar to earlier studies (e.g., Apple & O'Brien, 1983; Sampson & Bartusch, 1998; Schuman & Gruenberg, 1972), residential heterogeneity is negatively linked with the OM measurement of the police. However, other variables, including concentrated disadvantage, and residential stability, were unrelated to the sentiment measurement. A plausible explanation may be some potential explanatory variables in the multivariate model, such as political affiliation, are missing from the analysis. Prior studies have revealed political conservatism is positively correlated with the confidence in the police (Browning & Cao, 1992; Stack & Cao, 1998). Second, as revealed in the research by Stack and Cao (1998), individuals who achieve higher educational attainment are less likely to have confidence in the police. However, measurement errors can emerge when aggregating four items: high school diploma, below poverty line, female-headed household, and unemployment rates, to generate a single scale of concentrated disadvantage. Lastly, when it comes to the null effect of residential stability, Sampson and Bartusch (1998) also found residential stability within neighborhoods had no effect on satisfaction with the police. The findings of the null effect of residential stability on

Table 3 Results of multivariate regression analysis

	Coefficient	SE	β	t	VIF
Property Crime	.375	.307	.137	.99	1.53
Violent Crime	−2.634***	.995	−.313	−2.65	1.54
Racial Heterogeneity	−.107*	.036	−.368	−3.00	1.66
Disadvantage Factor	.005	.003	.142	1.45	1.07
Residential Stability	−.001	.001	.183	1.45	1.76

$N = 82$, *$p < .05$; ** $p < .01$; *** $p < .001$

attitudes toward police may indeed reinforce the validity of the newly developed measurement.

Results from our study provide several implications for policy and future research. First, it is possible to measure public sentiment toward government bodies, such as police, by collecting published online texts. Based on the remarkable development of NLP, computers can analyze human language and determine the overall sentiment of these texts. Relying on the real-time feature of OM, police departments may capture fluctuations in public responses to their agencies. As revealed by past studies, negative appraisal of the police can affect fear of crime (Oh et al., 2019), which in turn may impact collective efficacy (Markowitz, Bellair, Liska, & Liu, 2001). Police administrators should be cognizant of the changes in general sentiments toward the police. One of the benefits of the OM technique is that temporal changes in sentiment toward the police can be measured in real time. By doing so, departments can capture the impact of applied policies on citizens' views by comparing two-time points, before and after implementing these policies. For example, order maintenance policing was found to reduce police legitimacy among young minority males (Gau & Brunson, 2010). Policymakers and administrators may evaluate the rebound of new strategies by observing changes in general attitudes toward the police.

Second, future studies can employ available social media data as a compelling source of data when analyzing neighborhood disorder and crime. Although a few studies have attempted to measure the degree of social phenomena using Twitter (Williams, Burnap, & Sloan, 2017), social scientists underestimate the value of big data. In a recent study by Williams et al. (2017), the neighborhood disorder measurement developed by the number of "broken windows" related tweets significantly predicted crime rates in the United Kingdom. The results of our exploratory study provide support to the findings of Williams et al. (2017). Furthermore, when aggregating other sources of big data, such as administrative information (O'Brien, Sampson, & Winship, 2015), the use of big data can enable social scientists to generate more reasonable measurements to predict crime and other social problems.

The outcome of the current study should be interpreted with some caution. First, we analyzed the sentiment of text messages including the keyword "*Police*." The object of the message, however, cannot be identified. NLP technique used in this study is limited in detecting the semantic relationships between sentiment expressions and the objects, therefore, it is unclear whether responsibility is directed at the police or the offenders. For instance, in the sentence, *"This guy ran over a dog with his car and then got out of the car and killed the dog with force. If anyone knows who he is please call Olathe Police,"* the sentiment analysis tool returned negative scores for the sentence, although the writer was upset over the behavior of the offender. Future researchers must use caution in applying identification and classification methods to distinguish the object of the sentiment indicating verbs. Second, all tweets mentioning "*Police"* were collected which are not only written by citizens but also by police agencies. Although the tweets written by local police departments were eliminated, tweets reposted by citizens were not detected and removed. In fact, several tweets written by police agencies contained positive words to promote their programs and achievements. Future researchers should attempt to develop an instrument to exclude tweets written by the police. Third, our study only adopted a single keyword, "*Police"* instead of multiple ones referring to the police, such as law enforcement, cops or officers. It is possible that Twitter users who refer to the police as "cops" are more likely to embrace negative views (see Lund, 2018). Fourth, the accuracy of users' location is not clearly released from Twitter. According to the results of a recent study, less than a half (42%) of Twitter users reported valid information of their location in their profile (Hecht, Hong, Suh, & Chi, 2011). Future researchers should locate some innovative methods to identify the location of Twitter users (see Mahmud, Nichols, & Drews, 2014).

Police-community relations have been highly strained by the recent deaths of George Floyd, Breonna Taylor and others. Police legitimacy has been questioned, and there has even been talk of defunding or eliminating the police. Whereas community or neighborhood-oriented policing has been the dominant model since the early 1980s, there still appears to be a long way to go to establish public trust or confidence in the police, particularly among African Americans and Hispanics. The first order of business is to ascertain the gravity of this problem. Social media, such as Twitter provide another option. For social scientists, it may be one of the better tools to take the pulse of the community. Police research is constantly evolving, and big data appears to be an essential part of its future. As noted by Ferguson (2019:4) 'Predictive analytics, social network theory, and data mining technology have all developed to a point of sophistication such that big data policing is no longer a futuristic idea."

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