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A Bias-Free Predictive Policing Tool?: An Evaluation of the NYPD's Patternizr

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A BIAS-FREE PREDICTIVE POLICING TOOL?: AN EVALUATION OF THE NYPD’S PATTERNIZR

*Molly Griffard**

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INTRODUCTION

In December 2016, the New York City Police Department (NYPD) began using a new predictive policing tool called “Patternizr” to assist investigators in recognizing potential crime patterns.¹ The algorithm, built on past crime data, is currently used to spot patterns of robberies, burglaries, and grand larcenies that may have been committed by the same person or group of people.² The NYPD shared news of this development in February 2019 with the publication of an academic article by Patternizr’s developers, Alex Chohlas-Wood, former Director of Analytics at the NYPD, and Evan Levine, Assistant Commissioner of Data Analytics at the NYPD.³ Despite acknowledging the “growing concern that predictive policing tools may perpetuate disparate impact,” Chohlas-Wood and Levine explain how they designed Patternizr to minimize bias.⁴ They claim to have accomplished this goal by blinding the models to “sensitive suspect information” including race and gender, as well as “ke[eping] potential proxy variables for sensitive information — particularly location — extremely coarse” in order to avoid correlation of crime

1. Alex Chohlas-Wood & E. S. Levine, *A Recommendation Engine to Aid in Identifying Crime Patterns*, 49 *INFORMS J. ON APPLIED ANALYTICS* 154 (2019).

2. Brian Holak, *NYPD’s Patternizr Crime Analysis Tool Raises AI Bias Concerns*, *SEARCHBUSINESSANALYTICS.COM* (Mar. 14, 2019), <https://searchbusinessanalytics.techtarget.com/news/252459511/NYPDs-Patternizr-crime-analysis-tool-raises-AI-bias-concerns> [https://perma.cc/B6KA-HD29] (quoting NYPD spokesperson Devora Kaye).

3. Chohlas-Wood & Levine, *supra* note 1.

4. *Id.* at 160.

patterns with “sensitive attributes.”⁵ They asserted that “Patternizr is a new, effective, and fair recommendation engine . . . [that] when used properly, encourage[s] precision policing approaches instead of widespread, heavy-handed enforcement techniques.”⁶ This Article considers whether the developers’ goal to build a bias-free predictive policing tool is actually achievable given the limitations of its inputs — racially-biased historic criminal justice data — and its users — humans with the potential for errors and cognitive biases.

This Article further considers the problems that may arise as a result of the NYPD’s use of Patternizr and attempts to evaluate whether it is a “fair,” unbiased tool, as the NYPD and Patternizr developers claimed. Moreover, this Article seeks to further evaluate that claim based on the information disclosed in the Chohlas-Wood and Levine paper. This Article identifies specific areas where more information and independent review is needed to fully interrogate this claim.

In order to evaluate Patternizr, Part I reviews the extensive literature on the use of algorithms in the criminal legal system and then draws from these insights to evaluate potential issues raised by Patternizr. This Part also provides a brief background on predictive policing, tracking its evolution from computer-generated “heat maps” to increasingly sophisticated predictive models. Following this background, Part I provides an overview of racial justice and civil liberties issues raised by predictive policing in general.

Part II focuses on Patternizr, first providing background on its development and the capabilities of the software. Part II then considers whether and how Patternizr could be used in ways that run afoul of the rights of those accused of crimes, specifically looking at issues of potential for error and due process concerns, racial bias, and Fourth Amendment rights.

Part III provides recommendations for advocates to help curb the potential harms from this new predictive policing tool. It considers potential policy solutions, ranging from an outright ban of predictive policing algorithms to regulations that would increase transparency and accountability in the use of predictive policing. Further, Part III recommends methods for criminal defense attorneys to seek

5. *Id.* Chohlas-Wood and Levine give the example of race as a “sensitive suspect attribute.” *Id.* at 157. They characterize characteristics such as height, weight, force used, and number of suspects as “nonsensitive.” *Id.* at 158.

6. *Id.* at 163.

disclosure of the use of Patternizr in criminal cases under New York's new discovery statute, set to go into effect in January 2020.

The Article does not focus on Patternizr's potential efficacy of reducing crime or identifying individuals suspected of committing crimes. As such, traditional crime-solving efficacy measures are not used to evaluate the algorithm. Instead, this Article focuses on how the NYPD's use of Patternizr raises serious civil rights and liberties issues for those accused of crimes and how tools such as Patternizer contribute to racially-biased mass incarceration and mass surveillance of New York's communities of color.

I. BACKGROUND ON PREDICTIVE POLICING

Predictive policing is an umbrella term that encompasses “the application of analytical techniques . . . to identify likely targets for police intervention and prevent crime or solve past crime” by making statistical predictions.⁷ It is “based on directed, information-based patrol; rapid response supported by fact-based prepositioning of assets; and proactive, intelligence-based tactics, strategy, and policy.”⁸ Its proponents argue that predictive policing can revolutionize policing, help cash-strapped departments do more with less, and drastically increase public safety.⁹ Its critics, including academics and leading criminal justice reform advocacy groups, caution that “[p]redictive policing tools threaten to provide a misleading and undeserved imprimatur of impartiality for an institution that desperately needs fundamental change.”¹⁰ The following Section traces a brief history of predictive policing followed by racial justice and civil liberties concerns raised by the use of algorithms in the criminal legal system.

7. *Id.* at 154 (quoting WALTER L. PERRY ET AL., PREDICTIVE POLICING: THE ROLE OF CRIME FORECASTING IN LAW ENFORCEMENT OPERATIONS 1–2 (RAND Corp. 2013)).

8. Charlie Beck & Colleen McCue, *Predictive Policing: What Can We Learn from Wal-Mart and Amazon about Fighting Crime in a Recession?*, POLICE CHIEF MAG. (Mar. 13, 2014), <http://www.policechiefmagazine.org/predictive-policing-what-can-we-learn-from-wal-mart-and-amazon-about-fighting-crime-in-a-recession/> [<https://perma.cc/D52N-3U36>].

9. *Id.*

10. AMERICAN CIVIL LIBERTIES UNION & 16 CIVIL RIGHTS PRIVACY, RACIAL JUSTICE & TECH. ORGS., PREDICTIVE POLICING TODAY: A SHARED STATEMENT OF CIVIL RIGHTS CONCERNS (2016) [hereinafter ACLU & 16 CIVIL RIGHTS ORGS.], <https://www.aclu.org/other/statement-concern-about-predictive-policing-aclu-and-16-civil-rights-privacy-racial-justice> [<https://perma.cc/A459-SZ7Z>].

A. A Short History of Predictive Policing

Professor Andrew G. Ferguson divides predictive policing technology into three distinct generations.¹¹ First, police departments developed algorithms to predict the locations of property crimes.¹² Second, this evolved into a focus on predicting the locations of violent crimes, including robberies, shootings, and gang-related violence.¹³ The most recent evolution, noted by Ferguson, is a shift to predictive policing tools that can forecast specific individuals who are predicted to be involved in crimes either as perpetrators or victims.¹⁴ Professor Ferguson cautions that each generation of predictive policing tools “may be based on historical data with statistically significant correlations, but the analyses and civil liberties concerns differ.”¹⁵ Although his generation model does not include a category into which Patternizr can easily be characterized, as Patternizr neither predicts locations nor people who may be involved with future crimes, Ferguson’s approach of differentiating the various generations of predictive policing tools and evaluating each for specific concerns raised is important. For example, the concerns raised regarding place-based policing programs differ from a new pattern-based tool like Patternizr. However, it is important to understand concerns about predictive policing more broadly in order to effectively analyze this new generation of tools.

Ferguson and others note that the NYPD has long sought to increase policing efficiency through the use of data and technology.¹⁶ In 1994, the NYPD developed Compstat — computer comparison statistics — to “compile information on crimes, victims, times of day crimes took place, and other details that enable precinct officials to spot emerging crime patterns.”¹⁷ Following New York City’s lead, other cities implemented various data-driven systems to better allocate policing resources, often using a form of hotspot policing

11. Andrew G. Ferguson, *Policing Predictive Policing*, 94 WASH. U. L. REV. 1109, 1112–13, 1114, 1136 (2017) [hereinafter Ferguson, *Policing Predictive Policing*].

12. *Id.* at 1144.

13. *Id.* at 1126–37.

14. *Id.* at 1137–43.

15. *Id.* at 1114.

16. *Id.* at 1124; Harvard Gov’t Innovators Network, *Compstat: A Crime Reduction Management Tool*, INNOVATIONS IN AM. GOV. AWARDS (1996), <https://www.innovations.harvard.edu/compstat-crime-reduction-management-tool> [https://perma.cc/PLX9-ARLE].

17. Harvard Gov’t Innovators Network, *supra* note 16.

where analysts plotted crime reports on a map and sent officers to the areas where crime was most concentrated.¹⁸

Taking hotspot policing to the next level beyond Compstat, the Los Angeles Police Department (LAPD) collaborated with academics to develop an algorithm to predict likely areas where property crimes would occur.¹⁹ Starting in 2010, the LAPD used these predictions to deploy officers to specific areas where crimes were anticipated in the hopes of having a deterrent effect.²⁰ In an influential article directed at policing insiders, the LAPD Chief of Detectives and collaborating data scientist urged the law enforcement community to adopt lessons from business analytics and touted the success of the LAPD's early experiments with predictive policing.²¹

As advances in predictive policing gained national attention, the academics who developed the algorithm that predicted areas where crime was likely to occur formed PredPol, Inc., a company that sells predictive policing software to law enforcement agencies across the country.²² The early experiments in using algorithms to predict and deter crime morphed into “a multi-million dollar business, and large-scale marketing campaign to sell predictive policing programs.”²³ Other companies, such as Palantir, HunchLabs, and IBM, also sell technologies similar to PredPol's software to help police departments identify crime trends and forecast locations and offenders of future crimes.²⁴ Now that predictive policing is a profitable industry, developers of new predictive policing technologies may have financial incentives to trumpet claims of efficacy and fairness while competing for lucrative government contracts. As will be discussed later in this Article, these incentives raise the stakes for governing bodies and the public to seek outside audits of predictive policing tools and not simply take the assertions of fairness and efficacy from developers at face value.²⁵

18. Ferguson, *Policing Predictive Policing*, *supra* note 11, at 1126.

19. *Id.* at 1126–27.

20. Mark Puente, *LAPD Pioneered Predicting Crime with Data. Many Police Don't Think It Works*, L.A. TIMES (July 3, 2019), <https://www.latimes.com/local/lanow/la-me-lapd-precision-policing-data-20190703-story.html> [<https://perma.cc/YT75-PB8W>]; Ferguson, *Policing Predictive Policing*, *supra* note 11, at 1126–30.

21. Beck & McCue, *supra* note 8.

22. Ferguson, *Policing Predictive Policing*, *supra* note 11, at 1131.

23. *Id.* at 1132.

24. See Kristian Lum & William Isaac, *To Predict and Serve?*, SIGNIFICANCE 15, 16 (2016).

25. See *infra* Section III.B.i.

B. Critiques of Predictive Policing and “Actuarial Justice”

With the rise of the use of data and algorithms in many areas of criminal procedure — including risk assessments for bail determinations, sentencing, and parole determinations²⁶ in addition to predictive policing tools²⁷ — researchers and reform advocates alike have raised concerns about the transparency and fairness of the algorithms upon which the criminal legal system increasingly relies. These concerns center on issues of racial bias, automation and confirmation bias, Fourth Amendment issues, data accuracy and due process concerns, and democratic oversight of the use of these new policing tools. This Section briefly outlines each of these concerns and gathers insights from commentators and advocates about suggested steps to evaluate predictive policing tools.

i. Racial Biases

The potential for racial biases to be built into algorithms used in the criminal legal system has been the focus of much concern and research by social scientists, legal scholars, and advocates. Researchers point out that algorithms are prone to reproduce racial biases in the data sets on which the algorithms are trained, even when the data does not explicitly include race as a factor.²⁸ One reason is that police databases provide an incomplete and unrepresentative picture of all crimes, likely due to implicit and explicit racial bias informing areas where police patrol and who they stop, search, and arrest.²⁹ Professor Barry Friedman explains this dynamic:

Algorithms don’t have to look at race to be racist. Whether written by humans or a product of machine learning, algorithms take past facts and magnify them into future police actions. They rely heavily on criminal records. Much of street policing in recent years — stop and frisk, marijuana enforcement, catching fare-beaters — has been deployed disproportionately against minorities and in poor neighborhoods. Police may ‘go where the crime is,’ but because so

26. See Julia Angwin et al., *Machine Bias*, PROPUBLICA (May 23, 2016), <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing> [<https://perma.cc/G5DN-7QGQ>].

