

DATA-DRIVEN POLICE PROFILING

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Police departments increasingly rely on algorithms and other data-driven methods of identifying high-crime areas and people who are at high risk for involvement in crime. This Article examines several constitutional obstacles to this type of policing. First, to the extent that these algorithms rely on data entitled to privacy protection, they may violate the Fourth Amendment. Second, the steps police take in response to a “hot” place or person designation must also be subject to constitutional regulation. Further, the principle of legality should prohibit the police from acting on any risk designation, even one that is very likely accurate, in the absence of direct observation of risky conduct. For the same reason, and to combat the influence of racially based “dirty data,” algorithm developers must finely tune both the inputs and outputs of their profiles. Finally, a failure to disclose the inner workings of a predictive algorithm may violate the Confrontation Clause. Combined, these legal concerns could well spell the demise of profile-driven policing.

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INTRODUCTION

Police Officer Keener is cruising a heavily Black neighborhood in St. Louis, in part because an algorithm from a company called HunchLab has identified the area as one in which the risk of aggravated assault is relatively high. Keener spots a Chevy Impala and stops it, ostensibly because its dark-tinted windows are a violation of Missouri's traffic laws. The car turns out to be driven by a young Black man. Because—Keener later tells a reporter riding with him—he smelled marijuana through the open window, he thoroughly searches the car and finds a gun. However, he does not find any marijuana, and the gun is legal. After letting the young man drive on, Keener tells the reporter, “He could have been going to shoot somebody. Or not.”¹

Andrew Ferguson, who recounts this real-life example of what has come to be called “predictive policing,” asks, “Would Officer Keener have stopped the car without the HunchLab prediction?”² It is hard to know. As detailed later in this Article, police use traffic violations as pretexts to investigate all the time, and research shows they are especially likely to do so in neighborhoods populated by people of color.³ But the innuendo in Professor Ferguson's question is that the HunchLab algorithm increased the chances of such encounters.⁴ In other words, predictive policing might multiply the benefits and costs already inherent in traditional policing: it might lead police to more perpetrators but also might generate more false positives—stops of people who are doing nothing wrong. Algorithms might direct the police to areas with more crime but might also trigger investigations of innocent people—or people committing traffic and other types of infractions that all of us routinely commit—whom the police would otherwise never have stopped or questioned.

HunchLab (now a part of an outfit called SoundThinking)⁵ is just one of many companies that use computer modeling and artificial intelligence to produce maps indicating “hot spots” for crime during specific times of the day, relying not only on geographic crime data but also calls for service, weather patterns, census data, population density, and the number and location of abandoned properties, schools, bars, and transportation centers,

¹ ANDREW GUTHRIE FERGUSON, *THE RISE OF BIG DATA POLICING: SURVEILLANCE, RACE, AND THE FUTURE OF LAW ENFORCEMENT* 64 (2017).

² *Id.*

³ *See id.* at 67–69.

⁴ *See id.* at 63–64.

⁵ *See* SOUNDTHINKING, <https://www.soundthinking.com> [<https://perma.cc/76BU-PW8M>]; *see also* SoundThinking, CAL. POLICE CHIEFS ASS'N, <https://www.californiapolicechiefs.org/sponsors/soundthinking> [<https://perma.cc/MCN6-X59V>] (“SoundThinking (formerly ShotSpotter) is a public safety technology company that combines transformative solutions and strategic advisory services for sound decisions, to make neighborhoods safer and improve community confidence.”).

as well as upcoming events such as ball games.⁶ Of course, police have long been interested in ways of identifying those areas most in need of their presence. But the algorithms used by companies such as SoundThinking, sporting names like Risk Terrain Modeling,⁷ appear to provide more granular outputs; for instance, they may help pinpoint which neighborhoods are transitioning from high gun crime to high residential burglary areas, which buildings or blocks in those areas are particularly likely to experience violence, and which streets have experienced upticks in burglaries.⁸

