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Risk, race, and predictive policing: A critical race theory analysis of the strategic subject list

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Abstract

Predictive policing is a tool used increasingly by police departments that may exacerbate entrenched racial/ethnic disparities in the Prison Industrial Complex (PIC). Using a Critical Race Theory framework, we analyzed arrest data from a predictive policing program, the Strategic Subject List (SSL), and questioned how the SSL risk score (i.e., calculated risk for gun violence perpetration or victimization) predicts the arrested individual's race/ethnicity while accounting for local spatial conditions, including poverty and racial composition. Using multinomial logistic regression with community area fixed effects, results indicate that the risk score predicts the race/ethnicity of the arrested person while accounting for spatial context. As such, despite claims of scientific objectivity, we provide empirical evidence that the algorithmically-derived risk variable is racially biased. We discuss our study in the context of how the SSL reinforces a pseudoscientific justification of the PIC and call for the abolition of these tools broadly.

KEYWORDS

critical race theory, predictive policing, prison industrial complex, risk assessment

Highlights

- Guided by Critical Race Theory, this study assesses the racialization of risk in the SSL
- The PIC uses surveillance to aid the criminalization of racialized communities
- Multinomial logistic regression found strong bias in the SSL while controlling for spatial effects
- Predictive policing tools offer pseudoscientific justification of the PIC and cannot be reformed

INTRODUCTION

Predictive policing is a growing crime analysis strategy with the goal of strategically using big data to inform law enforcement daily operations and decision making (Brayne, 2018). In Chicago, one recently decommissioned predictive policing tool is the Strategic Subject List (SSL), a database of nearly 400,000 arrested individuals who were assigned an index score that determined predicted risk to be involved in gun violence (Chicago Data Portal, 2020; Jefferson, 2018; Tucek, 2019). While using data collection and analysis for crime "prevention" is appealing to some, previous arguments describe the SSL as inherently racially biased (Jefferson, 2018) and an evaluation study of the program found it to be ineffective (Saunders et al., 2016). Furthermore, the American Civil Liberties Union (ACLU) and other legal organizations have proposed that these technologies broadly can infringe upon citizen's Fourth Amendment rights, which mandate that police cannot stop a person beyond "reasonable suspicion" (ACLU, 2016). While the SSL specifically has been recently decommissioned, predictive policing is a growing multibillion-dollar industry (Wang, 2018) and empirical research is needed to further critique how these tools may exacerbate preexisting, racialized inequities in the criminal legal system (Henne & Troshynski, 2019).

Using a Critical Race Theory (CRT) as a guiding lens, this study empirically tests an assumption about the racialization of risk in a predictive policing tool. More critically, we situate our analysis in the context of the Prison Industrial Complex (PIC), which can be conceptualized as the interconnected web of governments, corporations, military, nonprofits, media, and other agents who have stake in maintaining and profiting from prisons, police, and surveillance (Davis, 2003). Incorporating the critiques of researchers (Benjamin, 2019; Jefferson, 2018; Wang, 2018), civil rights organizations (ACLU, 2016) and PIC abolitionists (Stop LAPD Spying Coalition & Free Radicals, 2020; Stop LAPD Spying Coalition, 2018, 2021), we question how "objective" and "color-evasive" tools such as the SSL reinforce pseudoscientific justifications of racist policing practices. "Color-evasion" is a purposeful phrase informed by Disability Critical Race Theory (Dis/Crit) that substitutes ableist language of "color-blindness" while building upon its theory (Annamma et al., 2017). Color or race-evasion recognizes how institutions and systems effortfully avoid race, ignore historical, social, and political contexts, and consider themselves to be "race-neutral" (i.e., not having any effect of race) while simultaneously maintaining racial hierarchy and subordination.

Last, in alignment with Quantitative CRT (Quant/Crit), our research is contextualized by the socio-historical and experiential knowledge of those communities most harshly affected by racism and other interlocking oppressive systems (Gillborn et al., 2018). A tool created by one such community that aids our interrogation of the SSL is the *Algorithmic Ecology* (See Figure 1), which helps us understand the broader social, economic, and political contexts of algorithms and data-driven technology (Stop LAPD Spying Coalition & Free Radicals, 2020). Created by community organizing collectives, Stop LAPD Spying Coalition and Free Radicals, the Algorithmic Ecology situates surveillance tools in their broader socioecological context by examining four levels that distinguish different power-holders and the relationships among them: ideologies (oppressive systems that maintain the surveillance state, e.g., anti-Black racism, colonialism, heteropatriarchy), institutions (entities and agents that create and maintain the algorithm, such as academic institutions), operations (the technical mechanics of the algorithm and the entities and agents who operate those mechanics, such as police departments), and community (those most impacted by the software and who has the power to resist it). In other words, the Algorithmic Ecology allows one to visualize power dynamics and relationships between those who have something to gain or lose with the changing of this technology. Thus, we name the ideologies of power, institutions, operations, and communities affected by the SSL. The study concludes with calls to engage in research