27. See *infra* Section II.A.

28. See, e.g., Lum & Isaac, *supra* note 24, at 17–18 (PredPol “has been described by its founders as a parsimonious race-neutral system that uses ‘only three data points in making predictions: past type of crime, place of crime and time of crime. It uses no personal information about individuals or groups of individuals, eliminating any personal liberties and profiling concerns.’”); see also Angwin et al., *supra* note 26.

29. Lum & Isaac, *supra* note 24, at 15–16.

much focus has been on low-level offenses in disadvantaged areas that are ignored elsewhere, these algorithms make it inevitable that the police will return to these places time and again.³⁰

Additionally, no one is immune from implicit bias. In addition to officers' biases, community members who report crimes also influence historic crime data with bias.³¹ As a result of biases held by officers and those reporting crimes, predictive policing algorithms are built with an incomplete and biased understanding of where crimes are taking place and who is committing them.

In two recent studies of different algorithms — NorthPointe's COMPAS risk assessment tool and PredPol's location-based predictive policing algorithm — social scientists found evidence of racially disparate impacts despite both software programs' claims that the algorithms do not use race as a factor.³² In ProPublica's report on COMPAS, researchers reported that the algorithm-based tool for assessing risk of reoffending for pretrial release, sentencing, and parole decisions accurately predicted recidivism in the total pool 61% of the time, but that “[B]lack [people] [were] almost twice as likely as whites to be labeled a higher risk but not actually re-offend.”³³ The researchers also found that the assessment tool made “the opposite mistake among whites” in that white people were more likely to be labeled lower risk but go on to commit other crimes.³⁴ The report explains that COMPAS's developers found it “difficult to construct a score that doesn't include items that can be correlated with race — such as poverty, joblessness, and social marginalization” and that omissions of such data reduces the accuracy of the predictions.³⁵

Another algorithm — PredPol — is unable to correct the flaws in the data produced as a result of racial bias. In a study published in 2016, Human Rights Data Analysis Group Lead Statistician Kristian

30. Barry Friedman, *The Worrisome Future of Policing Technology*, N.Y. TIMES (June 22, 2018), <https://www.nytimes.com/2018/06/22/opinion/the-worrisome-future-of-policing-technology.html> [<https://perma.cc/5FG6-53JS>].

31. Angwin et al., *supra* note 26; *see also* Jessica Gillooly, Opinion, *Want to Stop More Starbucks Scenarios? Train These People*, WASH. POST (May 25, 2018), https://www.washingtonpost.com/opinions/911-dispatchers-sit-between-police-and-people-of-color-they-need-better-training/2018/05/25/124b2bd6-5acf-11e8-858f-12becb4d6067_story.html [<https://perma.cc/64NR-G8F5>].

32. Lum & Isaac, *supra* note 24; *see also* CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY 86 (2016) (“Jeffrey Brantingham, the UCLA anthropology professor who founded PredPol, stressed to me that the model is blind to race and ethnicity.”).

33. Angwin et al., *supra* note 26.

34. *Id.*

35. *Id.*

Lum and PhD candidate William Isaac compared PredPol recommendations on enforcement areas, which were based on historic drug crime data, with public health data on drug use in Oakland, California.³⁶ They built a synthetic population of Oakland and mapped for drug use based on public health data, finding that “[v]ariations in our estimated numbers of drug users are driven primarily by differences in population density, as the estimated rate of drug use is relatively uniform across the city.”³⁷ However, the police-recorded data for drug crimes paints a very different picture, with arrests focused in “two areas with largely non-white and low-income populations.”³⁸ To show the impact of using this police-recorded data on the operation of a predictive policing model, Lum and Isaac applied a publicly available PredPol algorithm to the Oakland Police Department data on drug crimes, finding that the model flagged areas “already over-represented in the historical policing data” (compared to their drug use density map) for targeted enforcement.³⁹ Since PredPol cannot correct for racial bias, the resulting data only intensifies that bias. Thus, the researchers concluded that the algorithm reinforced racial biases in the original police data rather than correct for such bias.⁴⁰

Criminal law reform advocates echo similar concerns. Ezekiel Edwards, Director of the American Civil Liberties Union (ACLU) Criminal Law Reform Project, summarized the impact of racial biases throughout the criminal system:

If there is one reliable prediction about our criminal justice system, it is that unwarranted racial disparities infect every stage of the criminal law process. Time and again, analysis of stops, frisks, searches, arrests, pretrial detentions, convictions, and sentencing reveal differential treatment of people of color. From racial bias in stops and frisks in New York, Boston, and Baltimore, to unwarranted disparities nationwide in arrests of Black[] and white[] [people] for marijuana possession (despite comparable usage rates), to disparities in the enforcement of minor offenses in Minneapolis, New Jersey, and Florida, as sure as the sun rises police will continue to enforce laws selectively against communities of color.⁴¹

36. Lum & Isaac, *supra* note 24, at 16–17.

37. *Id.* at 17.

38. *Id.*

39. *Id.* at 17–18.

40. *Id.* at 19.

41. Ezekiel Edwards, *Predictive Policing Software Is More Accurate at Predicting Policing Than Predicting Crime*, AM. C.L. UNION: SPEAK FREELY (Aug. 31, 2016),

Echoing similar concerns regarding the use of criminal justice data to build predictive tools, Vincent Southerland, Executive Director of the Center on Race, Inequality, and the Law at New York University School of Law, cautions that

[A]ny system that relies on criminal justice data must contend with the vestiges of slavery, de jure and de facto segregation, racial discrimination, biased policing, and explicit and implicit bias, which are part and parcel of the criminal justice system. Otherwise, these automated tools will simply exacerbate, reproduce, and calcify the biases they are meant to correct.⁴²

While developers of predictive policing technologies may attempt to control for racial biases in their algorithms by removing race-specific data, legal scholars, social scientists, and advocates remain skeptical that race-blind algorithms will reduce racial biases in policing.⁴³ Instead, they warn that the use of these algorithms will compound existing biases in the criminal legal system.⁴⁴

ii. Unchecked Error: Data, Social Science, and Cognitive Biases

Commentators have also raised concerns that the use of algorithms may introduce hard-to-identify errors into the investigative process. Such problems can originate with simple data entry errors,⁴⁵ larger scale problems of flawed and untested social science theories informing the creation of the models,⁴⁶ and errors stemming from automation and confirmation biases. When left unchecked, these errors may compound and could lead to wrongful arrests and convictions.⁴⁷

<https://www.aclu.org/blog/criminal-law-reform/reforming-police-practices/predictive-policing-software-more-accurate> [<https://perma.cc/TX3Y-EZSE>].

42. Vincent Southerland, *With AI and Criminal Justice, the Devil Is in the Data*, AM. C.L. UNION (Apr. 9, 2018), <https://www.aclu.org/issues/privacy-technology/surveillance-technologies/ai-and-criminal-justice-devil-data> [<https://perma.cc/D9C9-LAJ6>].

43. See *infra* Section I.B.i.

44. *Id.*

45. Ferguson, *Policing Predictive Policing*, *supra* note 11, at 1145–50.

46. *Id.* at 1161–64 (“Social science, not simply technology, underlies the promise of predictive policing.”); see also O’NEIL, *supra* note 32, at 87–88.

47. See *infra* Section I.B.ii for a discussion of ways that unchecked errors may lead to wrongful arrests, prosecutions, and convictions.

1. Data Entry Errors

Predictive policing algorithms are built on data sets and respond to new data that are collected and entered by humans.⁴⁸ Data entry errors can occur during collection, input, and management of the data.⁴⁹ Professor Ferguson notes that examples of the data entry error may include that of an officer mistakenly writing down the wrong address of a crime scene (a collection error), transposing a number or misspelling a name when entering notes into a computer (an input error), and the accidental creation of duplicate entries or deletion of entries when the data is integrated into a database (data management errors).⁵⁰ Such errors — especially when compounded with other sources of human error discussed in the following Sections — can lead to flawed predictions and unjust results.⁵¹

2. Flawed Social Science

Cathy O’Neil, author of *Weapons of Math Destruction*, cites “broken windows policing”⁵² and the use of PredPol to predict and patrol for nuisance level crimes as an example of how a questionable social science theory can lead to issues in the creation and deployment of predictive policing tools.⁵³ Some researchers credit the impressive drop in violent crime in New York City to the rise of broken windows policing.⁵⁴ On the other hand, other theories attribute the drop in crime to phenomena such as “the falling rates of

48. See, e.g., Ferguson, *Policing Predictive Policing*, *supra* note 11, at 1145.

49. *Id.* at 1145–46.

50. *Id.*

51. *Id.*

52. O’NEIL, *supra* note 32, at 87. “Broken windows policing” refers to the theory advanced by public policy expert James Q. Wilson and criminologist George Kelling in the influential article, *Broken Windows*, that argued that disorder “leads to increased fear and withdrawal from residents, which then allows more serious crime to move in because of decreased levels of informal social control.” George L. Kelling & James Q. Wilson, *Broken Windows: The Police and Neighborhood Safety*, ATLANTIC (Mar. 1982), <https://www.theatlantic.com/magazine/archive/1982/03/broken-windows/304465/> [<https://perma.cc/E6CN-365K>]. The theory of broken windows policing is that “[t]he police can play a key role in disrupting this process. If they focus in on disorder and less serious crime in neighborhoods that have not yet been overtaken by serious crime, they can . . . prevent serious crime from infiltrating.” *Broken Windows Policing*, GEORGE MASON UNIV., DEP’T CRIMINOLOGY, L., & SOC’Y, CTR. FOR EVIDENCE-BASED CRIME POL’Y, <https://cebc.org/evidence-based-policing/what-works-in-policing/research-evidence-review/broken-windows-policing/> [<https://perma.cc/M59Q-5RWP>] (last visited Nov. 3, 2019).

53. O’NEIL, *supra* note 32, at 86–88.

54. *Id.* at 87–88.

crack cocaine addiction to the booming 1990s economy,” and to the legalization of abortion in the 1970s.⁵⁵

Despite competing theories explaining NYC’s drop in crime, police are “[r]aised on the orthodoxy of zero tolerance [and] have little more reason to doubt the link between small crimes and big ones than the correlation between smoke and fire.”⁵⁶ As a result, this commitment to particular social science theories, such as broken windows policing, has informed the development and use of predictive policing tools including PredPol. While these predictive policing tools have the appearance that they are “not only scientific but fair,” they also may magnify the biases inherent in the models’ underlying theories, such as the tendency of broken windows policing to over-police poverty.⁵⁷

3. Cognitive Biases

Commentators caution that biases including automation bias — the tendency to believe a computer-generated report over that of a human-created report⁵⁸ — and confirmation bias⁵⁹ can distort the

55. *Id.* at 87–88; see also STEVEN D. LEVITT & STEPHEN J. DUBNER, *Where Have All the Criminals Gone?*, in *FREAKONOMICS: A ROGUE ECONOMIST EXPLORES THE HIDDEN SIDE OF EVERYTHING* 115, 121 (2005); Steven D. Levitt, *Abortion and Crime: Who Should You Believe?*, FREAKONOMICS BLOG (Mar. 15, 2005), <http://freakonomics.com/2005/05/15/abortion-and-crime-who-should-you-believe/> [https://perma.cc/92N3-PEES].