Increasingly combined with hot spot policing is the use of big data to identify “hot people.”⁹ Relying on eleven crime-related variables, as well as age and gang membership, the city of Chicago famously developed a “heat list” (formally known as the Strategic Subjects List, or SSL) that assigned “risk scores” from 1 to 500 to people with criminal records.¹⁰ According to developers of the list, the higher the score, the greater the chance the person would be either a perpetrator of violence or its victim.¹¹ In a similar attempt to compute “threat scores” in connection with people encountered after 911 calls, Intrado, a now-defunct company, introduced a program called Beware that coded people and places red, yellow, or green (with red indicating the highest threat), based on data from publicly available criminal and mental health records and trolling of social media for gang associations and violent comments.¹² Taking Intrado’s place are businesses like ShadowDragon, which sucks in data from social media, Amazon, dating apps, posts on Twitter, WhatsApp, and Facebook in an effort to help police both identify trouble spots and learn more about potential suspects.¹³ In addition to

⁶ See, e.g., SOUNDTHINKING, *supra* note 5; GEOLITICA, <http://www.geolitica.com> [<https://perma.cc/X29S-WLC2>].

⁷ See RISK TERRAIN MODELING, <https://www.riskterrainmodeling.com> [<https://perma.cc/9GUG-29AL>] (“RTM diagnoses environmental conditions that lead to crime (and other problems).”); see also Department Notice by William Scott, Applications for the 30x30 Women in Policing Fellowship Opportunity, San Francisco Police Dep’t (Feb. 22, 2023), <https://www.sanfranciscopolice.org/sites/default/files/2023-02/SFPDDN-23-020-20230227.pdf> [<https://perma.cc/6YGU-AWAP>] (“RTM analysis brings multiple sources of data together by connecting them to geographic places. It adds context to ‘big data’ and forecasts new risk patterns for certain areas.”).

⁸ See FERGUSON, *supra* note 1, at 63.

⁹ Nissa Rhee, *Can Police Big Data Stop Chicago’s Spike in Crime?*, CHRISTIAN SCI. MONITOR (June 2, 2016, 4:30 PM), <https://www.csmonitor.com/USA/Justice/2016/0602/Can-police-big-data-stop-Chicago-s-spike-in-crime> [<https://perma.cc/29TF-CYXH>]; see also FERGUSON, *supra* note 1, at 34.

¹⁰ Rhee, *supra* note 9.

¹¹ *Id.*

¹² Justin Jouvenal, *The New Way Police Are Surveilling You: Calculating Your Threat ‘Score’*, WASH. POST (Jan. 10, 2016), https://www.washingtonpost.com/local/public-safety/the-new-way-police-are-surveilling-you-calculating-your-threat-score/2016/01/10/e42bccac-8e15-11e5-baf4-bdf37355da0c_story.html [<https://perma.cc/7GFC-3NUB>].

¹³ Michael Kwet, *ShadowDragon: Inside the Social Media Surveillance Software That Can Watch Your Every Move*, THE INTERCEPT (Sept. 21, 2021, 5:03 PM), <https://theintercept.com/2021/09/21/surveillance-social-media-police-microsoft-shadowdragon-kaseware/> [<https://perma.cc/4VNH-V4P9>].

Chicago, Los Angeles, Kansas City, Baltimore, San Francisco, and numerous other cities have tried their hand at this type of predictive policing.¹⁴

Despite their popularity, the efficacy of data-driven hot spot and hot people policing—which this Article will henceforth call place-based and person-based policing—is highly questionable. When focused on a small area, place-based policing has been shown to be one of the more successful proactive policing techniques at reducing crime.¹⁵ But the most robust research on that point examined traditional place-based policing.¹⁶ The jury is still out on algorithm-driven stops like the one carried out by Officer Keener. While some studies indicate that these techniques do have an effect on crime,¹⁷ other studies suggest they are no more effective than less computerized approaches.¹⁸

The evidence on data-driven person-based policing is even less positive. Although the Chicago Police Department claimed that eighty percent of the fifty-one people shot over a two-day period were on the SSL, a subsequent RAND study showed the list was composed of unvalidated risk factors, haphazardly applied, and very poor at separating those who committed violent crime from those who did not over a ten-year period.¹⁹ An inspector general's report on the person-based policing data program developed in Los Angeles, called Los Angeles Strategic Extraction and Restoration (LASER), similarly found no evidence of crime reduction, as well as unreliability in both the data inputs and outputs used by LASER and a lack of clarity about what officers were supposed to do if the program designated a person as high

¹⁴ See FERGUSON, *supra* note 1, at 44.