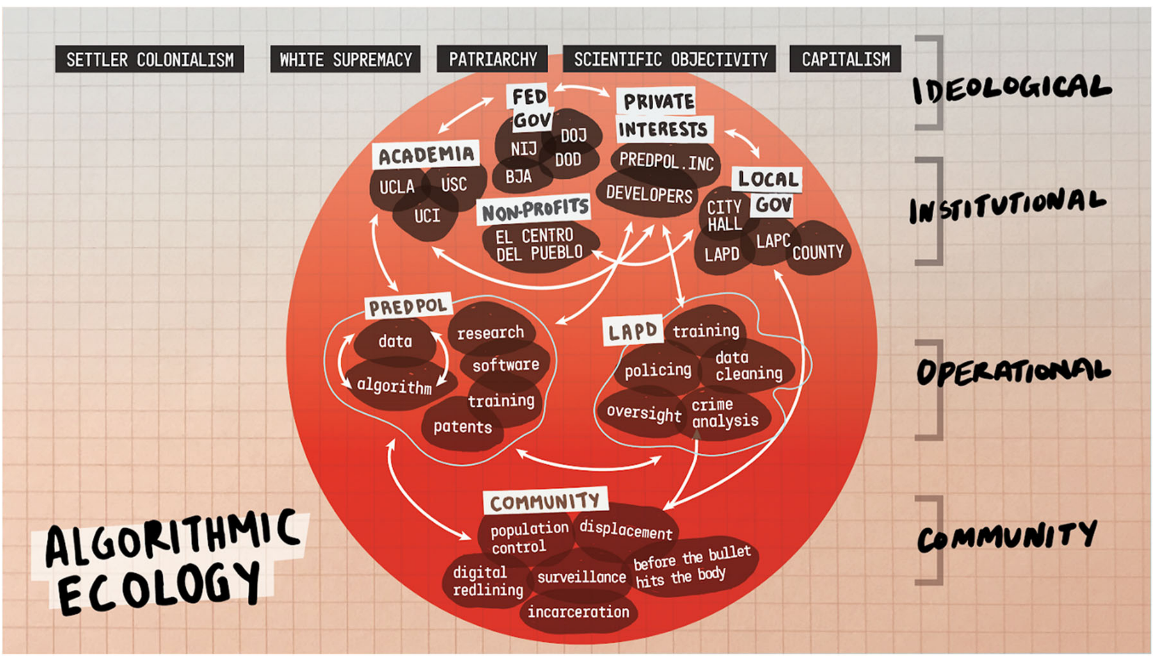

FIGURE 1 Stop LAPD Spying and Free Radicals (2020).

and organizing that builds the evidence-base for the abolition of algorithmic surveillance and the PIC.

LITERATURE REVIEW

An overview of predictive policing

Predictive policing can be defined as "the collection and analysis of data about previous crimes for identification and statistical prediction of individuals or geospatial areas with an increased probability of criminal activity to help developing policing intervention and prevention strategies and tactics" (Meijer & Wessels, 2019; p. 1033). As a form of crime analysis and "intelligence-led policing," predictive policing tools analyze historical data (e.g., crime and arrest data) to predict crime events or phenomena (Hardyns & Rummens, 2018). That is, predictive policing utilizes advanced data collection and analysis to predict where or when crimes occur, who commits crimes, or who is victimized by crimes. In theory, predictive policing is supposed to a method to improve law enforcement accountability by using an "objective" and "scientific" tool to strategically allocate policing resources to the places, people, and times when crime is meant to occur (Brayne, 2018). Advocates of predictive policing claim that there are no empirically associated negative implications with its use (Meijer & Wessels, 2019). Therefore, predictive policing has been described as a method to inform crime prevention and police reform (Brayne, 2017; Schenwar & Law, 2020).

The SSL itself is a database that includes arrest data spanning 2012–2016, including any person who was arrested or fingerprinted since 2013 (Tucek, 2019), who were then assigned a risk indicator for gun violence perpetration *or* victimization. The original list was created by Miles Wernick at the Illinois Institute of Technology, who reported that its original purpose was to alert law enforcement to individuals who were estimated to be a "party to violence," such that they could receive information on social services and police attention (Kunichoff & Sier, 2017). The research was funded through a Department of Justice Bureau of Justice Assistance grant to create a risk assessment algorithm that would use several person-centered variables to predict whether an individual would later be involved as either the shooter or victim of gun violence (Chicago Data Portal, 2020). The variables used to calculate risk included the number of times being the victim of a shooting incident, age at the latest arrest, number of times being the victim of aggravated battery or assault, number of prior arrests for violent offenses, supposed "gang affiliation," number of prior narcotic arrests, trend in recent criminal activity, and number of prior unlawful use of weapon arrests (Chicago Data Portal, 2020). While the algorithm does not include race or sex as predictor variables, many would argue that the previous list of measures may be highly correlated with race and gender, and thus function as "proxies" for those variables (Eckhouse et al., 2019; O'Neil, 2016).

There is relatively inconsistent evidence on the effectiveness of predictive policing (Hardyns & Rummens, 2018; Meijer & Wessels, 2019; Santos, 2014). A systematic review by Meijer and Wessels (2019) concludes that every individual model should be thoroughly evaluated, due to variations in efficacy across different software and types of crime. In fact, a pilot evaluation of the SSL found no significant reductions on gun-related crime (Saunders et al., 2016). Critical to this study, individuals on the SSL were more likely to be arrested, inferring that being strategically surveilled by police increases an individuals' contact with police and subsequently, increases risk of being arrested (Saunders et al., 2016). It is possible that these effects were due to theory failure, i.e., the underlying mechanisms or reasons as to how the prevention should work are erroneous (Welsh & Rocque, 2014). In another evaluation study testing a predictive policing program in Shreveport, Louisiana, researchers found no significant impact on property crime (Hunt et al., 2014). Yet other research found that predictive policing was the better predictor of future crime compared to analysts using hot spots mapping and that the predictive program led to greater reductions in crime (Mohler et al., 2015). However, it was aptly noted by Saunders et al. (2016) that two of the authors on that study are predictive policing software developers, a pattern of potential conflicting interests also observed by Stop LAPD Spying (2018).