56. O’NEIL, *supra* note 32, at 89.

57. *Id.* at 91.

PredPol, even with the best of intentions, empowers police departments to zero in on the poor, stopping more of them, arresting a portion of those, and sending a subgroup to prison. And the police chiefs, in many cases, if not most, think that they’re taking the only sensible route to combating crime The result is that we criminalize poverty, believing all the while that our tools are not only scientific but fair.

Id.

58. See generally M.L. CUMMINGS, AMERICAN INST. OF AERONAUTICS AND ASTRONAUTICS, *AUTOMATION BIAS IN INTELLIGENT TIME CRITICAL DESIGN SUPPORT SYSTEMS* (2004), <http://hal.pratt.duke.edu/sites/hal.pratt.duke.edu/files/u13/Automation%20Bias%20in%20Intelligent%20Time%20Critical%20Decision%20Support%20Systems.pdf> [https://perma.cc/36T5-UE6N].

59. See, e.g., Margit E. Oswald & Stefan Grosjean, *Confirmation Bias*, in *COGNITIVE ILLUSIONS: A HANDBOOK ON FALLACIES AND BIASES IN THINKING, JUDGEMENT AND MEMORY* 79 (Rudiger F. Pohl ed., 2004); see also Erin Murphy, *Databases, Doctrine, and Constitutional Criminal Procedure*, 37 FORDHAM URB. L.J. 803, 830 (2010) (“The true risk is a leaping-to-conclusions, or confirmation bias. It is the fear that the individual will be sucked into a morass of suspicion from which escape is arduous or impossible — Kafka’s *The Trial*, not Orwell’s Big Brother.”).

investigative process and make errors less likely to be checked than in a human-driven process.⁶⁰ Professor M.L. Cummings cautions that:

Automation bias occurs in decision-making because humans have a tendency to disregard or not search for contradictory information in light of a computer-generated solution that is accepted as correct and can be exacerbated in time critical domains. Automated decision aids are designed to reduce human error but actually can cause new errors in the operation of a system if not designed with human cognitive limitations in mind.⁶¹

Due to automation bias, officers may place undue confidence in automated recommendations, whether a PredPol recommended hotspot or an algorithm-generated list of individuals likely to be involved in crime. Lindsey Barrett, author of *Reasonably Suspicious Algorithms*, explains this phenomenon, noting that:

An algorithmic risk prediction seems like the automation of an officer weighing fact-specific circumstances, and determining the possibility of a crime occurring based on those facts. But an algorithm's determination of a high crime area or an individual's threat level is qualitatively and quantitatively distinct from an officer's judgment. An automated assessment is the product of a greater volume of information, which furthermore may be riddled with unknown errors, bias, or both. While an officer may make a mistake in judgment — a possibility the preexisting standard acknowledges — courts can understand and contextualize human error.⁶²

As a result, automation bias presents the two-fold risk that computer-generated recommendations are trusted above human judgment while simultaneously concealing potential unchecked errors.

Another bias with the potential to distort the investigative process is confirmation bias. This is the process in which “information is searched for, interpreted, and remembered in such a way that it systematically impedes the possibility that the hypothesis could be rejected.”⁶³ Put another way, confirmation bias in law enforcement occurs when “[officers] form an opinion, create a theory, and then

60. Ferguson, *Policing Predictive Policing*, *supra* note 11, at 1178; see Lindsey Barrett, *Reasonably Suspicious Algorithms: Predictive Policing at the United States Border*, 41 N.Y.U. REV. L. & SOC. CHANGE 327, 348–49 (2017).

61. Cummings, *supra* note 58, at 1.

62. Barrett, *supra* note 60, at 348–49.

63. Oswald & Grosjean, *supra* note 59, at 79.

work to prove it right instead of proving it wrong.”⁶⁴ Confirmation bias may lead officers to confirm the recommendations of a predictive policing algorithm through their follow-up investigation. Research has shown that confirmation bias affects people not only in motivated processes (where the person finds information to support a desired conclusion), but also in unmotivated processes (where the person has no interest in a particular conclusion) due to psychological phenomena such as the primacy effect, in which “information encountered early in the process is likely to carry more weight than that acquired later.”⁶⁵ Early information gained by an officer — that an area is prone to crime or that a person is likely to be involved in crime — may influence the information they unintentionally seek out, process, and remember.

Together, automation bias and confirmation bias have the potential to create feedback loops in which officers receive information from predictive policing software — information likely to be presumed accurate and bias free — that primes the officers to believe crime is afoot in certain areas or within certain lists of people. By increasing vigilant patrol of the area or list, the officers are likely to find information — and make arrests — supporting the hypothesis.

Human errors in data recording, entry, and processing will inevitably inform and be a byproduct of any predictive policing software.⁶⁶ Professor Ferguson urges police departments to acknowledge this room for error, which he argues “does not discount the value of predictive policing technologies but only qualifies the findings and tempers the unquestioning acceptance of the information.”⁶⁷ This step may help to reduce automation bias as well as “set the state for correcting error, auditing error, and training humans to prevent error.”⁶⁸

iii. Fourth Amendment Concerns

Commentators also raise concerns regarding the impact of predictive policing tools on reasonable suspicion and probable cause determinations. Under the Fourth Amendment, police need

64. Amaury Murgado, *Dealing with Confirmation Bias*, POLICE MAG. (July 17, 2014), <https://www.policemag.com/341175/dealing-with-confirmation-bias> [https://perma.cc/ADW7-LXYH].

65. Raymond S. Nickerson, *Confirmation Bias: A Ubiquitous Phenomenon in Many Guises*, 2 REV. GEN. PSYCHOL. 175, 187 (1998).

66. See *infra* Section I.B.ii.

67. Ferguson, *Policing Predictive Policing*, *supra* note 11, at 1151.

68. *Id.*

probable cause and a warrant (or one of any number of valid exceptions to the warrant requirement recognized by the Supreme Court) for a search,⁶⁹ and they need reasonable suspicion for a *Terry* investigative stop.⁷⁰ The Supreme Court defines probable cause as “more than bare suspicion: Probable cause exists where ‘the facts and circumstances within their (the officers’) knowledge and of which they had reasonably trustworthy information (are) sufficient in themselves to warrant a man of reasonable caution in the belief that’ an offense has been or is being committed.”⁷¹ In cases where an informant shares information, an officer has probable cause when she has reason to believe the tip based on a totality of the informant’s basis of knowledge (for example, the informant personally observed or participated in the criminal activity), their reliability (whether the officer knows the informant to be trustworthy), and the veracity of the tip, usually determined through independent police corroboration.⁷²

Such determinations inherently rely upon prediction and probabilities. As Professor Ferguson points out, “determining what is ‘reasonable’ or whether sufficient probable cause exists in a given

69. The Fourth Amendment states that:

[t]he right of the people to be secure in their persons, houses, papers, and effects, against unreasonable searches and seizures, shall not be violated, and no warrants shall issue, but upon probable cause, supported by oath or affirmation, and particularly describing the place to be searched, and the persons or things to be seized.

U.S. CONST. amend. IV. The Supreme Court has carved out a number of exceptions to this requirement. *See, e.g.*, *Warden v. Hayden*, 387 U.S. 294, 298 (1967) (holding that the exigency exception to the warrant requirement applies when officers are in hot pursuit of a suspect or there is danger to the officer’s or others’ safety); *United States v. Robinson*, 414 U.S. 218, 235 (1973) (holding that the search incident to lawful arrest exception to the warrant requirement applies to all arrests regardless of underlying rationale); *Schneekloth v. Bustamonte*, 412 U.S. 218, 227, 248 (1973) (explaining that valid consent to a search waives the warrant and probable cause requirement); *Horton v. California*, 496 U.S. 128, 132 (1990) (explaining the plain view exception to the warrant requirement); *Wyoming v. Houghton*, 526 U.S. 295, 307 (1999) (extending the automobile exception to the warrant requirement to passenger’s belongings).

70. *See Terry v. Ohio*, 392 U.S. 1, 27 (1968).

71. *Brinegar v. United States*, 338 U.S. 160, 175–76 (1949) (alterations in original) (quoting *Carroll v. United States*, 267 U.S. 132, 162 (1925)).

72. *Illinois v. Gates*, 462 U.S. 213, 230–31 (1983) (clarifying that probable cause exists when the totality of the circumstances suggests that the tip is reliable, without requiring a rigid analysis of basis of knowledge, reliability, and veracity).

case involves a predictive judgement by a judge or law enforcement official.”⁷³ Similarly, Barrett notes that:

Prediction is already a part of Fourth Amendment jurisprudence, explicitly and implicitly. A search warrant might rely on the prediction, based on probable cause, that contraband will be found in a certain location Fourth Amendment analysis also frequently relies on anchoring broad probabilities to individual suspects, such as profiles, and high crime areas, or individualized predictions of possibly questionable reliability, such as reliance on informant tips.⁷⁴

Despite the reliance on prediction and probability in traditional Fourth Amendment jurisprudence, it is not clear how predictive policing technologies factor into reasonable suspicion and probable cause determinations. In the realm of place-based predictive policing, magistrate judges will likely treat the prediction of areas for increased patrol as a “relevant characteristic[] of a location in determining whether the circumstances are sufficiently suspicious to warrant further investigation.”⁷⁵ While the determination that an area is a “high crime area” or “hotspot” is not sufficient for a stop or search on

73. Andrew G. Ferguson, *Predictive Policing and Reasonable Suspicion*, 62 EMORY L.J. 259, 286 (2012) [hereinafter Ferguson, *Reasonable Suspicion*].

74. Barrett, *supra* note 60, at 345.

75. *Illinois v. Wardlow*, 528 U.S. 119, 124 (2000); *see also* Ferguson, *Reasonable Suspicion*, *supra* note 73, at 308. At the time of writing, the issue of how predictive policing affects Fourth Amendment analysis has not yet been addressed in a published court opinion. However, the lack of litigation on the topic does not mean that the use of predictive policing tools in probable cause analyses is not an issue. One reason for the lack of litigation may be that officers can simply refer to an area as “high crime” as part of a reasonable suspicion analysis without revealing whether predictive policing tools led to the determination of the area as “high crime.” *See, e.g., Wardlow*, 528 U.S. at 124 (“[W]e have previously noted the fact that the stop occurred in a ‘high crime area’ among the relevant contextual considerations in a *Terry* analysis.” (citing *Adams v. Williams*, 407 U.S. 143, 144, 147–48 (1972))). Further, police departments have historically been hesitant to reveal the use of new technologies, claiming that secrecy helps them “to prevent criminals from being apprised in advance of what the police may be doing in a particular investigation.” *See, e.g.,* Transcript of Oral Argument at 5–6, *Brennan Ctr. v. NYPD* (N.Y. Sup. Ct. Aug. 30, 2017) (No. 160541/2016), [https://www.brennancenter.org/sites/default/files/Brennan 20-v- 20NYPD.PDF](https://www.brennancenter.org/sites/default/files/Brennan%20v-20NYPD.PDF) [https://perma.cc/K683-GGWM]. Law enforcement have gone to great lengths to conceal and avoid litigation on the constitutionality of new technologies, in some cases, officers have even refused to testify regarding the use of policing technologies such as cell-site simulators, leading prosecutors to dismiss serious cases to protect the secrecy of police technology. *See* Brad Heath, *Police Secretly Track Cellphones to Solve Routine Crimes*, USA TODAY (Aug. 23, 2015), <https://www.usatoday.com/story/news/2015/08/23/baltimore-police-stingray-cell-surveillance/31994181/> [https://perma.cc/Q7FB-UUYU].