¹⁵ See THE NAT'L ACADEMIES OF SCI., ENG'G & MED. ET AL., PROACTIVE POLICING: EFFECTS ON CRIME AND COMMUNITIES 276 (David Weisburd & Malay K. Majmundar eds., 2018); see also CYNTHIA LUM & CHRISTOPHER S. KOPER, EVIDENCE-BASED POLICING: TRANSLATING RESEARCH INTO PRACTICE 76 (2017) (stating, based on the research, that “[t]argeting high-crime places is one of the most effective approaches that the police can use to prevent crime and increase their legitimacy,” although also noting that this effectiveness depends on numerous implementation variables); Jerry H. Ratcliffe & George F. Rengert, *Near-Repeat Patterns in Philadelphia Shootings*, 21 SEC. J. 58, 58 (2008).

¹⁶ THE NAT'L ACADEMIES OF SCI., ENG'G & MED. ET AL., *supra* note 15, at 125.

¹⁷ Jerry H. Ratcliffe et al., *The Philadelphia Predictive Policing Experiment*, 17 J. EXPERIMENTAL CRIMINOLOGY 15, 32 (2021) (showing a 31% drop in property crime through placement of police cars in algorithmic-identified locations); Jeremy G. Carter et al., *The Indianapolis Harmspot Policing Experiment*, 74 J. CRIM. JUST. 1, 9 (2021) (finding a decrease in “aggregated social harm” and “violent offenses” resulting from various place-based interventions in areas identified through data analysis).

¹⁸ Aaron Sankin & Surya Mattu, *How We Assessed the Accuracy of Predictive Policing Software*, THE MARKUP (Oct. 2, 2023, 10:00 AM), <https://themarkup.org/show-your-work/2023/10/02/how-we-assessed-the-accuracy-of-predictive-policing-software> [<https://perma.cc/7UCM-SUZB>] (finding after a study of Plainsfield, New Jersey's use of Geolitica's place-based algorithm that “rates of arrest in predicted areas remained the same, regardless of whether Geolitica predicted a crime that day,” and that “around 6 out of every 1,000 predictions successfully anticipated reported robberies or aggravated assaults”).

¹⁹ See Jessica Saunders et al., *Predictions Put into Practice: A Quasi-Experimental Evaluation of Chicago's Predictive Policing Pilot*, 12 J. EXPERIMENTAL CRIMINOLOGY 347, 347 (2016) (comparing 426 individuals with the highest threat scores on the Chicago SSL to 247 matched individuals who differed by score and known associates with criminal histories).

risk or a chronic offender.²⁰ Under both programs, a Latino or Black male was far more likely to be classified as a high crime risk than a white male.²¹ Both programs have now been discontinued.²² Other research over the past two decades reached similar conclusions about person-based policing. For instance, an overview of research conducted before 2010 comparing place-based to person-based policing asserted that “the police have to approach four times as many targets to identify the same level of overall crime when they focus on people as opposed to places.”²³

The following discussion assumes, however, that the use of big data to facilitate both place-based and person-based policing (which together will be called profile-driven policing) is likely to continue for a number of reasons. Police departments are always under considerable pressure to do more with fewer personnel, and the allure of data programs may lead them to conclude that technology can fill the gap.²⁴ They also may believe that, despite the research outcomes so far, profile-driven policing can at least outperform traditional policing, not only because it is more accurate but also because it is less subject to bias.²⁵ Further, despite past failures, private companies have been very successful at repackaging their products as efficient crime-fighting mechanisms and convincing police departments to adopt them.²⁶

Thus, it is important to analyze the legality of profile-driven policing. This Article concludes that, even if it vastly improves, profile-driven policing—especially person-based prediction—faces several obstacles. First, to the extent police algorithms rely on data entitled to privacy protection, they may

²⁰ MARK P. SMITH, OFF. OF THE INSPECTOR GEN., L.A. POLICE COMM’N, REVIEW OF SELECTED LOS ANGELES POLICE DEPARTMENT DATA-DRIVEN POLICING STRATEGIES 23, 25 (2019).

²¹ *Id.* at 15 (79.8% of people on the “chronic offender” list were Black or Latino males); Saunders et al., *supra* note 19, at 358 (77% of the highest threat individuals on the SSL were African American males).