While the effectiveness of these programs is clearly in question, researchers, legal scholars, and advocates have concerns about the ethics and implications of predictive policing (Barrett, 2017; Jefferson, 2018). In addition to eroding civilian's Fourth Amendment rights, a signed statement by ACLU (2016) shares several more concerns regarding predictive policing's usage and lack of transparency or accountability, particularly how such practices exasperate inequities in the criminal legal system by targeting racialized people. Jefferson asserted that the SSL "cannot fail but reinscribe place-based racial discrimination" (2018, p. 12) and similar concerns were raised by the City of Chicago Office of the Inspector General (2020). Furthermore, as a form of actuarial risk assessment (i.e., using data to calculate an individual's "risk"), predictive policing strategies may unfairly target communities that are already compounded by other sources of oppression and disadvantage, such as economic inequality and poverty (Silver & Miller, 2002). While these critiques pose grave concerns over how these tools reproduce and reinforce racial/ethnic disparities in the criminal legal system, predictive policing continues to flourish as a multibillion-dollar industry (Jefferson, 2020; Wang, 2018). To interrogate predictive policing broadly, we use SSL as case study to question how this tool racializes algorithmically-derived risk.

CRT and the PIC

CRT is a not a singular theory but rather a framework that helps us analyze subtle and systemic racism developed in United States (U.S.) institutions (Delgado & Stefancic, 2007), including the PIC. CRT makes explicit acknowledgments to the social construction of race, racism, and power as tools of subordination and social control (Brewer & Heitzeg, 2008). One of the central tenets of CRT holds that racial privileges for Whites and related oppression for racialized communities are deeply rooted in both U.S. history and law, thus making racism a "normal and ingrained feature of our landscape" (Delgado & Stefancic, 2000, p. xvii). Furthermore, CRT aims to challenge racial inequality by promoting race consciousness (Capers, 2009). Holding race at the center of analysis allows one to examine how racial social hierarchy is maintained through multiple systems of oppression and orients us to investigate bias, discrimination, and their consequences among racialized communities (Bonilla-Silva, 2002). At the same time, CRT allows for intersectional analysis, i.e., examining race in the context of other social identities and contexts to understand the unique experiences of individuals at multiple margins of society (Crutchfield et al., 2017; Dottolo & Stewart, 2008; Henne & Troshynski, 2019).

CRT holds that American laws are structured to maintain White privilege (Fornili, 2018) via initiatives that serve to benefit Whites and further marginalize non-White groups in predominantly urban settings. Essentially, these initiatives confound crime, race, and class resulting in one-dimensional discourse about criminals, gangs, and drug-infested neighborhoods (Brewer & Heitzeg, 2008). Coupled with new technological policing strategies such as the SSL, these initiatives result in over-policing of economically-divested communities and racialized people, especially of young Black men (Fagan, 2017). New policing strategies with technology are tools that help police departments achieve their goal: population control of poor urban communities for the benefit of White and privileged groups (Robinson, 2017; Vargas & Amparo Alves, 2010). For example, predictive policing has been praised as a cost-effective solution to help control crime with a guise of scientific objectivity (Benjamin, 2019; Eckhouse et al., 2019; Stop LAPD Spying Coalition, 2021). Tools like SSL do not use race as a predictor in their algorithms, yet they still strategically and discriminately target and surveille racialized communities (Schenwar & Law, 2020).

To be unequivocal: A CRT perspective demands that we name the PIC as an oppressive system that reproduces harm, stratification, and segregation through criminal legal enforcement that constrains mobility among poor folk living in racialized communities (Brewer & Heitzeg, 2008; Fagan, 2017; Robinson, 2017). As a result of the PIC, targeted communities are subject to unequal violence and/or protection of the law, hyper-surveillance, segregation, and neo-slave labor via mass incarceration, all in the name of public safety and crime control (Brewer & Heitzeg, 2008). There is a plethora of research demonstrating that the self-perpetuating PIC systematically harms people who are Black (Brown, 2020), Indigenous (Perry, 2006), immigrant (García Hernández, 2019), disabled (McCauley, 2017), and transgender (Stotzer, 2014) and others. There is a growing transnational movement to abolish the PIC (see DaViera et al., in press, this issue).

The role of predictive policing tools and technology are to use "science" to legitimize and incentivize profit from the PIC (B. Jefferson, 2020; Wang, 2018). For example, Wang (2018) details the history and expanse of PredPol, a predictive policing software originally developed by researchers at the University of California, Los Angeles (UCLA) for the U.S. military to track insurgents and casualties in Iraq. At the same time, the Los Angeles Police Department (LAPD) received grant funding to conduct predictive policing research. This police-university partnership resulted in the legitimization and use of PredPol (Stop LAPD Spying Coalition & Free Radicals, 2020; Stop LAPD Spying Coalition, 2018). PIC abolitionists argue that data-driven applications such as the SSL are a common reformist panacea to societal problems that would be better addressed through material and social investment in community (Davies et al., 2021; Schenwar & Law, 2020; Stop LAPD Spying Coalition, 2021; DaViera et al., in press, this issue). For example, abolitionist organizers from Stop LAPD Spying (2021) investigated the links between predictive policing, land, and gentrification in Skid Row and describe four kinds of state violence: *banishment* (i.e., removal from communities and homes), *containment* (restricting people from certain places), *blight* (neglecting communities to maintain race and class hierarchies), *extraction* (taking wealth and resources, divesting from communities) and *elimination* (killing and incarcerating people). This is an example of how "reforms" that aim to address social ills beget more state violence (Davies et al., 2021; Davis, 2003; Stop LAPD Spying Coalition, 2021).