its own, Ferguson predicts that “with some relevant corroboration, a predictive tip will serve the basis of a constitutional stop.”⁷⁶

However, it is less clear how predictive policing tools will affect probable cause or reasonable suspicion analyses in scenarios where algorithms predict people likely to be involved in crime or link individual suspects to potential crime patterns. Ultimately, using such information in probable cause determinations raises serious civil liberties concerns. The ACLU and a coalition of sixteen additional civil rights organizations argue that:

The Fourth Amendment forbids police from stopping someone without reasonable suspicion — a specific, individualized determination that is more than just a hunch. Computer-driven hunches are no exception to this rule, and a computer’s judgment is never a further reason (beyond the articulable facts that intelligibly caused that judgment) for a stop, search, or arrest. Similarly, predictive policing must not be allowed to erode rights of due process and equal protection. Systems that manufacture unexplained “threat” assessments have no valid place in constitutional policing.⁷⁷

It is not yet clear to what extent predictive policing tools are being used for such determinations of reasonable suspicion and probable cause, but scholars and advocates alike raise concerns regarding the potential of predictive policing tools to reshape and further weaken Fourth Amendment jurisprudence.⁷⁸

II. PATTERNIZR: THE NYPD’S NEWEST PREDICTIVE TOOL

A. Background on Patternizr

Data scientists at the NYPD created Patternizr in order to assist crime analysts with identifying patterns of crimes that were committed by the same suspect or group of suspects.⁷⁹ Prior to the development of Patternizr, NYPD analysts manually searched through computerized records of past crimes to try to identify patterns in criminal activity. This manual process was time intensive and often limited to a small geographic focus, as crime analysts tend

76. Ferguson, *Reasonable Suspicion*, *supra* note 73, at 312.

77. ACLU & 16 CIVIL RIGHTS ORGS., *supra* note 10.

78. *See, e.g., id.*; Barrett, *supra* note 60, at 345, 346; Ferguson, *Policing Predictive Policing*, *supra* note 11, at 1169..

79. Chohlas-Wood & Levine, *supra* note 1.

to focus on crimes that have occurred within their precincts.⁸⁰ Patternizr software allows investigators to pull up a crime report on any NYPD computer and, with the push of a button, “patternize” the seed crime. The algorithm quickly returns a report listing ten potentially related crimes from the NYPD’s database.⁸¹ Each potentially related crime is scored between 0-1, representing the strength of the software’s recommendation on whether the crimes are related to the seed complaint.⁸² The investigator then manually reviews the potential matches and decides whether or not to group the crimes together in a pattern, reflecting a belief that the same suspect or group of suspects are responsible for the crimes in the pattern.⁸³ If the investigator groups the crimes together, the crimes are then investigated as a pattern and information from one incident, such as a known suspect, would be used to further the investigation of the crimes within the pattern.⁸⁴

i. Examples of How Patternizr Works

The NYPD’s most cited Patternizr success story is how the software helped them “crack[] the case of the needle-wielding shoplifter.”⁸⁵ In that case, an analyst used Patternizr to identify similarities between two robberies in distant precincts where the accused person was shoplifting power drills from a hardware store, and upon being confronted, threatened — and on one of the occasions, attacked — an employee with a hypodermic needle.⁸⁶ The analyst was able to combine these two robberies with near-identical fact patterns with two other larcenies they believed were committed

80. See Steven Melendez, *NYPD Unveils Controversial algorithm to Track Crime Patterns*, FASTCOMPANY (Mar. 20, 2019), <https://www.fastcompany.com/90321778/nypd-unveils-controversial-algorithm-to-track-crime-patterns> [<https://perma.cc/E8DZ-ZNM4>] (quoting Evan Levine, co-developer of Patternizr).

81. Chohlas-Wood & Levine, *supra* note 1, at 161–62.

82. *Id.* at 159.

83. *Id.* at 162.

84. *Id.* at 154.

85. *Resoundingly Human*, INFORMS (Feb. 15, 2019), <https://informs.libsyn.com/2019/02> [<https://perma.cc/4SNN-G8QA>] (interviewing Alex Chohlas-Wood and Evan Levine about Patternizr); see also Michael R. Sisak, *Modern Policing: Algorithm Helps NYPD Spot Crime Patterns*, AP NEWS (Mar. 10, 2019), <https://www.apnews.com/84fb03384368458db3d85763b5bf5b94> [<https://perma.cc/W9Q6-UADL>]; Melendez, *supra* note 80.

86. Chohlas-Wood & Levine, *supra* note 1, at 162.

by the same suspect.⁸⁷ The analyst then passed the information to an NYPD detective who investigated the crimes and ultimately arrested a suspect who later pleaded guilty to larceny and felony assault.⁸⁸

Chohlas-Wood and Levine also share the example of identifying a pattern of thefts of unattended watches and jewelry from gym lockers in Midtown Manhattan. At the time of publication of their paper, the investigation was ongoing, though two suspects had been identified through video footage.⁸⁹ This series of gym larcenies and the “needle-wielding shoplifter” case are, at the time of writing, the only two examples that the NYPD has shared with the public regarding Patternizr’s use in identifying patterns of crime.

ii. Patternizr’s Design

Patternizr’s developers were inspired by an initial test of a machine-learning program called “Series Finder” created by MIT researchers in partnership with the Cambridge Police Department.⁹⁰ In this initial proof-of-concept, MIT researchers created an algorithm that identified burglary patterns that had taken analysts months to identify manually, while also identifying patterns that the analysts had missed.⁹¹ With a team of data scientists, Chohlas-Wood and Levine were able to build the initial experiment into a city-wide program using the data of the country’s largest municipal police force.⁹²

87. *Id.* The paper does not specify how these additional charges were matched to the pattern.

88. *Id.* The exact charges and underlying facts to which the accused pleaded guilty are not disclosed, nor is any of the underlying evidence that led to the suspect. As a result, it is impossible to make an independent assessment of the likelihood that the investigators “got it right.” It is critical to note that while a guilty plea amounts to legal guilt, it may be a strategic choice made by the defendant and not a reflection of factual guilt.

89. *Id.*

90. Tong Wang et al., *Learning to Detect Patterns of Crime*, in *MACHINE LEARNING AND KNOWLEDGE DISCOVERY IN DATABASES* 515, 516 (H. Blockeel et al. eds., 2013); *Resoundingly Human*, *supra* note 85.

91. Robin A. Smith, *Cynthia Rudin: Training Computers to Find Patterns That Humans Miss*, *DUKE TODAY* (Oct. 2, 2016), <https://today.duke.edu/2016/10/cynthia-rudin-training-computers-find-patterns-humans-miss> [<https://perma.cc/7L8L-FJG6>]. *See generally* Wang et al., *supra* note 90.

92. Melendez, *supra* note 80; *see also About NYPD*, N.Y.C. POLICE DEP’T <https://www1.nyc.gov/site/nypd/about/about-nypd/about-nypd-landing.page> [<https://perma.cc/W3JC-JXCC>] (last visited Oct. 29, 2019) (“The New York City Police Department (NYPD) is the largest and one of the oldest municipal police departments in the United States, with approximately 36,000 officers and 19,000 civilian employees.”).

In their analytics-focused article, Chohlas-Wood and Levine provide an overview of how they built the models that recommend potentially related crimes to NYPD investigators.⁹³ While the article was written for an audience well-versed in applied analytics, key takeaways for stakeholders who are not data scientists include a better understanding of the underlying assumptions and several key design choices that inform the software.

While other iterations of predictive policing tools have focused on either places or people, Patternizr focuses on crimes, or, more specifically, on the *modus operandi* (M.O.) of those committing the crimes.⁹⁴ Patternizr, like Series Finder, is based on the assumption that many crimes are committed by serial offenders.⁹⁵ As defined by the MIT researchers behind Series Finder, “the M.O. is the set of habits that the offender follows, and is a type of motif used to characterize the pattern.”⁹⁶ The underlying assumptions, as explained by developers of Series Finder, include:

- *Each M.O. is different.* Criminals are somewhat self-consistent in the way they commit crimes. However, different criminals can have very different M.O.’s. Consider the problem of predicting housebreaks (break-ins): Some offenders operate during weekdays while the residents are at work; some operate stealthily at night, while the residents are sleeping. Some offenders favor large apartment buildings, where they can break into multiple units in one day; others favor single-family houses, where they might be able to steal more valuable items. Different combinations of crime attributes can be more important than others for characterizing different M.O.’s.
- *General commonalities in M.O. do exist.* Each pattern is different but, for instance, similarity in time and space are often important to any pattern and should generally be weighted highly. Our method incorporates both general trends in M.O. and also pattern-specific trends.
- *Patterns can be dynamic.* Sometimes the M.O. shifts during a pattern. For instance, a novice burglar might initially use bodily force to open a door. As he gains experience, he might bring a tool with him to pry the door open. Occasionally, offenders switch entirely from one neighborhood to another. Methods that consider

93. Chohlas-Wood & Levine, *supra* note 1.

94. See Chohlas-Wood & Levine, *supra* note 1, at 154; Wang et al., *supra* note 90, at 516.

95. Chohlas-Wood & Levine, *supra* note 1, at 154.

96. Wang et al., *supra* note 90, at 516.

an M.O. as stationary would not naturally be able to capture these dynamics.⁹⁷

In order to build Patternizr, Chohlas-Wood and Levine focused on three types of property crimes — robbery, burglary, and grand larceny. They selected these crimes because there is sufficient pattern data on these crimes, the NYPD considers them significantly serious to warrant police intervention, and the NYPD already dedicates a significant amount of investigative resources to more serious violent crimes.⁹⁸ The developers isolated a list of 39 distinct attributes, including various measures of distance, date and time of occurrence, premise type and name, whether a weapon was used, the number of suspects, suspect height(s), suspect weight(s), property taken, unstructured text, and the complaint narrative.⁹⁹ Chohlas-Wood and Levine then trained three models — one for each type of crime — on “approximately 10,000 patterns between 2006 and 2015” built from “manually identified official patterns” and “complaint records where the same individual was arrested for multiple crimes of the same type within a span of two days.”¹⁰⁰ The models learned nuances in which crime factors may be related in patterns using a complex decision-tree based classification algorithm.¹⁰¹ Chohlas-Wood and Levine use the example that grand-larceny pickpocketing is likely to happen closer in space and time — for example, around a specific corner — than a grand larceny shoplifting pattern, which is more likely to be spread out across the city.¹⁰² As a result, the model would learn to weight distance more heavily in pickpocketing complaints than in shoplifting complaints.¹⁰³

Chohlas-Wood and Levine emphasize the choice to “intentionally design[] the algorithm to minimize disparate impact on any specific group” by making the algorithm “completely blind to sensitive information about potential suspects, including race and gender, which was not included as a similarity feature for the predictive model.”¹⁰⁴ Additionally, they “kept potential proxy variables for sensitive information — particularly location — extremely coarse to

97. *Id.* (alterations in original).

98. Chohlas-Wood & Levine, *supra* note 1, at 155; *Resoundingly Human*, *supra* note 85.

99. Chohlas-Wood & Levine, *supra* note 1, at 156.

100. *Id.* at 155.

101. *Id.* at 159.