²² Grace Baek & Taylor Mooney, *LAPD Not Giving Up on Data-Driven Policing, Even After Scrapping Controversial Program*, CBS NEWS (Feb. 23, 2020, 7:00 AM), <https://www.cbsnews.com/news/los-angeles-police-department-laser-data-driven-policing-racial-profiling-2-0-cbsn-originals-documentary> [<https://perma.cc/VF8K-T4C3>] (LASER was discontinued); Annie Sweeny & Jeremy Gomer, *For Years Chicago Police Rated the Risk of Tens of Thousands Being Caught Up in Violence. That Controversial Effort Has Quietly Been Ended.*, CHI. TRIB. (Jan. 25, 2020, 2:55 AM), <https://www.chicagotribune.com/2020/01/24/for-years-chicago-police-rated-the-risk-of-tens-of-thousands-being-caught-up-in-violence-that-controversial-effort-has-quietly-been-ended/> [<https://perma.cc/MJ2C-YUGF>] (SSL was discontinued).

²³ ANTHONY A. BRAGA & DAVID L. WEISBURD, POLICING PROBLEM PLACES: CRIME HOT SPOTS AND EFFECTIVE PREVENTION 225 (2010).

²⁴ See Baek & Mooney, *supra* note 22 (noting that even after LASER was shut down, the LAPD chief of police stated, “[f]undamentally, I believe that data-driven strategies improve policing, and that improves community safety”).

²⁵ Elizabeth E. Joh, *The Undue Influence of Surveillance Technology Companies on Policing*, 92 N.Y.U. ONLINE 19, 36 (2017), https://nyulawreview.org/wp-content/uploads/2017/08/NYULawReviewOnline-92-Joh_0.pdf [<https://perma.cc/YE6A-YXP8>] (“In theory, algorithms in policing, sentencing, bail, and other criminal justice areas may represent an improvement on traditional methods of assessment: human beings alone.”).

²⁶ See *id.* at 21 (discussing “the commercial self-interest of surveillance technology vendors that overrides principles of accountability and transparency normally governing the police”).

violate the Fourth Amendment. Second, the steps police take in response to a “hot” designation must also be subject to Fourth Amendment regulation. Limiting even further what police can do based on a profile, the principle of legality should prohibit the police from acting on a high-risk designation—even one that meets Fourth Amendment dictates—in the absence of direct observation of risky conduct. For the same reason, and to combat the influence of racially based “dirty data,” algorithm developers must be careful about both the inputs and outputs of their profiles. Finally, a failure to disclose the inner workings of a predictive algorithm may violate the Confrontation Clause. Combined, these legal concerns could well spell the demise of profile-driven policing.

I. THE FOURTH AMENDMENT AND PROFILE-DRIVEN POLICING

Fourth Amendment lore is that a search or seizure requires probable cause.²⁷ At the same time, the Supreme Court has made clear that this level of justification is not necessary for every search or seizure. In fact, read closely, the caselaw construing the Fourth Amendment’s Reasonableness Clause endorses what could be called a “proportionality principle.”²⁸ Stated simply, the principle posits that the justification for a search or seizure should be roughly proportionate to its intrusiveness. Less intrusive searches and seizures might be permissible on lesser suspicion; more intrusive searches and seizures would be permissible on probable cause or something more.

If profile-driven policing required probable cause, it would likely never get off the ground. Place-based policing merely indicates where criminals might be; it provides no basis for concluding that any particular person, like the young man Officer Keener searched, is committing or is about to commit a crime. Person-based policing could, in theory, provide probable cause to arrest or search a particular person, but for reasons developed below, is unlikely ever to do so. Under proportionality reasoning, however, profile-driven policing might survive, if certain conditions are met. After briefly describing the Fourth Amendment caselaw from which the proportionality principle derives, the following discussion explains the limitations that principle places on the types of data that policing algorithms may access and the types of actions the police can take based on algorithmic output.

²⁷ *New Jersey v. T.L.O.*, 469 U.S. 325, 340 (1985) (“Ordinarily, a search—even one that may permissibly be carried out without a warrant—must be based on ‘probable cause’ to believe that a violation has occurred.”); *Texas v. Brown*, 460 U.S. 730, 742 (1983) (requiring “probable cause for seizure in the ordinary cases,” citing *Payton v. New York*, 445 U.S. 573, 587 (1980)).

²⁸ See Christopher Slobogin, *The World Without a Fourth Amendment*, 39 UCLA L. REV. 1, 68–75 (1991) (where the author first suggested this principle); see also CHRISTOPHER SLOBOGIN, *PRIVACY AT RISK: THE NEW GOVERNMENT SURVEILLANCE AND THE FOURTH AMENDMENT* 23–47 (2007).