Predictive policing and the "New Jim Code"

Why and how are predictive policing tools and technologies actually mechanisms of the broader PIC? Ruha Benjamin's exemplar *Race After Technology: Abolitionist Tools for the* New Jim Code (2019), details much of harm resulting from the "technological advances" that are meant to reform the PIC. Benjamin defines the "New Jim Code" as "the employment of new technologies that reflect and reproduce existing inequities but that are promoted and perceived as more objective or progressive than the discriminatory systems of a previous era" (Benjamin, 2019; p. 10). The *New Jim Code* is an intentional wordplay that linguistically connects the *Jim*

Crow era, when the U.S. enforced legalized racial segregation after the "abolition" of slavery, and the *Black Codes*, laws that restricted Black Americans rights. These policies created U.S. racial capitalist caste system that reinforced the same social control that was created during slavery (Pierce, 2017). Conceptualized as four dimensions, the New Jim Code highlights four technological mechanisms of social control: *engineered inequity*, the ways in which inequities are inherent in the design of technologies, *default discrimination*, inequities produced because of the lack of attention to these tools social and historical contexts, *coded exposure*, the under- and over-exposure of individuals to racialized technologies, and *technological benevolence*, such that "race-evasive" technology offers such "fixes" for societal ills while perpetuating them all the while. Benjamin stresses that "automated systems are in the business of not simply "predicting" but *producing* crime" (2019, p. 126, emphasis in the original).

Benjamin's toolkit provides further basis to question how the SSL is by design programmed to criminalize racialized communities. The risk variables that create the SSL risk score may function as "proxies" for race (Eckhouse et al., 2019; O'Neil, 2016), therefore, promoting *engineered inequity*. For example, "age at the latest arrest" and "number of prior narcotic arrests" are used as predictor variables, yet previous research has found that younger Black and Latine[1] individuals are more likely to be arrested for drug crimes compared to Whites (Mitchell & Caudy, 2015). "Number of times for being a victim of an aggravated battery or assault" and "being the victim of a shooting incident" may function as "proxies" for race because Black individuals are more likely than Whites to be victimized by gun violence (Berg, 2014) and Latine individuals also are victimized at rates higher than Whites (Langley & Sugarmann, 2018). This also relates to how the SSL promoted *default discrimination* because of how such crime and arrest data is created for the intent of criminalizing Black and Brown people (Schenwar & Law, 2020; Stop LAPD Spying, 2018). Non-White individuals are arrested at much greater rates both generally (Kochel et al., 2011) and in Chicago (Chicago Police Department, 2017). Furthermore, for both Black and Latine groups, darker skinned individuals are more likely to be arrested than those with lighter skin tones (Alcalá & Montoya, 2018; Kizer, 2017; Monk, 2019). Thus, one can infer that Black and Latine Chicagoan's *coded exposure* would place them at both over-representation in the SSL and heightened risk of being arrested again. Finally, the SSL demonstrates *technological benevolence* because this tool was designed to supplement police decision making through "objective" and "scientific" methods that does not "see" race (i.e., "evades color," Annamma et al., 2017) for the simple fact that it is not a predictor in the algorithm (Eckhouse et al., 2019).

Accounting for spatial context

In this study, we examine the racialization of "risk" in the context of where the person was arrested and henceforth placed in the SSL. Increasingly, researchers are examining how neighborhood environments influence arrest outcomes. A focus on neighborhoods is integral to analyses of predictive policing programs because their algorithms rely on historical, geographically-embedded data to predict (and therefore create) crime and criminals. Geographical data is not ahistorical, as it is reflects spatial conditions of manufactured oppression such as red-lining and gentrification, all of which have purpose for the PIC (Stop LAPD Spying Coalition, 2021). For example, previous research has found that neighborhood criminogenic characteristics (e.g., poverty, crime, and disadvantage) can influence arrest decision making (Gaston, 2019a) and concentrated poverty can explain statistical differences in arrest disparities (Kirk, 2008). The racial composition of the neighborhood where the person was arrested also influences these outcomes, such that Black individuals have greater risk of arrest in places with lower proportions of Black residents (Andersen, 2015; Fielding-Miller et al, 2020; Gaston 2019b). Notably, in St. Louis, Missouri, Black individuals are arrested for drug crimes at greater rates overall but moreover, were more likely to be arrested in majority White neighborhoods (Gaston, 2019b). Conversely, Whites were more likely to be arrested for drug crimes in majority Black neighborhoods, suggesting evidence of "out-of-place" racial profiling (Gaston, 2019b). However, when Black individuals are arrested in predominately Black neighborhoods, it may be via *proactive* policing practices, including officer-initiated stops and surveillance (Gaston, 2019a). Incorporating an abolitionist framing (Stop LAPD Spying Coalition, 2021), these findings highlight how police criminalize racialized and poor communities disparately in different neighborhoods. Similar to the types of violence observe in Stop LAPD Spying's research (2021), arresting and criminalizing poor people in poor places (e.g., Gaston 2019a and Kirk, 2008) is a form of "elimination" via incarceration. However, arresting Black people in non-Black spaces (Andersen, 2015; Fielding-Miller et al, 2020; Gaston 2019b) is a way to "contain" Black people from White communities. Taken together, analyses on race and arrests must also account for the spatial context of where the arrest occurred.