102. *Id.*

103. *Id.*

104. *Id.* at 160.

ensure correlation with sensitive attributes had a very low degree of certainty while retaining some very general information about location.”¹⁰⁵ Finally, and according to the developers, “most important[ly], several levels of expert human review are still required to establish a pattern, minimizing the potential for a seemingly likely (but incorrect) recommendation to result in any enforcement action.”¹⁰⁶ To test the fairness of the model, Chohlas-Wood and Levine looked at whether Patternizr recommended pairs of crimes with suspects of specific racial groups at a different rate than existing identified patterns or random pairings.¹⁰⁷ Their findings show “no evidence that Patternizr recommends any suspect race at a higher rate than exists with random pairing.”¹⁰⁸

B. Is Patternizr “Fair”?

While the NYPD and Patternizr’s developers tout its fairness and efficacy as a predictive policing tool, advocates and technology experts have raised concerns. A recent TechTarget article on Patternizr cited concerns from Gartner Analyst Darin Stewart that:

As Patternizr casts its net, individuals who fit a profile inferred by the system will be swept up. At best, this will be an insult and an inconvenience. At worst, innocent people will be incarcerated. The community needs to decide if the benefit of a safer community overall is worth making that same community less safe for some of its members who have done nothing wrong.¹⁰⁹

Additionally, the New York Civil Liberties Union (NYCLU) cautioned that “[t]o ensure fairness the NYPD should be transparent about the technologies it deploys and allow independent researchers to audit these systems before they are tested on New Yorkers.”¹¹⁰ From available reporting on Patternizr, it appears that no one outside of the NYPD’s in-house developers has independently assessed how Patternizr works and whether it unintentionally replicates the problems in other types of predictive policing.¹¹¹

105. *Id.*

106. *Id.* at 160–61.

107. *Id.* at 161.

108. *Id.*

109. Holak, *supra* note 2.

110. Sisak, *supra* note 85 (quoting Christopher Dunn, Legal Director, NYCLU).

111. *See generally infra* Section II.A.

i. Patternizr and Racial Bias

Chohlas-Wood and Levine assert that the software is “fair” because it leaves out “sensitive suspect attributes” such as race, gender, and precise location.¹¹² However, Patternizr, like other forms of predictive policing, remains vulnerable to replicating and compounding the racial disparities of the data on which it was trained.¹¹³ As demonstrated in studies of both COMPAS and PredPol, which do not include racial data but still produce racially-disparate results, simply leaving out racial data does not mean that the algorithm will not produce racially-disparate results.¹¹⁴

As the makers of COMPAS conceded, algorithms that do not include race as a category can still produce racially disparate results.¹¹⁵ Patternizr’s attributes, specifically unstructured text and complaint narratives, could allow “sensitive attributes” such as race, gender, and socioeconomic status to enter the algorithm through coded language (for example, “dark complexion,” and “homeless”). Beyond ‘back-door’ methods of race entering the algorithms, it is likely that analysts check the suspect descriptions, including the race and gender of suspects, when manually checking Patternizr’s recommendations for a possible match to a seed complaint. This is only logical; if a seed complaint describes the suspect as a 5’8”, 170-pound white woman, the analyst can quickly eliminate any recommendations where the suspect is not a white woman, as Patternizr has already screened for height and weight similarities. This may have the inadvertent effect of making sensitive suspect attributes like race and sex more material in the investigator’s manual review process. If the algorithm already suspects the crimes are a match, and the investigator can rule out other recommendations due to the suspect’s demographic information, an investigator might overvalue a match of race and sex, as it would confirm rather than reject the software’s recommendation.¹¹⁶ This design feature, intended to eliminate racial bias from Patternizr, could actually increase analysts’ reliance on racial data when matching crimes to a pattern.

Matching race and sex with individual suspect descriptions is not inherently problematic. In their review, an investigator would likely

112. Chohlas-Wood & Levine, *supra* note 1, at 157, 163.

113. *See supra* Section I.B.i.

114. *See supra* notes 32–35 and accompanying text.

115. Angwin et al., *supra* note 26.

116. *See infra* Section I.B.ii.

ensure that a suspect matches all available data points, whether those data points include race, sex, height, facial features, or tattoos.¹¹⁷ However, the confluence of automation bias, confirmation bias, and racial bias could lead investigators to rush to conclusions.¹¹⁸ Due to automation bias, analysts are likely to believe Patternizr's recommendation is correct.¹¹⁹ Additionally, implicit and explicit racial biases may enter into the manual check of race and sex by the analyst at this stage. For example, an analyst who implicitly or explicitly believes that Black men are more likely to commit burglaries may be less likely to question a Patternizr recommendation of a Black man as a suspect for a burglary than a recommendation of a white woman for the same crime. If the sex and race match — and this data conforms to the analyst's notion of what is likely in the given scenario — the analyst may gain confidence in the recommendation and then seek out additional inculpatory information while failing to seek out or overlooking information that might be exculpatory for the suspect recommended by Patternizr.¹²⁰

In a test for racial impact, Patternizr's developers determined that the software is no more likely to group patterns of crimes together by race of the suspect than crime analysts' manual pattern matching or random matching.¹²¹ Chohlas-Wood and Levine do not include statistics on the racial makeup of the database of crimes on which they trained the models. It is likely that the NYPD crime database significantly overrepresents people of color, specifically Black and Latinx men, due to over-policing and biases in crime reporting.¹²²

117. *See, e.g.*, N.Y. DIV. OF CRIM. JUST. SERVS., NEW YORK STATE STANDARD PRACTICES MANUAL 75 (2018), <https://www.criminaljustice.ny.gov/stdpractices/downloads/standardpractices.pdf> [<https://perma.cc/V6CF-ZFNQ>]. This manual advises law enforcement that “[a]rrest warrants should contain as many available identifiers as possible,” including identifiers such as hairstyles, scars, marks and tattoos, complexion, and facial hair. *Id.*

118. *See supra* Section I.B.ii.3.

119. *See supra* Section I.B.ii.3.

120. *See supra* Section I.B.ii.3.

121. Chohlas-Wood & Levine, *supra* note 1; *Resoundingly Human*, *supra* note 85.

122. *See, e.g.*, GREG RIDGEWAY, RAND CORP., ANALYSIS OF RACIAL DISPARITIES IN THE NEW YORK POLICE DEPARTMENT'S STOP, QUESTION, AND FRISK PRACTICES (2007); Brendan Cheney, *NYPD Hosted Government-Wide Conference on Racial Disparities*, POLITICO (Nov. 13, 2018), <https://www.politico.com/states/new-york/city-hall/story/2018/11/12/nypd-hosted-secret-government-wide-conference-on-racial-disparities-693271> [<https://perma.cc/7VAK-QUNY>]; *Racial Disparities Evident in New York City Arrest Data for Marijuana Possession*, INNOCENCE PROJECT (May 14, 2018), <https://www.innocenceproject.org/racial-disparities-in-nyc-arrest-data-marijuana-possession/> [<https://perma.cc/HZN2-NM88>]; *see also* Friedman, *supra* note 30; Gillooly, *supra* note 31; *infra* note 199 and accompanying text.

When Black and Latinx men are already disproportionately over-represented in the suspect pool due to biased policing, they will be more likely to be recommended as matches to new crimes. The racial bias works similarly as in Lum and Isaac's study of PredPol, but instead of narrowing in on 500 square feet of a city for likely crime, Patternizr narrows in on a list of likely crime (and, in cases with leads, suspect) matches.¹²³ The data populating the system are derived from policing and community-reporting, which are often rife with bias.¹²⁴ For this reason, advocates should be concerned that Patternizr will compound these biases as the software focuses its enforcement on the universe of previously-identified suspects.

ii. Patternizr and the Potential for Unchecked Errors

The use of Patternizr may lead to errors that are particularly challenging to detect, based on a series of data and human interpretation vulnerabilities. These include the theoretical underpinnings informing the design of Patternizr, data accuracy vulnerabilities, and cognitive biases that may compound potential errors, including automation and confirmation biases.¹²⁵ A mistaken pattern and string of events leading to the arrest and prosecution of the wrong person has dire consequences. All too often, criminal defendants plead guilty to crimes they did not commit as a risk-mitigation strategy.¹²⁶ For those who do go to trial, there are still far too many cases where individuals are convicted but later determined not to be guilty.¹²⁷ While the right to a fair trial should serve as a

123. See Lum & Isaac, *supra* note 24, at 15–16.

124. See *supra* note 122 and accompanying text.

125. See *supra* Section I.B.

126. See, e.g., NAT'L ASS'N OF CRIMINAL DEF. LAWYERS, THE TRIAL PENALTY: THE SIXTH AMENDMENT RIGHT TO TRIAL ON THE VERGE OF EXTINCTION AND HOW TO SAVE IT 6 (2018), <https://www.nacdl.org/Document/TrialPenaltySixthAmendmentRighttoTrialNearExtinct> [<https://perma.cc/GT24-8M5V>].

The virtual elimination of the option of taking a case to trial has so thoroughly tipped the scales of justice against the accused that the danger of government overreach is ever present. And on a human level, for the defense attorney there is no more heart-wrenching task than explaining to a client who very likely may be innocent that they must seriously consider pleading guilty or risk the utter devastation of the remainder of their life with incalculable impacts on family.

Id.

127. See, e.g., *DNA Exonerations in the United States*, INNOCENCE PROJECT, <https://www.innocenceproject.org/dna-exonerations-in-the-united-states/> [<https://perma.cc/9HKF-59F3>] (last visited Nov. 3, 2019).

bulwark against wrongful prosecutions, this aspiration is simply not the reality of the criminal legal system.¹²⁸ As such, it is critical that developers and departments using Patternizr or similar predictive policing tools critically evaluate and seek to remedy the potential for unchecked error.

Patternizr is built upon the criminological theories that many crimes are committed by serial offenders and that these offenders have habits or M.O.s that can be detected as crime patterns.¹²⁹ Chohlas-Wood and Levine discuss the many choices that they made while designing Patternizr, but they rarely explain *why* they made these choices and the theories informing these choices.¹³⁰ More transparency on these design choices and theories would allow observers to point out its inevitable blind spots.

Just as it is important to evaluate the underlying theories informing the algorithm, it is also important to consider what theories did *not* inform Patternizr's design. For example, analysts might consider the research on juveniles in the criminal legal system that shows that most juveniles "age out" of crime.¹³¹ However, a juvenile's prior acts committed during a distinct phase might lead Patternizr to identify them as a suspect of similar crimes for years after they are likely to have matured and ceased committing crimes.¹³² Similarly, analysts might consider whether a case received media attention to better determine whether a similar crime was likely committed by the same suspect or a copycat.¹³³

Regardless of the underlying criminological theories informing Patternizr, predictive policing tools are based on theories and

128. See NAT'L ASSOCIATION OF CRIMINAL DEF. LAWYERS, *supra* note 126.

129. See Chohlas-Wood & Levine, *supra* note 1, at 154; Wang et al., *supra* note 90, at 515–16. Chohlas-Wood & Levine support this assumption with only one source from the 1980s.

130. See Chohlas-Wood & Levine, *supra* note 1.

131. See, e.g., Alexandra O. Cohen et al., *When Does a Juvenile Become an Adult? Implications for Law and Policy*, 88 TEMPLE L. REV. 769, 786 (2016); Marc D. Rudolph et al., *At Risk of Being Risky: The Relationship Between "Brain Age" Under Emotional States and Risk Preference*, 24 DEVELOPMENTAL COGNITIVE NEUROSCIENCE 93 (2017).

132. See Chohlas-Wood & Levine, *supra* note 1. Chohlas-Wood and Levine do not discuss factoring this phenomena of juveniles "aging out" of crime into the development of Patternizr.

133. See Ray Surette, *Copycat Crime and Copycat Criminals: Concepts and Research Questions*, 18 J. CRIM. JUST. & POP. CULTURE 49, 50 (Dec. 2016) ("For a crime to be a media generated copycat crime it must have been inspired by an earlier, media-publicized or portrayed crime — that is, there must be a pair of crimes linked through the media.").

assumptions made by humans.¹³⁴ Those acting on Patternizr’s recommendations should not lose sight of the human choices — including potential blind spots and flaws — that inform its recommendations. While these serious issues raise questions as to whether such predictive tools should be used at all, investigators and officers who use Patternizr should, at the very least, be trained on the limitations and potential errors of Patternizr.