A. *The Rationale for the Proportionality Principle*

As I have developed at length elsewhere,²⁹ the strongest support for constitutionalizing the proportionality principle comes from the Supreme Court’s seizure jurisprudence and the Court’s technological policing cases. In *Terry v. Ohio*, the Supreme Court famously permitted stops and frisks based solely on “reasonable suspicion,” a lesser standard than the traditional probable cause standard found in the Fourth Amendment.³⁰ Quoting from the year-old decision in *Camara v. Municipal Court*,³¹ the *Terry* Court explained that there is “no ready test for determining reasonableness other than by balancing the need to search [or seize] against the invasion which the search [or seizure] entails.”³² That is a proportionality test, and the Court has routinely applied it in analyzing the justification required for a seizure.³³

Admittedly, the Court has proceeded somewhat differently in its search cases. Even though both *Camara* and *Terry* involved searches, for many years the Court claimed that it would “ordinarily” adhere to the probable cause standard in the search setting.³⁴ But that claim is much harder to sustain now, in light of several Supreme Court decisions involving the use of technology, as well as its so-called “special needs” decisions. In *United States v. Jones*,³⁵ five justices distinguished between short-term and “prolonged” tracking, with only the latter situation requiring a warrant.³⁶ In *Carpenter v. United States*, the Court expressly limited its warrant requirement to the facts of the case, which involved acquisition of seven days of cell site location data,³⁷ in a footnote the Court stated that “we need not decide whether there is a limited period for which the Government may obtain an individual’s historical CSLI free from Fourth Amendment scrutiny,

²⁹ See SLOBOGIN, *PRIVACY AT RISK*, *supra* note *, at 38–46.

³⁰ *Terry v. Ohio*, 392 U.S. 1, 27 (1968).

³¹ *Camara v. Mun. Court of San Francisco*, 387 U.S. 523, 536–37 (1967).

³² *Terry*, 392 U.S. at 21 (quoting *Camara*, 387 U.S. at 536–37 (brackets in original)); *see also* *Navarette v. California*, 572 U.S. 393, 397 (2014) (“Although a mere ‘hunch’ does not create reasonable suspicion, *Terry*, [392 U.S. at 27], the level of suspicion the standard requires is ‘considerably less than proof of wrongdoing by a preponderance of the evidence,’ and ‘obviously less’ than is necessary for probable cause, *United States v. Sokolow*, 490 U.S. 1, 7 (1989).”).

³³ *See, e.g., Michigan v. Summers*, 452 U.S. 692, 697–98 (1981) (detention during house search); *see also, e.g., Rodriguez v. United States*, 575 U.S. 348, 354 (2015) (traffic stop); *see also, e.g., United States v. Martinez-Fuerte*, 428 U.S. 543, 555–56 (1976) (checkpoint).

³⁴ *New Jersey v. T.L.O.*, 469 U.S. 325, 340 (1985).

³⁵ *United States v. Jones*, 565 U.S. 400, 401, 411–12 (2012).

³⁶ *See id.* at 418, 431 (Alito, J., concurring) (noting that three justices joined Justice Alito’s concurring opinion making this distinction); *see id.* at 416 (Sotomayor, J., concurring) (where Justice Sotomayor appeared to agree with the distinction, expressing concern about the “aggregated” data that tracking devices allow).

³⁷ *Carpenter v. United States*, 585 U.S. 296, 302 (2018).

and if so, how long that period might be.”³⁸ In another case involving technology and searches, *Riley v. California*,³⁹ the Court dismissed the relevance of centuries-old precedent holding that a warrant is not required to search an arrestee’s effects (such as a wallet or purse) by asserting that comparing those actions to search of an arrestee’s phone “is like saying a ride on horseback is materially indistinguishable from a flight to the moon.”⁴⁰ And in over a dozen cases involving “special needs, beyond the normal need for law enforcement,”⁴¹ the Court has permitted searches on less than probable cause because of its perception that they infringed lesser privacy interests.⁴² All of these cases explicitly or implicitly relied on proportionality reasoning.⁴³

While it would not always require probable cause, proportionality analysis would still have three significant implications for profile-driven policing. First, it would require proportionate justification both for accessing the data inputted into predictive algorithms and for the police actions taken based on their output. Second, to measure whether these two requirements are met, algorithm developers would need to generate data about the “hit rate” for the algorithm—that is, the extent to which the algorithm accurately identifies places or people associated with crime. Third, before any physical confrontation takes place based on an algorithm, the proportionality principle will usually also mandate triggering conduct by the targeted individual. An independent basis for this third requirement is the legality principle’s requirement that state intervention be bottomed on predefined conduct, an

³⁸ *Id.* at 310 n.3.