The current study

Amongst researchers, legal scholars, and abolitionist organizers, there are many arguments and critiques

[1] *Latine* is a gender-inclusive and culturally and linguistically relevant term for those of Latin American heritage (Blas, 2019).

against predictive policing, yet advocates claim that there are no empirically associated negative drawbacks (Meijer & Wessels, 2019) and critical empirical analyses of these programs are lacking (Henne & Troshynski, 2019). Thus, our analyses assess whether the SSL risk score is racialized while accounting for the local spatial, socioeconomic, and racial characteristics. The research question includes: *How does the SSL risk score predict the arrested individual's race/ethnicity while accounting for the census tract level, poverty and racial composition?*

As a "race critical code study" (Benjamin, 2019; p 25) we follow Henne and Troshynski's (2019) urgent recommendations to interrogate surveillance systems like the SSL with a CRT lens to question how such tools use social control to reinforce racial hierarchy. This research is critical because while the SSL has been recently and discretely decommissioned, predictive policing represents a multi-billion-dollar industry that will continue to expand (Jefferson, 2020; Wang, 2018). By examining the relationship between risk and race/ethnicity embedded in spatial context, this study expands upon previous literature and questions how scientifically "validated" and objective tools like the SSL are inherently designed to police Black and Latine individuals. To accomplish this goal, we draw upon publicly available data and utilize geospatial techniques to question the role of race in producing risk. Geocoding techniques created a dataset that linked individual-level data (SSL risk score and corresponding arrest of Black, Black Latine, White Latine, and White people) to census-tract levels data (the local poverty and racial composition of the neighborhood where the person was arrested). This allowed us to test for how the SSL risk score predicts the race/ethnicity of the arrested individual while controlling for the spatial context.

Hypothesis

Guided by the previously described history and literature, we only propose one hypothesis: *the SSL risk score will predict the race/ethnicity of the arrested individual, such that higher SSL scores will be associated with Black, Black Latine, and White Latine arrests, and lower SSL scores will be associated with White arrests, while accounting for the local spatial context*. Essentially, we propose that the analysis will reveal that the algorithmically-derived risk variable is racialized because the PIC disproportionately profiles, arrests, and incarcerates Black and Latine individuals at greater rates compared to Whites (Kochel et al., 2011). This is critical because previous research suggests that this manufactured risk would increase police attention and interactions in racialized communities, and result in greater risk of arrect (Saunders et al., 2016) and subsequently neighborhoods with concentrated criminalization and disenfranchisement. Regarding the local socioeconomic and racial/ethnic context, we do not propose specific hypotheses, however, we anticipate that contextual effects will relate uniquely to different racial/ethnic groups.

METHODS

The study employs multinomial logistic regression to assess the relationship between risk and race while controlling for spatial effects. However, a CRT approach would recognize that historically and currently, quantitative data, methods, and applications have been used against racialized communities to promote White supremacist ideology, maintain unjust systems, and uphold the status quo (Zuberi & Bonilla-Silva, 2008). However, these methods can be rectified by centering the principles of Quant/Crit (Garcia et al., 2018; Gillborn et al., 2018; Suzuki et al., 2021). Quant/Crit emphasizes that "all data are manufactured," and "all analyses are driven by human decisions" (Gillborn et al., 2018; p. 167). Therefore, no data nor category are neutral, as they all are shaped by racism (Suzuki et al., 2021). We add to the canon of Quant/Crit as these tenets guided our analytic approach and the broader scope of this study.

Sample and procedure

This study utilizes two sources of publicly available data, the SSL and the American Community Survey (ACS)—5 Year Estimates (2012–2016). The SSL is a publicly available dataset of 398,684 individuals who were arrested between August 1, 2012, to July 31, 2016 (Chicago Data Portal, 2020). Each of row of the database represents one unique person and includes several predicted risk indicators and arrest characteristic data, including the SSL score (i.e., predicted risk of being involved in gun violence), race/ethnicity, gender, age, a geographical positioning system (GPS) indicator of the census tract of where the individual was most recently arrested, and the corresponding community area (i.e., a larger spatial unit that comprises census tracts and commonly distinguishes neighborhood boundaries in Chicago) where the individual was arrested. The ACS was used to measure socioeconomic and racial characteristics of Chicago census tracts, including poverty and racial composition. Geocoding techniques linked all SSL data with a GPS point to census tract characteristics of where the arrest occurred.

This study uses a subsample of the SSL based on two criteria. Essential to this analysis is that each arrest was linked to a GPS indicator corresponding to the census tract where the arrest occurred. Importantly, out of the nearly 400,000 individuals in the SSL, only 224,235 had a corresponding GPS indicator. Using Welsch two sample *t*-tests, preliminary analyses investigated the difference between individuals with GPS data and those without, finding significant differences across the SSL score and race/ethnicity (see Table 1). Specifically, the analytic sample had higher mean SSL score, included more Black arrests, more Black Latine arrests, less White Latine arrests, and less White arrests. It is unknown as to why some individuals have GPS data, but this nevertheless poses implications for the interpretation and generalizability of this study. The second criteria restricted the sample to arrested individuals who were Black, Black Latine, White Latine, or White; notably, these populations comprised 98.2% of the full sample. The final sample included 210,074 arrested individuals.

Measures

SSL risk score

The SSL risk score is an algorithmically derived variable that determines risk of gun violence perpetration or victimization. The value ranges from 0 (*lowest risk*) to 500 (*highest risk*) with a mean score of 283.04 (SD = 61.09) in the analytic sample.

SSL race/ethnicity

Data were coded by the Chicago Police Department as "Black," "Black Hispanic," "White Hispanic," (Black Latine and White Latine, respectively) "White," "Asian/Pacific Islander," "American Indian/Alaskan Native" (formerly just "Indian"), and "Unknown." For the purpose of this study, we focus on four groups within this database, those coded as Black, Black Latine, White Latine, and White. Descriptive statistics demonstrate that the SSL predominately includes Black arrests (n = 143,917) and White Latine arrests (49,257). Less represented are White arrests (27,078) and Black Latine arrests (1,252).