Patternizr may introduce error into the pattern-analysis process because of issues in data recording and entry.¹³⁵ This could be the result of errors in the original data set on which the model was trained, where an error as simple as a mistyped word could skew the algorithm’s understanding of the factors creating a pattern.¹³⁶ Errors in the seed complaint could also lead to false positives. For example, if an officer writes that a shoplifter threatened an employee with a needle, this case might match the much-talked about hypodermic needle-wielding shoplifter of power drills. However, the story sounds very different if additional details are recorded, such as that the shoplifter threatened the employee with a knitting needle and walked off with several bundles of yarn at a craft store. Or, take for example if the word drill is mistyped ‘drinl.’ Did the shoplifter take a power drill or a soft drink? Will Patternizr match this seed complaint to a series of larcenies at hardware stores or low-level drink and snack thefts from neighborhood corner stores?

Patternizr’s developers emphasize that multiple levels of expert review are still needed to establish a pattern — mitigating the risk that a seemingly likely, but false, recommendation results in police action.¹³⁷ Debra Piehl, the NYPD’s senior crime analyst, assured reporters that “it still allows the analysts that work for me to apply their own thinking and analysis. The science doesn’t overwhelm the art.”¹³⁸ While crime analysts will hopefully be able to catch errors in many circumstances, Patternizr could make such error-detection harder based on cognitive biases in favor of automated information.¹³⁹ Patternizr, like other algorithms, is vulnerable to errors arising from data quality control issues,¹⁴⁰ flawed assumptions

134. See Chohlas-Wood & Levine, *supra* note 1.

135. See *supra* Section I.B.ii.1.

136. See, e.g., Ferguson, *Policing Predictive Policing*, *supra* note 11, at 1145–50.

137. Chohlas-Wood & Levine, *supra* note 1, at 161–61.

138. Holak, *supra* note 2.

139. See *supra* Section I.B.ii.

140. See *supra* Section I.B.ii.1.

informing the design of the models,¹⁴¹ and cognitive biases that lead people to believe computers and to seek information confirming an early hypothesis.¹⁴²

Patternizr may make investigators more efficient, but it may also make investigators less accurate. It is not clear from available information what, if any, steps are being taken to acknowledge and counteract these vulnerabilities for error. Patternizr's developers and departments using Patternizr or similar predictive policing tools should work to ensure accuracy in the data recording and input processes, rigorously question the underlying theories informing the creation of the model and implement protocols to combat the rush to judgement to which automation and confirmation biases contribute.

iii. Patternizr and Fourth Amendment Issues

Patternizr holds the potential to link new crime reports to cases with an identified suspect, allowing investigators to narrow in on a single suspect whose M.O. may match prior crime(s).¹⁴³ This raises important questions of how potential pattern matches are being used in determinations of reasonable suspicion and probable cause. For example, if an investigator "patternizes" a burglary and Patternizr suggests that it matches a closed case to which the suspect pleaded guilty, the investigator now has a name and address for a top suspect. A critical and unanswered question is: Can the investigator use this tip from Patternizr to articulate probable cause? While there may be a temptation to use a Patternizr recommendation as justification for a search warrant, Patternizr should not be used as an independent factor in probable cause determinations.

A Patternizr score is only as strong as the underlying data giving rise to the recommendation. If an investigator relies upon the underlying data alone (surfaced by Patternizr), and not the Patternizr score, the probable cause analysis will be the same as if the pattern had been manually identified by an analyst.¹⁴⁴ However, the Fourth Amendment analysis is weakened and made more difficult for judges

141. *See supra* Section I.B.ii.2.

142. *See supra* Section I.B.ii.3.

143. Chohlas-Wood & Levine, *supra* note 1.

144. There may be other constitutional issues related to the underlying information used in the probable cause analysis. For example, the Bronx Defenders are currently challenging the NYPD's continued storage of sealed criminal arrest records in their database and continued use of these records for investigatory purposes. *See, e.g.*, Brief for Petitioner, R.C. v. City of New York (N.Y. App. Div. 2018) (No. 153739-2018).

to review if the investigator is permitted to use the Patternizr recommendation *itself* as part of the probable cause determination. The data informing the recommendation is made up of police reports, and the evidence in the reports and any additional officer corroboration should be enough to form the basis for probable cause without a Patternizr recommendation.¹⁴⁵ The fact that a computer algorithm suggests two crimes might be linked should not be considered evidence in its own right.

For the same reason, a Patternizr recommendation or score should not count towards the totality of the circumstances giving rise to probable cause. Counting it towards the totality of the circumstances risks double-counting factors already taken into account by the algorithm. For example, if the investigator in the hypodermic needle-wielding shoplifter case cited the similarities between the crimes (the underlying data) *and* the high Patternizr score as reasons for granting a warrant, the inclusion of the Patternizr score in the analysis would be inappropriate double-counting.¹⁴⁶ While there is no reporting to suggest that Patternizr scores and recommendations are being used in probable cause determinations, attorneys should remain vigilant to the potential expanded use of Patternizr in probable cause and reasonable suspicion determinations.

III. RECOMMENDATIONS FOR ADVOCATES AND POLICYMAKERS

Advocates and policymakers face important questions regarding the use of predictive policing technologies. A first critical question is whether such technologies should be used at all. While some commentators believe predictive policing is inevitable and should be better managed, many activists and advocacy organizations have urged lawmakers to ban predictive policing technologies altogether.¹⁴⁷ This debate over the use of predictive policing largely occurs outside

145. *See supra* Section I.B.ii.4.

146. This is similar to the issue of judges using COMPAS scores in addition to other factors in sentencing, raised in a ProPublica report on COMPAS and racial bias. *See* Angwin et al., *supra* note 26. The reason for this is that the factors the judge considers separate from the score is likely already built into the score. *Id.*

147. *See* Eva Ruth Moravec, *Do Algorithms Have a Place in Policing?*, ATLANTIC (Sept. 5, 2019), <https://www.theatlantic.com/politics/archive/2019/09/do-algorithms-have-place-policing/596851/> [<https://perma.cc/VA8W-Q4X5>]. Activists like Hamid Khan and Jamie Garcia, of the Stop LAPD Spying Coalition work to ban the use of predictive policing technologies altogether. *Id.*; *see also* Ferguson, *Policing Predictive Policing*, *supra* note 11. Professor Ferguson suggests that predictive policing is inevitable, but he puts forward a framework for evaluating and better managing the technologies as they are developed. *Id.* at 1188–89.

of the realm of police decision-making, however, as police policies are seldom subjected to the same level of democratic review as those of other government agencies.¹⁴⁸ As such, a good starting place would be to ensure a robust public debate and democratic oversight over whether, and how, these tools are used.¹⁴⁹ The following considers two potential strategies for reform-minded advocates and policy-makers to eliminate or reduce the potential harms of predictive policing tools like Patternizr, including an outright ban and steps towards better regulation of such tools.

A. Considerations for Banning the Use of Predictive Policing Tools Such as Patternizr

In the current context of policing in the United States, many advocates and activists warn against equipping law enforcement with any new predictive tools that may perpetuate racially-biased policing practices and which may erode Fourth Amendment protections.¹⁵⁰ The Movement for Black Lives policy agenda includes a goal of the “[t]otal prohibition on the acquisition of any new surveillance technology or development of surveillance program,” and a demand that “[f]ederal and local agencies should prevent the use of predictive systems that erode the Fourth Amendment.”¹⁵¹ The ACLU and a coalition of sixteen civil rights organizations, including the Leadership Conference on Civil and Human Rights, 18 Million Rising, the Brennan Center for Justice, the NAACP, Data & Society Research Institute, and the Electronic Frontier Foundation, caution that:

The institution of American policing, into which these systems are being introduced, is profoundly flawed: it is systemically biased against communities of color and allows unconscionable abuses of police power. Predictive policing tools threaten to provide a

148. See Barry Friedman & Maria Ponomarenko, *Democratic Policing*, 90 N.Y.U. L. REV. 1827, 1907 (2015).

149. This is, in part, underway in New York City with the creation of the Automated Decision Systems Task Force. See NYC AUTOMATED DECISION SYSTEMS TASK FORCE, <https://www1.nyc.gov/site/adstaskforce/index.page> [https://perma.cc/K9HB-DRGF] (last visited Oct. 30, 2019).

150. See Chinyere Tutashinda & Malkia Cyril, *An End to the Mass Surveillance of Black Communities, and the End to the Use of Technologies that Criminalize and Target Our Communities (Including IMSI Catchers, Drones, Body Cameras, and Predictive Policing Software)*, MOVEMENT FOR BLACK LIVES, <https://policy.m4bl.org/end-war-on-black-people/> [https://perma.cc/N6X3-X6Z6] (last visited Nov. 3, 2019); *End Broken Windows Policing: Policy Solutions*, CAMPAIGN ZERO, <https://www.joincampaignzero.org/brokenwindows> [https://perma.cc/4V48-C7EZ] (last visited Oct. 30, 2019); ACLU & 16 CIVIL RIGHTS ORGS., *supra* note 10.

151. Tutashinda & Cyril, *supra* note 150.

misleading and undeserved imprimatur of impartiality for an institution that desperately needs fundamental change. Systems that are engineered to support the status quo have no place in American policing.¹⁵²

Campaign Zero, a campaign to end police violence in America, lists ending the use of predictive policing technology among its recommended policy solutions for ending broken windows policing.¹⁵³ Campaign Zero explains that predictive policing technology “uses systematically biased data to enhance police profiling of Black people and communities.”¹⁵⁴

While NYPD leadership claims that Patternizr is immune from the issues that plague earlier versions of predictive policing technologies,¹⁵⁵ this Article argues that Patternizr is likely to further exacerbate racial biases that are entrenched within policing and the criminal legal system at large.¹⁵⁶ This Article has also investigated the potential of cognitive biases, such as automation bias and confirmation bias, that are likely to further exacerbate problems caused by racially-biased data, in addition to raising unanswered questions concerning Fourth Amendment protections and the use of Patternizr.¹⁵⁷ Patternizr should not be immune from the criticisms of other predictive policing technologies, nor should advocates and policymakers take the NYPD’s word that it is bias-free without a rigorous independent review.

Given what is known about Patternizr and the troubling findings on the impacts of other predictive policing tools built on similarly racially biased data, policymakers and advocates who seek to ban Patternizr and other predictive policing technologies are not taking a radical position. Nearly every leading advocacy organization in the field of police accountability has either issued a dire warning against the use of predictive policing technologies¹⁵⁸ or gone further to adopt the ban of predictive policing technologies as part of their policy platform.¹⁵⁹ Advocates and police-reform-aligned policymakers at

152. ACLU & 16 CIVIL RIGHTS ORGS., *supra* note 10.

153. *End Broken Windows Policing: Policy Solutions*, *supra* note 150.

154. *Id.*

155. Chohlas-Wood & Levine, *supra* note 1.

156. *See supra* Section I.B.i.

157. *See supra* Sections I.B.iii, I.B.iv.

158. ACLU & 16 CIVIL RIGHTS ORGS., *supra* note 10.

159. *End Broken Windows Policing: Policy Solutions*, *supra* note 150; Tutashinda & Cyril, *supra* note 150.

the local and state level can and should push for the halt of the use of predictive policing technologies by law enforcement.