³⁹ *Riley v. California*, 573 U.S. 373, 378–79 (2014).

⁴⁰ *Id.* at 382, 386, 393.

⁴¹ *New Jersey v. T.L.O.*, 469 U.S. 325, 351 (1985) (Blackmun, J., concurring). This terminology is now applied to a wide array of “administrative” searches and seizures. *See, e.g.*, *City of Los Angeles v. Patel*, 576 U.S. 409, 420 (2015) (stating that “[s]earch regimes where no warrant is ever required may be reasonable where ‘special needs . . . make the warrant and probable-cause requirement impracticable’” (quoting *Skinner v. Ry. Labor Executives’ Ass’n*, 489 U.S. 602, 616 (1989)), and citing probationer, drug testing, checkpoint, and inspection cases as examples).

⁴² *See, e.g.*, *T.L.O.*, 469 U.S. at 348 (Powell, J., concurring) (permitting search of a purse on less than probable cause because, *inter alia*, “students within the school environment have a lesser expectation of privacy than members of the population generally”); *Vernonia Sch. Dist. 47J v. Acton*, 515 U.S. 646, 657–58 (permitting drug testing of student athletes for the same reason); *O’Connor v. Ortega*, 480 U.S. 709, 725 (1987) (permitting searches of employee’s effects because, *inter alia*, “[a]s with the building inspections in *Camara*, the employer intrusions at issue here ‘involve a relatively limited invasion’ of employee privacy.” (quoting *Camara v. Mun. Court of San Francisco*, 387 U.S. 523, 537 (1967))); *Griffin v. Wisconsin*, 483 U.S. 868, 879 (1987) (permitting searches of probationers on less than reasonable suspicion, because “we deal with a situation in which there is an ongoing supervisory relationship—and one that is not, or at least not entirely, adversarial—between the object of the search and the decisionmaker”).

⁴³ In my work, I have relied on this point in arguing that, while *Jones* and *Carpenter* correctly required probable cause for the searches in those cases, short-term tracking and limited digital searches should only require reasonable suspicion. *See* SLOBOGIN, *supra* note *, at 40–46.

idea captured in *Terry*'s assertion that a seizure may occur only upon a determination that "criminal activity may be afoot."⁴⁴

The following discussion focuses on how these three requirements interact with street policing, the setting in which profile-driven searches and seizures are most likely to occur.

B. Proportionality Requirements for Data Access and Police Stops

In the traditional police setting, police and courts engage in a qualitative assessment of whether "articulable facts" support a stop and frisk or an arrest.⁴⁵ For instance, the police might justify a stop by saying the individual seemed conspicuously out of place or engaged in "furtive movements" (a police favorite).⁴⁶ Such subjective judgments can, of course, be biased or pretextual. The possible advantage of algorithm-based policing is that, done well, it relies on risk factors that are *quantitatively* shown to predict crime and are thus likely to be less prone to manipulation.

But that can be true only if the algorithm can produce a satisfactory "hit rate" (again, the percentage of people identified by the algorithm who are involved in crime). Further, if proportionality reasoning applies, that hit rate must be proportionate not only to the police action it purports to justify (e.g., an arrest, a stop, or prolonged surveillance) but also to the type of data that needs to be accessed to learn the risk associated with a place or a person. For instance, if the police want to arrest someone based on an algorithm that requires accessing financial information and private social media posts, they would need to demonstrate a higher hit rate than if they merely want to stop and question the individual based on matters of public record such as arrest history. In contrast, perhaps no justification would be needed if police access only public information solely for the purpose of identifying people who might need social services or a warning about possible danger from others (as apparently sometimes occurred with Chicago's heat list).⁴⁷

With respect to the data access issue, person-placed policing is much more likely than place-based policing to run into trouble on proportionality grounds. The place-based algorithm developed by HunchLab relies on population-wide statistics such as area crime reports, weather analysis, or

⁴⁴ *Terry v. Ohio*, 392 U.S. 1, 30 (1968); see also SLOBOGIN, *supra* note *, at 70–71.