Poverty

Measured at the census tract level, this was operationalized as the income-to-needs ratio (INR), which includes the percentage of individuals who reported an INR of less than 1, meaning living below the federal poverty level (M = 29.34%, SD = 14.44).

Racial composition

Also at the census tract, racial composition was operationalized as the percent of the population that identified as White (M = 29.61%, SD = 31.21).

Analytic approach

We employed a multinomial logistic regression model to assess the relationship between risk and race/ethnicity while controlling for spatial contextual variables because our outcome of interest is a non-ordered categorical variable. Specifically, our dependent variable whether a person who was arrested was recorded as Black, Black Latine, White Latine, or White. White is the reference group in our analysis so we can clearly identify the extent to which SSL risk scores disproportionately impact non-White individuals relative to White individuals. The key independent variables were the SSL risk score, which was divided by a constant of 100 and standardized (i.e., z-scored) to facilitate interpretation. To try to ensure that associations between the SSL risk score and race/ethnicity were not driven by spatial factors, we controlled for standardized measures of the census tract level poverty rate and racial composition. Importantly, we also include community area fixed effects (dichotomous measures of the 78 community areas). This allows us to account for all factors that do not change over time that differentiate one community area from another (Allison, 2005; Gottlieb & Flynn, 2021). To account for additional spatial spillover effects, we also controlled for the census tract level latitude and longitude. To further address lack of independence of observations across geographic space, we clustered standard errors by community areas. In sum, we assess the strength and direction of the relationship between risk and race while accounting for important confounders, such as census track level poverty and racial composition, all time invariant factors that differ between community areas, and geography (longitude and latitude). The results

TABLE 1 Welsch t-tests comparing the analytic sample (with GPS data) to the full sample (no GPS data).

	M (analytic sample)	M (full sample)	$t(df)$	p
SSL score	283.042	279.840	20.139 (437881)	<.001
Black	0.650	0.521	99.862 (475538)	<.001
Black Latine	0.005	0.004	3.6087 (432767)	<.001
White Latine	0.222	0.250	−24.785 (473378)	<.001
White	0.122	0.207	−89.131 (540666)	<.001

Abbreviation: GPS, geographical positioning system.

are reported as relative risk ratios (RRR), which can be interpreted such that an RRR higher than 1 indicates increased likelihood of the arrest being a specific race/ethnicity compared to White and an RRR of less than 1 infers a decreased likelihood of an arrest being that specific race/ethnicity relative to White. An RRR equaling 1 would infer no likelihood either way.

RESULTS

The results suggest a strong association between the SSL risk score and the race/ethnicity of the arrested individual (see Table 2). Overall, we find that as the SSL risk score increases, the likelihood that a person who was arrested is recorded as non-White relative to White increases. Specifically, we find that increases in the SSL score are associated with an increased likelihood that the arrested person was recorded as Black instead of White (RRR = 1.25, $p < .001$). This suggests that for every one-hundredth unit increase in the SSL score, the arrested person was 1.25 times more likely to be recorded as Black. We similarly found that the higher the SSL score, the more likely the individual was recorded as Black Latine relative to White (RRR = 1.36, $p < .001$) or White Latine (RRR = 1.32, $p < .001$). Taken together, our results lend support to our hypothesis: Black, Black Latine, and White Latine individuals who are arrested have higher risk scores than White individuals, even after accounting for differences in geographic location.

While not being the focus of this research, census tract level poverty and racial composition did nonetheless predict arrestee's race/ethnicity, such that being arrested in census tracts with greater poverty increased the likelihood that an arrested person was recorded as Black (RRR = 1.18, $p < .01$), while being in a census tract with fewer White people reduced the likelihood that an arrested person was recorded as Black (RRR = 0.37, $p < .001$). Being arrested in high poverty also significantly increased the likelihood that an arrested person was recorded as Black Latine (RRR = 1.36, $p < .001$) and White Latine (RRR = 1.30, $p < .001$) relative to White.

DISCUSSION

The purpose of this study was to provide empirical support for previous critiques (Henne & Troshynski, 2019; Jefferson, 2018) suggesting that predictive policing tools are problematic and designed to profile racialized people, leading to subsequent criminalization, disenfranchisement, and inequity. To do so, we examined Chicago's decommissioned predictive policing program, the SSL, with a CRT lens and found that the greater the SSL score (i.e., predicted gun violence risk), the more likely the arrested person was labeled as Black, Black Latine, or White Latine compared to being White, with notable variation across race and ethnicity. The results of study suggest that the SSL contains inexorable racial/ethnic bias, which we suggest implicates other predictive policing tools. Moreover, these programs are particularly insidious because of how they promote a pseudoscientific justification of racist policing practices (Jefferson, 2018, 2020). That is, while being objective, seemingly scientific on the surface, these tools merely reflect and reproduce violence and social control in the PIC, what Benjamin (2019) would call the purpose of the New Jim Code. Because predictive policing is treated as a crime prevention or variant of police reform (Brayne, 2017; Schenwar & Law, 2020), these results may be determined to be simply iatrogenic effects, i.e., ill effects of a well-intended intervention. However, similarly articulated by several scholars (Benjamin, 2019; Eckhouse et al., 2019; Wang, 2018) and the communities most oppressed by these technologies (Stop LAPD Spying Coalition, 2021) we concur that these effects are not by chance, but inherent in the design and intent of algorithmic (in)justice.

In our goal to provide an empirical support against predictive policing, we counteract arguments found in previous scholarships (e.g., Meijer & Wessels, 2019) and indeed find that there is racial/ethnic bias in the SSL. The higher the SSL score, the more likely the arrest was Black, Black Latine, or White Latine, while accounting for conditions of the spatial context, supporting the hypothesis. Black arrests were grossly overrepresented in the database, while Black Latines demonstrated the

TABLE 2 SSL risk score and census tract level characteristics predicting race/ethnicity.