B. Regulating the Use of Patternizr to Minimize Harm

Alternatively, advocates and policymakers may seek to take a more pragmatic approach to regulating the use of predictive policing technologies including Patternizr. This Section outlines several steps that policymakers and advocates can take to minimize the potential harm of predictive policing tools like Patternizr.

i. Ensure Democratic Accountability and Transparency

As policing tools and surveillance tactics become more advanced, democratic oversight is critical to ensure that civil rights and liberties are adequately protected.¹⁶⁰ In order to have true democratic accountability over the tools and tactics used by our police forces, we must first have transparency.¹⁶¹ The NYPD should open up its database and use of Patternizr to an independent audit to determine whether the algorithm risks perpetuating racial disparities within the criminal legal system.¹⁶² Policymakers in local and state government can facilitate such an audit by requiring the NYPD to stop using Patternizr and any other predictive policing technologies until an

160. See generally AM. CIVIL LIBERTIES UNION, COMMUNITY CONTROL OVER POLICE SURVEILLANCE: TECHNOLOGY 101 2 (2016) [hereinafter ACLU, COMMUNITY CONTROL], <https://www.aclu.org/report/community-control-over-police-surveillance-technology-101> [<https://perma.cc/JHB2-ZZ9A>]; Friedman & Ponomarenko, *supra* note 148, at 1831.

161. The NYPD closely guards and avoids disclosing information regarding its use of predictive policing tools. In 2016, the Brennan Center for Justice requested information about the NYPD's use of predictive policing tools pursuant to New York's Freedom of Information Law (FOIL). See N.Y. PUB. OFF. LAW §§ 84–90 (McKinney 2017). After two years of litigation, the Brennan Center was able to obtain some documents regarding the NYPD's tests, purchases, and implementation of predictive tools. NYPD PREDICTIVE POLICING DOCUMENTS, BRENNAN CTR. FOR JUST. (July 12, 2019), <https://www.brennancenter.org/our-work/research-reports/nypd-predictive-policing-documents> [<https://perma.cc/RBA6-JFAZ>]. According to the Brennan Center, “[t]he difficult process to get access to this information, and the piecemeal production [the Brennan Center] ultimately received . . . reveal[s] the NYPD’s quest to keep the public in the dark about this technology.” *Id.*

162. See Melendez, *supra* note 80.

Any predictive policing platform runs the risks of perpetuating disparities because of the over-policing of communities of color that will inform their inputs. To ensure fairness, the NYPD should be transparent about the technologies it deploys and allows independent researchers to audit these systems before they are tested on New Yorkers.

Id. (quoting NYLCU Legal Director Christopher Dunn).

independent audit has been conducted. After a thorough, independent audit, policymakers should require a public presentation of the findings. A robust and informed public discussion should then precede a vote by a democratically accountable assembly, such as the City Council.¹⁶³ Such democratic safeguards are critical for the legitimacy of law enforcement and ensuring that modern policing techniques do not overstep Constitutional limitations.¹⁶⁴

ii. Require Disclosure of Predictive Policing Tools in Criminal Cases

In addition to calling for more transparency and oversight regarding the use of predictive policing tools by the NYPD and other police departments, advocates — especially criminal defense attorneys — should push for requirements that prosecutors disclose the use of predictive policing tools and decision support models in arriving at the arrest and prosecution of individual defendants. The same problems identified in Section I.B.i, including racial, automation, and confirmation biases may compromise investigations, reveal a lack of probable cause, and could possibly exculpate individual defendants. Criminal defense attorneys, judges, and juries should have this information in order to better evaluate the government’s case against the defendant and to more fully interrogate the process leading to the arrest and prosecution.

Absent proactive disclosure from the prosecution, criminal defense attorneys have no way of knowing whether a predictive policing tool like Patternizr helped to identify their client. Defense attorneys in jurisdictions using Patternizr¹⁶⁵ should be alert to the potential use of Patternizr in their cases involving charges of robbery, burglary, or grand larceny — the crimes for which the NYPD is currently using Patternizr¹⁶⁶ — where the defendant is charged with two or more similar crimes, or where their current charge is similar to a past crime for which they were charged.¹⁶⁷ Defense attorneys should be

163. See ACLU, *COMMUNITY CONTROL*, *supra* note 160, at 2; Friedman & Ponomarenko, *supra* note 148, at 1838.

164. See ACLU, *COMMUNITY CONTROL*, *supra* note 160, at 2; Friedman & Ponomarenko, *supra* note 148, at 1838.

165. At the time of writing, the NYPD — the initial developer of Patternizr — was the only police department that had publicly announced its use of Patternizr.

166. Chohlas-Wood & Levine, *supra* note 1, at 154. In an interview, Chohlas-Wood commented that he would like to see Patternizr expanded to include petit larceny. *Resoundingly Human*, *supra* note 85.

167. According to a lawsuit brought by the Bronx Defenders, the NYPD regularly uses sealed arrest information in criminal investigations. See Complaint at 1–2, R.C.

especially alert to the potential use of Patternizr in situations where their clients are accused of committing crimes across precinct and police command jurisdictions, as it is unlikely that the NYPD would have recognized such a pattern without the use of Patternizr.¹⁶⁸

In cases where defense attorneys suspect predictive policing tools were used to identify their client, they may be able to argue that the prosecution has a constitutional obligation to disclose whether a predictive algorithm was used as well as any reports generated by the tool.¹⁶⁹ Under *Brady v. Maryland*, the government is required to disclose all material, exculpatory evidence in advance of trial to the defense.¹⁷⁰ However, this argument will not succeed without showing a “reasonable probability” that the disclosure of the use of predictive policing tools will affect the outcome of the trial.¹⁷¹ This is a tall order in the context of predictive policing, where the algorithm is an investigative tool — albeit, a tool with flaws that could lead to wrongful convictions¹⁷² — and, in most contexts, not actual evidence in its own right.¹⁷³ As a result, it may be challenging for a defense attorney to show that the disclosure of the use of predictive policing tools would have been exculpatory and material enough to affect the outcome of a case.¹⁷⁴

In the context of Patternizr, however, defense attorneys can argue that a Patternizr report with other potential crime patterns and alternative suspects should be considered *Brady* material. Prosecutors have an obligation to disclose evidence that suggests someone other than the accused committed the crime.¹⁷⁵ Defense attorneys can argue that a high Patternizr probability score for a crime committed by another person must be disclosed.¹⁷⁶ A failure to investigate other

v. City of New York (N.Y. App. Div. 2018) (No. 153739-2018). It is likely that Patternizr also uses sealed records that defense attorneys may not have access to. Defense attorneys concerned about the use of Patternizr in a case should ask their client whether they have any past arrests related to the crime, even if those arrests happened when the client was a juvenile or have been dismissed and sealed.

168. Chohlas-Wood & Levine, *supra* note 1, at 155.

169. *See Brady v. Maryland*, 373 U.S. 83, 88 (1963).

170. *Id.*

171. *Kyles v. Whitley*, 514 U.S. 419, 422 (1995).

172. *See supra* notes 126–27 and accompanying text.

173. However, the defense could question investigating officers regarding the use of a flawed predictive policing tool in order to call into question the credibility of the investigation.

174. *See Brady*, 373 U.S. at 87; *Kyles*, 514 U.S. at 422.

175. *See Brady*, 373 U.S. at 87.

176. The defense can make a similar argument that a probable pattern containing a crime for which the defendant is very likely *not* to have committed should be

suspects from a list of potential crime patterns raises questions about the validity of the investigation, and therefore should be made available to the defense as impeachment material against investigating officers.

In jurisdictions with discovery laws that are more expansive than constitutional requirements,¹⁷⁷ statutory arguments may prove more fruitful in obtaining disclosure of the use of predictive policing tools under provisions calling for the disclosure of police reports and notes related to the case.

New York State recently passed a law reforming its discovery practices, which will go into effect on January 1, 2020.¹⁷⁸ The new law — N.Y. CRIM. PROC. LAW § 245 — replaces New York’s current discovery statute, called the “blindfold” law because it “keep[s] people accused of crimes completely in the dark about critical evidence against them,” allowing prosecutors to withhold evidence until the day of trial.¹⁷⁹ The new law requires prosecutors to share discoverable materials with the defense within fifteen calendar days of the defendant’s arraignment.¹⁸⁰ In addition to drastically reforming the timeframe in which evidence must be disclosed, § 245 also enumerates a non-exhaustive list of automatically discoverable materials — materials that the prosecution is required to disclose even if not specifically requested by the defense.¹⁸¹ These materials include evidence such as statements by the defendant and co-defendants to law enforcement, grand jury testimony, names and

disclosed as *Brady* material. This could apply to situations where Patternizr recommends a crime pattern that is rejected by an analyst, but where the defendant could not have committed one of the crimes in the likely pattern — that is, if the defendant has a reliable alibi for the similar crime or evidence suggests that the crime pattern was committed by someone else.

177. According to a report by the Center for Court Innovation, New York joined 46 other states that have adopted comparable open discovery laws. KRYSTAL RODRIGUEZ, CTR. FOR COURT INNOVATION, DISCOVERY REFORM IN NEW YORK: MAJOR LEGISLATIVE PROVISIONS 3 (2019), https://www.courtinnovation.org/sites/default/files/media/document/2019/Discovery-NYS_Full.pdf [<https://perma.cc/79SH-OBMU>] (citing DONNA LIEBERMAN & ISABELLE KIRSHNER, N.Y. CIVIL LIBERTIES UNION, TAKE OFF THE BLINDFOLD: REFORM NEW YORK DISCOVERY LAW (2019), <https://www.nyclu.org/en/publications/take-blindfold-reform-ny-discovery-law-commentary> [<https://perma.cc/2AAN-ARLX>]).

178. N.Y. CRIM. PROC. LAW § 245 (McKinney 2020); *see also* RODRIGUEZ, *supra* note 177.

179. LIEBERMAN & KIRSHNER, *supra* note 177.

180. N.Y. CRIM. PROC. LAW § 245.10(1).

181. *Id.* § 245.20(1)(a)–(u).

contact information for witnesses, police reports, notes taken by police and other investigators, and law enforcement agency reports.¹⁸²

Section 245's enumeration of automatically discoverable materials offers promising avenues for defenders to obtain information on the NYPD's use of predictive policing tools like Patternizr in individual cases.¹⁸³ Under subsection (e), the government must automatically disclose "all police reports, notes of police and other investigators, and law enforcement agency reports."¹⁸⁴ When a crime analyst or officer enters a crime into their system and selects to "patternize" the crime,¹⁸⁵ the output of the Patternizr process — a list of potential crime patterns and scores — should be interpreted to be a law enforcement report, falling under the plain language of subsection (e), and as such, subject to automatic disclosure.¹⁸⁶ While these reports *should* be automatically disclosed, it is likely that the NYPD and prosecutors will argue for a narrow interpretation of the new law, and as such, defense attorneys will need to push for disclosure of Patternizr reports. When the new law takes effect, defense attorneys should request Patternizr reports in all property crime cases, arguing that they fall under § 245.20(1)(e).

iii. Implement Training and Procedures to Reduce the Impact of Cognitive Biases

Cognitive biases, including automation bias and confirmation bias, may be ingrained in the human brain and, as a result, may be impossible to completely overcome and challenging to reduce.¹⁸⁷ Police departments and the creators of predictive policing technologies such as Patternizr would benefit from engaging with experts on cognitive biases¹⁸⁸ to better understand the impacts of such biases and specific methods to reduce the harms of cognitive biases when developing and implementing predictive technologies. The

182. *Id.*

183. *See id.*

184. *Id.* § 245.20(1)(e).

185. *Resoundingly Human*, *supra* note 85.

186. N.Y. CRIM. PROC. LAW § 245.20(1)(e).

187. *See, e.g.* RÜDIGER F. POHL ET AL., COGNITIVE ILLUSIONS: A HANDBOOK ON FALLACIES AND BIASES IN THINKING, JUDGEMENT AND MEMORY 3 (Rüdiger F. Pohl ed., 2005) ("[A cognitive] illusion is *hard if not impossible to avoid*. . . . For some illusions, a proper instruction, careful selection of the material, or other procedural variations may reduce or even eliminate the illusion . . . while for other illusions, most (if not all) attempts to overcome the effect have failed." (alterations in original)).

188. Experts on cognitive biases can be found in several social science fields, including behavioral economics and psychology. *See, e.g., id.* at xi–xii.