⁴⁵ See Ben Grunwald & Jeffrey Fagan, *The End of Intuition-Based High-Crime Areas*, 107 CALIF. L. REV. 345, 359 (2019).

⁴⁶ See *id.* at 353 ("[O]nce courts recognized 'furtive movement' as a cognizable factor in the reasonable suspicion analysis, police began to see furtive movements everywhere." (footnote omitted)).

⁴⁷ See Jeremy Gomer, *Chicago Police Use 'Heat List' as Strategy to Prevent Violence*, CHI. TRIB. (Aug. 21, 2013), http://articles.chicagotribune.com/2013-08-21/news/ct-met-heat-list-20130821_1_chicago-police-commander-andrew-papachristos-heat-list [https://perma.cc/GKJ7-29LQ].

location data that is not person-specific.⁴⁸ It then tries to predict where crime might occur, not who might commit it.⁴⁹ Little or no intrusion into personal information is involved.

Person-placed algorithms are a different story. These algorithms are usually constructed based on a theory of crime—say, a theory that crime is correlated with number of arrests, membership in a gang, age, and gender—or they are generated through artificial intelligence—a computer analyzing hundreds or thousands of data points and correlating them with criminal activity.⁵⁰ To develop the necessary correlations and see if they apply to a particular person, data about specific individuals are crucial. Although, in theory, data analysts and computers working with “training data” can use anonymization techniques in developing the algorithm and police can simply be fed a “threat score” that does not reveal how it was arrived at, actions based on a predictive algorithm will still associate particular individuals with particular risk factors. In other words, for the algorithm to work, the government will still need to associate an identified individual with specific characteristics, traits, and transactions.

If the risk factors are all a matter of public record, then perhaps proportionality norms are not violated when they are accessed. But some algorithms, such as the ones developed by Intrado and ShadowDragon, claim to include risk factors gleaned from private postings on social media.⁵¹ If so, in the absence of sufficient justification (described in more detail below), their use would violate the proportionality principle.

While person-placed policing may thus face more challenges than place-based policing in connection with the data access inquiry, when it comes to the second proportionality issue—the grounds need to justify police action—place-based and person-based algorithms are in the same boat. If police want to stop someone based on either type of algorithm, under *Terry* they need a hit rate equivalent to reasonable suspicion.⁵² If they want to arrest someone based on data, they need a hit rate amounting to probable cause.⁵³

⁴⁸ See SOUNDTHINKING, *supra* note 5; see also SOUNDTHINKING, SHOTSPOTTER CONNECT: PRODUCT FAQ 2 (2021), <https://www.soundthinking.com/wp-content/uploads/2021/01/Connect-FAQ-1-2021.pdf> [<https://perma.cc/UU3B-CU9Q>] (explaining how ShotSpotter Connect works and that it was developed based on algorithms resulting from the purchase of HunchLab); see also *PredPol*, GOVLAUNCH, <https://govlaunch.com/products/predpol> [<https://perma.cc/HMW6-W275>] (“PredPol uses ONLY 3 data points—crime type, crime location, and crime date/time—to create its predictions. No personally identifiable information is ever used. No demographic, ethnic or socio-economic information is ever used.”).

⁴⁹ SOUNDTHINKING, SHOTSPOTTER CONNECT, *supra* note 48, at 1.

⁵⁰ See generally Tim Lau, *Predictive Policing Explained*, BRENNAN CTR. FOR JUST. (Apr. 1, 2020), <https://www.brennancenter.org/our-work/research-reports/predictive-policing-explained> [<https://perma.cc/K9YM-XFKK>].

⁵¹ See *supra* notes 12–13 and accompanying text.

⁵² See SLOBOGIN, *supra* note *, at 104; see also *Terry v. Ohio*, 392 U.S. 1, 30 (1968).

⁵³ *Beck v. Ohio*, 379 U.S. 89, 91 (1964).