	Black			Black Latine			White Latine		
Predictors	RRR	CI	p	RRR	CI	p	RRR	CI	p
SSL risk score	1.25	[1.17, 1.34]	**.000**	1.36	[1.23, 1.51]	**.000**	1.32	[1.26, 1.38]	**.000**
Poverty	1.18	[1.06, 1.32]	**.003**	1.36	[0.72, 1.37]	**.000**	1.30	[1.15, 1.47]	**.000**
Population white	0.37	[0.29, 0.49]	**.000**	0.99	[1.17, 1.58]	.956	1.10	[0.85, 1.42]	0.453
Observations	210,074								
Pseudo R^2	0.32								

Note: The reference group is arrests identified as White. Not shown (but were added in the model) includes latitude, longitude, and community area fixed effects variables. Full results are available from the authors upon request. The exact significant values have been added in bold.

Abbreviations: CI, confidence intervals; RRR, relative risk ratios; SSL, Strategic Subject List.

highest "risk" of being predicted to be "at-risk" of gun violence involvement. This is the expected result based on our previously described theory and literature. Because the variables comprising the SSL algorithm function as race "proxies" (Eckhouse et al., 2019; O'Neil, 2016), there is *engineered inequity* in the design of these tools. Black and Latine individuals are therefore subjected by *default discrimination* because the SSL would inherently predict higher SSL scores, and therefore Black and Latine individuals would be more likely to be arrested and re-arrested (Saunders et al., 2016). This *coded exposure*, i.e., de facto overrepresentation in the database, would promote racially discriminatory policing (Jefferson, 2018). Nevertheless, the SSL and other predictive policing tools are promoted as scientific because of the fact that they are developed by academic researchers and police-university partnerships (Jefferson, 2020; Wang, 2018), resulting a *technological benevolence*.

Our CRT approach revealed that there are notable differences across estimates of risk predicting race/ethnicity. This study found that the higher the SSL score, the more likely the arrest was Black, Black Latine, or White Latine, while accounting for conditions of the social context; however, the RRR (i.e., predicted likelihood that arrest would be categorized as a specific race/ethnicity) was greater for Black Latine and White Latine than for Black arrested individuals. That is, while controlling for poverty, racial composition, and other spatial effects, for every one-hundredth increase in the SSL score, the arrest is 1.36 times as likely to be Black Latine than White, 1.32 times as likely to be White Latine than White, and 1.25 times as likely to be Black than White. This demonstrates the import of utilizing a CRT approach to interrogate predictive policing systems (Henne & Troshynski, 2019). An intersectional interpretation would suggest that doubly marginalized individuals may be most at risk to be profiled and arrested. Additionally, these results could also suggest that there are other conditions not measured in the data that may relate to Black communities' "risk" in the SSL. It is critical that future research explores multiple axes of social identity and social context in how they explain and unveil inequities in the PIC.

In our efforts to contextualize our analysis with exploring the role of place, we also make contributions to the literature on the spatial and neighborhood context of arrest disparities. While this study resounded with previous research on how socioeconomic conditions relate to racial disparities in arrests, we did not find evidence of "out-of-place" racial profiling (Gaston, 2019b). That is, racial composition, operationalized as the percent population White, marginally negatively predicted Black arrests. This could be due to the specifications of our model or that we analyzed all police-generated SSL data, and not data that pertained to just drug-related arrests. It is also possible that this effect is due to the nature of predictive policing in practice, specifically, how the tool is used. Previous research (Gaston, 2019a) found that *proactive* policing tactics, including surveillance, increased Black individuals arrests in impoverished and predominately non-White places. Official city records (City of Chicago Office of the Inspector General, 2020) show that the SSL was utilized to proactively surveille and interact with arrested individuals in four ways: The custom notification program, where individuals are referred to social services, which is managed by the John Jay College of Criminal Justice (Kunichoff & Sier, 2017). The targeted repeat-offender apprehension and prosecution (TRAP) program, where the SSL risk score could be one of 10 potential criteria for "enhanced prosecution to detain, convict, and incarcerate" individuals deemed at risk. Thirdly, the Gang Violence Reduction Strategy (GVRS), a multicomponent strategy designed to gather, analyze, disseminate information about gangs, associates, and factions. Lastly, the SSL score was used in arrest reports. Because these tactics are largely proactive (instead of reactive) they may increase the likelihood that arrests in Black neighborhoods are more likely to be people who simply live in those communities.

Limitations and future research directions

This study has limitations and there are several considerations for future research. First, this study closely explored the SSL, but there are many other predictive policing programs and software that operate differently and may pose unique risks and implications for communities targeted by the PIC. We urge other researchers to take upon the responsibility to question these "technological advances" in police reform and further analyze them through a race conscious and critical lens. It must be discussed that using police data comes with several uncertainties. It is unknown as to what each individual was arrested for, and it is unclear why some individuals in the database had GPS data and some did not. The analytic sample had higher SSL scores and included more Black and Black Latine arrests compared to the entire SSL dataset. We speculate that the differences in risk and race/ethnicity may be because the SSL is largely a proactive approach that could be targeting darker-skinned individuals (Alcalá & Montoya, 2018; Kizer, 2017; Monk, 2019). Some researchers will search for situational or psychological reasons as to why these disparities exist. While this is important, a CRT perspective would argue that racism, colonialism, among other structures of violence, undergird the reasons why police disproportionately surveille Black and Latine communities. *Dark Matters: On the Surveillance of Blackness* (Browne, 2015) traces the history of how Black people have surveilled in the U.S. since the days of transatlantic slavery and how modern practices replicate the same social control, violence, surveillance and branding. We suggest that this historical perspective is applied to all future research on the criminal legal system and PIC.