NYPD could, for example, work with an outside expert to consult on the impact of cognitive biases on the use of Patternizr and the risk of unchecked error that such biases exacerbate. Such experts may be able to tailor specific recommendations in terms of training and procedures to avoid making bias-influenced errors.

Existing literature on the impacts of cognitive biases on policing suggest two main ways of reducing the impact of automation and confirmation biases on the use of predictive policing tools.¹⁸⁹ These suggestions include providing law enforcement with training on the limits and problems of predictive tools as well as requiring procedures to disrupt the influence of biases and rigorously test hypotheses.¹⁹⁰

In his recommendations for responding to issues arising from problems with flawed data, Professor Ferguson advocates for predictive policing systems to acknowledge error as a contrast to the conventional assumption that algorithms cannot be biased or incorrect.¹⁹¹ Ferguson argues that, by acknowledging room for error, police departments will be more likely to audit for errors and better able to correct errors by training the staff who use the algorithms to prevent the errors to which the algorithm may be susceptible.¹⁹² Additionally, training on the limitations of predictive policing tools like Patternizr may empower officers using the decision-support system to more critically evaluate the recommendations made by the system, helping to reduce the impact of automation bias.¹⁹³

In addition to training, protocols that create opportunities to question hypotheses and disrupt confirmation bias may help reduce the combined impact of automation bias and confirmation bias in the context of predictive policing tools like Patternizr. Behavioral economists suggest mental exercises to overcome biased thinking including making at least three different estimates (for example, asking oneself who are three possible suspects, or what are three possible M.O.s for this crime), using “premortems” where the task requires “imagin[ing] a future failure and then explain[ing] the cause,” attempting to evaluate the hypothesis as an “outsider” to the work, seeking outside advice or review from others, contemplating other options that perhaps have not been fully considered, and challenging motivated biases by establishing “trip wires” (i.e., setting

189. For a discussion of the impact of automation and confirmation biases on how predictive policing tools are used, see *supra* Section I.B.ii.3.

190. See Murgado, *supra* note 64, at 4.

191. Ferguson, *Policing Predicting Policing*, *supra* note 11, at 1151.

192. See *id.*

193. See *supra* Section I.B.i.3.

a date by which an investigation must be sufficient to move along or the investigation must be abandoned).¹⁹⁴

Amaury Murgado, a retired special operations lieutenant with a Florida Sheriff's Office, applies similar suggestions to the law enforcement context in his article *Dealing with Confirmation Bias* published by Police Magazine.¹⁹⁵ Murgado suggests that officers “try to disprove [their] theories instead of trying to prove them.”¹⁹⁶ He cautions that gut instincts can be helpful in providing possible avenues for exploration by the officer, but that they should not be treated as conclusive.¹⁹⁷ By summarizing D. Kim Rossmo's *Criminal Investigative Failures*, Murgado provides a list of ten key techniques for officers to reduce confirmation bias, including recommendations ranging from trainings for officers on confirmation bias, encouraging a culture of impartiality, neutrality, and open inquiry, organizing brainstorming sessions where creativity is sought and early consensus or groupthink is avoided, asking “how do we know what we think we know” throughout the investigative process, and seeking out expert opinions when appropriate.¹⁹⁸

In an effort to reduce the impact of automation bias and confirmation bias on the use of Patternizr, the NYPD should implement trainings to ensure that officers understand how these common biases may lead to incorrect — and, in the context of the criminal legal system, terribly unjust — results. Further, the NYPD should implement procedures for the use of Patternizr, that integrate the above-discussed methods, such as requiring officers to write down the reason for deciding that a series of crimes is a pattern, what other options existed (other crimes, other suspects, deciding that there was no match, etc.), and why they did not select those other options. Additionally, the NYPD could require regular check-ins with supervisors or peers where analysts and officers' hypotheses are challenged and alternatives are seriously considered. Such trainings and procedures are unlikely to fully eliminate the impact of cognitive biases on the use of Patternizr and other predictive policing tools, but

194. See Jack B. Soll et al., *Outsmart Your Own Biases*, HARV. BUS. REV. 4, 5, 11 (May 2015), <https://hbr.org/2015/05/outsmart-your-own-biases> [<https://perma.cc/LF7E-UA4W>].

195. Murgado, *supra* note 64.

196. *Id.*

197. *Id.*

198. *Id.* at 4 (citing D. KIM ROSSMO, CRIMINAL INVESTIGATIVE FAILURES: AVOIDING THE PITFALLS (2005), <http://www.law.northwestern.edu/legalclinic/wrongfulconvictions/events/documents/Avoiding%20Pitfalls%20Article.pdf> [<https://perma.cc/SKD2-NYQ5>]).

they may help to reduce the chances of unchecked biases leading to wrongful arrests, prosecutions, and convictions.

iv. Acknowledge and Address Racial Disparities in Underlying Crime Data

In addition to providing trainings and procedures to reduce the impact of cognitive biases, police departments using Patternizr and other predictive policing tools must take steps to eliminate the racial biases of the underlying data from which predictive tools are built. The first step is to acknowledge — and to be transparent — about the racial biases embedded in the algorithm’s source data. Publicly available NYPD crime data shows that Black and Latinx people are vastly overrepresented in the suspect and arrest pool for crime overall, including property crimes.¹⁹⁹ Based on available information, Patternizr was likely trained on racially biased data that oversamples crimes where people of color have been identified as suspects.²⁰⁰

Researchers and criminal justice stakeholders from a range of perspectives agree that people of color are overrepresented in arrests for low-level offenses due to the aggressive broken windows policing in neighborhoods of color.²⁰¹ However, there is less research as to why racial disparities exist in victim-reported crimes, including property crimes. A report by the Sentencing Project grapples with this question, suggesting that, “[t]he disproportionate rate of [B]lack crime should not be surprising given that African Americans are far more likely than whites to experience and to live in communities with concentrated disadvantage.”²⁰² The report goes on to suggest that

199. See JAMES P. O’NEILL, NYPD, CRIME AND ENFORCEMENT ACTIVITY IN NEW YORK CITY (JAN. 1 – DEC. 31, 2018) 4 (2019), https://www1.nyc.gov/assets/nypd/downloads/pdf/analysis_and_planning/year-end-2018-enforcement-report.pdf [<https://perma.cc/H5L5-8ELL>]. “Robbery arrestees are most frequently Black (60.5%) or Hispanic (30.5%).” *Id.* “Grand Larceny arrestees are most frequently Black (51.8%) or Hispanic (28.3%).” *Id.* at 6. According to the latest information from the U.S. Census Bureau, 24.3% of New York City residents identify as Black or African American, and 29.1% of New York residents identify as Hispanic or Latinx. *QuickFacts: New York City, New York*, U.S. CENSUS BUREAU, <https://www.census.gov/quickfacts/newyorkcitynewyork> [<https://perma.cc/S267-CUQX>] (last visited Nov. 3, 2019).

200. See generally O’NEILL, *supra* note 199; *QuickFacts: New York City, New York*, *supra* note 199.

201. See, e.g., THE NAT’L ACADS. OF SCIS., ENG’G, & MED., PROACTIVE POLICING: EFFECTS ON CRIME, COMMUNITIES, AND CIVIL LIBERTIES 251 (David Weisburd & Malay K. Majmudar eds., 2018).

202. NAZGOL GHANDNOOSH & CHRISTOPHER LEWIS, THE SENTENCING PROJECT, RACE AND PUNISHMENT: RACIAL PERCEPTIONS OF CRIME AND SUPPORT FOR

“the criminal justice system does not simply mirror these differences in crime rates — it exacerbates them through codified policies and individual discretion.”²⁰³

Individual discretion in the reporting and response to property crimes may at least partially explain racial disparities in property crime data.²⁰⁴ For example, people of color may be more likely to be reported for shoplifting offenses because of a heightened suspicion of shoplifting by store employees and security.²⁰⁵ While many shoplifting offenses are charged as petit larceny,²⁰⁶ shoplifting offenses can rise to the level of a grand larceny charge if the items taken are valued at \$1000 or more.²⁰⁷ Additionally, some New York City retailers have a practice of presenting low-level shoplifters with a trespass notice, alerting them that they are not welcome to return to the store, after which even low-dollar shoplifting can lead to felony burglary charges.²⁰⁸ In this example, the racial biases of store employees lead to increased surveillance of Black customers and subsequent disproportionate reporting of Black suspects of shoplifting offenses.²⁰⁹ As a result, the racial bias of private actors impacts the reporting of crime and therefore contributes to the overrepresentation of people of color in both the data used to train Patternizr and the suspect pool of potential crime patterns to which Patternizr suggests matches.

These racial biases that are built into algorithms cannot easily be undone. Unlike training users of Patternizr on automation and confirmation biases so that they can more critically engage with Patternizr’s recommendations, Patternizr’s racial bias problem starts

PUNITIVE POLICIES 20 (2014), <https://www.sentencingproject.org/wp-content/uploads/2015/11/Race-and-Punishment.pdf> [<https://perma.cc/35P8-DC8V>].

203. *Id.*

204. See Gillooly, *supra* note 31.

205. See, e.g., Cassi Pittman Claytor, ‘Shopping While Black’: Yes, Bias against Black Customers Is Real, *GUARDIAN* (Jun. 24, 2019), <https://www.theguardian.com/commentisfree/2019/jun/24/shopping-while-black-yes-bias-against-black-customers-is-real> [<https://perma.cc/56EH-JKV4>].

206. N.Y. PENAL LAW § 155.25 (McKinney 2019). The developers of Patternizr expressed interest in expanding the use of the algorithm to petit larceny, however, at the time of writing, the NYPD has only disclosed that Patternizr is used for grand larceny, robbery, and burglary crimes. *Resoundingly Human*, *supra* note 85.

207. N.Y. PENAL LAW § 155.30.

208. Chelsea Rose Marcius, *Manhattan Store’s Legal Maneuver Makes Minor Theft Charges Serious Crimes Punishable by Prison Time*, N.Y. DAILY NEWS (Sep. 8, 2019), <https://www.nydailynews.com/new-york/ny-minor-theft-charges-prison-time-shoplifting-20190909-fdqngueu3qrclnmlbkntu3yd3da-story.html> [<https://perma.cc/N84F-8JFH>].

209. See Claytor, *supra* note 205.

with its source data.²¹⁰ No amount of implicit bias trainings for officers or crime analysts can solve the problem of vast racial disparities in the very data from which the algorithm was built. The only way to solve the problem of racial bias in the data predictive policing tools use is to eliminate racial biases from policing as a whole. Without first addressing racial biases in policing as a whole, tools that make police more efficient will, at best, make police more efficient at the status quo of biased policing, and at worst, compound racial biases in the criminal legal system.²¹¹

CONCLUSION

The NYPD has developed a new and potentially powerful predictive tool that will help investigators more efficiently identify crime patterns. Whether the tool is “fair,” as its developers claim, is yet to be determined — though unlikely from the information that is available. Advocates for over-policed communities and those accused of crimes have reason to be concerned and to remain vigilant. Prior generations of predictive policing and actuarial justice tools — including algorithms that do not include race in their design — produce racially-disparate results that intensify policing of already over-policed communities. It is likely that Patternizr will produce similar results due to the over-representation of people of color presently in NYPD databases. The combination of racial, automation, and confirmation biases may produce particularly devastating results for individuals who appear in Patternizr’s recommendations. Advocates and policymakers should act quickly to address the issues arising from Patternizr and other predictive policing tools. While waiting for policymakers to act to limit its harms, the city’s criminal defense attorneys will need to serve as a bulwark against the potential misuse of Patternizr. In a justice system that relies on quick plea deals, defense attorneys will need to do their due diligence to ensure that officers and prosecutors are not relying on computerized matches and scant evidence when charging new crimes based on past M.O.s that may — or may not — be linked in a pattern.

210. *See supra* Section I.B.ii; note 199 and accompanying text.

211. *See supra* Section I.B.i.