There is also the question of how individual's race/ethnicity is coded in the database. That is, it is currently unknown if individuals are allowed to self-identify their race/ethnicity during arrest. These codes may be in fact reflect *perceived*, and not quite actual, race/ethnicity, such as if the arresting officer speculated the arrestee's race/ethnicity without asking the arrested individual. A race critical and conscious perspective argues that we recognize the social construction and production of race and racialized data as a mechanism of oppressive systems (Brewer & Heitzeg, 2008; Delgado & Stefancic, 2007). This raises several questions. Is the low representation of Black Latine individuals due to a lower arrest rate or were those individuals incorrectly coded as either Black or White Latine in the database? What role does the local racial composition play in how police perceive race/ethnicity when making arrests? Testing these questions was not possible with the data utilized for this study. Future studies utilizing police arrest data should be critical of how such data is collected and coded.

Another consideration that this research could not address but emphasizes that we must explore the material implications of being surveilled. Grassroots research like that completed by Stop LAPD Spying (2018) documents the lived experience of residing under algorithmic surveillance, finding that individuals are generally aware of what predictive policing is but also *feel* that they are being surveilled. As described by one focus group participant, "I feel like they already know who you are by the time they stop you or give you a citation. They already know your name and who you are hanging out with" (Stop LAPD Spying, 2018; pg. 37). This research found that 71% of surveyed participants reported feeling that they or their community are "profiled, abused, targeted, or stalked" by the police. Being stopped by police and the feeling of being "watched" has several psychological implications (Gottlieb & Wilson, 2019; Sewell et al., 2016; Toro et al., 2019). Police stops are known to lead to psychological distress and delinquency over time among Black and Latino boys (Toro et al., 2019). This is compounded by the psychological distress of living in a community where police stops are common (Sewell et al., 2016). Sewell et al. (2016) tested for differences in how community-level measures of direct (i.e., being stopped) and indirect police contact (surveillance), finding that both have detrimental impacts on the mental health of Black men, contributing to further health inequity.

Implications and conclusion

Researchers must reject this surveillance as "science" and continue to unveil inequities and harm produced by the PIC (DaViera et al., in press, this issue). The state of the literature, and in fact much of the research synthesized for this study, generally makes suggestions that the PIC can be reformed. Reforming the PIC makes assumptions that systems such as police and prisons are designed to protect communities, however abolitionist deconstructions of this structures find that these attempts fail to make prolonged, systemic change (DaViera & Grant, 2020). We argue that you cannot reform these tools; effort, resources, and time could be better spent on actively supporting those most impacted by the PIC. The SSL itself was a "reform" with goals of preventing crime and violence, and reducing racial/ethnic bias in policing (Brayne, 2017). Using science and technology to supplement and refine policing is a practice that goes back to the early 19th century (Jefferson, 2020) that has long been utilized to advance political agendas (Schenwar & Law, 2020). For example, Jefferson (2020) accounts for how data-driven policing in Chicago extended out of efforts to fight the "wars" on poverty and crime, more recently popularized by former Chicago Mayor Rahm Emanuel. He "proposed big data analytics as a remedy to the social wreckage of the recession. Digitally enhanced law enforcement, he proclaimed, could stop the most destitute of neighborhoods from turning into a "lost generation that slides into crime and poverty" (Jefferson, 2020; p. 127). This demonstrates how racialized power hierarchies are maintained through the use of science and objectivity. Thus, epistemology becomes a tool of oppression, created by researchers and operated by the state. The SSL may be seen as scientific and objective, albeit a failed experiment, and was therefore decommissioned (in addition to the end of funding); however, this study poses a warning that there will be more tools, more surveillance, and subsequently, more racialized harm, and a more expansive, supposed "gentler" PIC (Schenwar & Law, 2020).

We must contend that the real root of racially discriminatory policing is not that the data they use is merely biased, but the problem is the actual system of policing and the broader PIC (Stop LAPD Spying & Free Radicals, 2020; DaViera et al., in press, this issue). Community-based organizers and abolitionists like the Stop LAPD Spying Coalition and Free Radicals (2020) have demanded that researchers that move beyond critiques of "dirty data." Arguments that focus on data bias alone give premise to the suggestions that "better data" would produce better outcomes, thus still legitimizing predictive policing. They specifically state: "No matter the intent, academics and nonprofits who limit their criticisms of data-driven policing to the details and call for the reform of these practices buy into the racist premise that there are people whose policing can be scientifically or objectively justified" (Stop LAPD Spying Coalition, 2021; p. 73). As researchers, it is our responsibility to demand and ensure that our science is not used as a tool of the oppressor (Grant & DaViera, in press). To garner the support and evidence needed to abolish predictive policing, and the PIC broadly, we must document its oppression and validate the lived experiences of those affected by racist and colonial institutions. It is with urgency that we specify that tools like the SSL are intentionally oppressive, and it is critical that we provide research supported justification for their abolition.

AUTHOR CONTRIBUTIONS

Andrea DaViera, Marbella Uriostegui, Cynthia Onyeka, and Aaron Gottlieb: contributed to the overall goal, concept, and design of the study. **Andrea DaViera and Aaron Gottlieb**: gathered and analyzed all data. **Andrea DaViera, Marbella Uriostegui, and Cynthia Onyek**a: assisted in the writing of the initial draft. **Andrea DaViera**: wrote the remaining drafts of the paper and all authors reviewed the final draft.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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