C. Calculating Hit Rates

From the foregoing, it should be clear that, under proportionality reasoning, the hit rate of a place-based or person-based algorithm is all-important. Given the mathematical nature of algorithms, figuring out the hit rate that justifies accessing the data used by a policing algorithm and the policing actions it permits can (and should) depend on how concepts such as probable cause and reasonable suspicion are quantified. Fortunately, we have some information about how judges might do so. A survey of federal judges found that, on average, probable cause was associated with around a 45% level of certainty and reasonable suspicion with approximately a 30% level of certainty.⁵⁴ An opinion from the Seventh Circuit Court of Appeals suggests that a 28% hit rate might be sufficient to justify a stop.⁵⁵ Because they represent the views of the judiciary, these figures can provide baseline quantifications of probable cause and reasonable suspicion.

However, adjustments might be made under certain circumstances. For instance, some might argue for a lower hit rate if the crime sought to be prevented is serious. The Supreme Court seems to have concluded that cause requirements should not be adjusted based on the seriousness of the crime.⁵⁶ However, that holding involved solving an already-completed crime.⁵⁷ If, instead, a profile purports to be able to *predict* a serious crime rather than solve a past one, the state's interest in preventing harm to the public may justify lowering the justification required.⁵⁸ The Court's cases permitting preventive detention on a lower standard of proof than is required for conviction of crime indicate as much.⁵⁹ Along these lines, Justice Scalia speculated that a 5–10% hit rate might be permissible if the stop is based on suspicion that a driver is drunk and thus endangers the public.⁶⁰

Unfortunately, most algorithms do not do even this well. Place-based policing tools do not even try to identify high risk individuals, and the typical person-based algorithm in use today is a long way off from a 10% hit rate,

⁵⁴ C.M.A. McCauliff, *Burdens of Proof: Degrees of Belief, Quanta of Evidence, or Constitutional Guarantees?*, 35 VAND. L. REV. 1293, 1327–28, tbl. 8 (1982).

⁵⁵ *Anderson v. Cornejo*, 355 F.3d 1021, 1025 (7th Cir. 2004) (“A 27.6% success rate for a particular kind of border search is not to be sneezed at. It may imply that the Customs officials are conducting too few searches, not too many.”).

⁵⁶ *Mincey v. Arizona*, 437 U.S. 385, 393 (1978) (refusing to adopt a “homicide exception” to the warrant requirement, stating “[n]o consideration relevant to the Fourth Amendment suggests any point of rational limitation’ of such a doctrine” (quoting *Chimel v. California*, 395 U.S. 752, 766 (1969))).

⁵⁷ See *id.* at 385 (where the search was of an already completed homicide).

⁵⁸ See SLOBOGIN, *supra* note *, at 70–71 (discussing a “danger exception” to Fourth Amendment justification requirements).

⁵⁹ See, e.g., *Addington v. Texas*, 441 U.S. 418, 425–33 (1979) (permitting involuntary civil commitment on “clear and convincing evidence” of dangerousness to self or others); *United States v. Salerno*, 481 U.S. 739, 741 (1987) (permitting pretrial detention based on “clear and convincing” evidence of risk).

⁶⁰ *Navarette v. California*, 572 U.S. 393, 410 (2014) (Scalia, J., dissenting).

much less a one-in-three rate.⁶¹ Taking at face value the Chicago Police Department's statement that 80% of the fifty-one people arrested for involvement in a shooting during a particular weekend were on the SSL,⁶² that amounts to a hit rate of only 0.014%, because the list contained over 280,000 people with a score above 250⁶³ (the score at which, according to a spokesperson for the department, people "come on our radar").⁶⁴ It is not difficult to compile a list that contains most of the people involved in violence if the list includes almost everyone in the jurisdiction with a criminal record or a gang affiliation! Had the goal of the SSL instead been to identify people who possessed weapons on the weekend in question rather than who would shoot, or be shot by, a gun, the hit rate undoubtedly would have been higher. But it still would have been nowhere near the 20–30% range that proportionality analysis might require to justify a stop based on reasonable suspicion.

This is not to say that a predictive algorithm cannot reach that goal. Using data from field interrogation cards that described the reasons police gave for close to a half-million stops carried out by the New York Police Department during 2008–2010, a research group led by Sharad Goel developed an algorithm with five variables (out of eighteen that police identified as relevant to their stop decisions) that were positively correlated with possession of a weapon: "suspicious object," "sights and sounds of criminal activity," "suspicious bulge," "witness report," and "ongoing investigation."⁶⁵ Those factors were then reduced to the first three because

⁶¹ See discussion *infra* Section II.C.

⁶² The Editorial Board, *Who Will Kill or Be Killed in Violence-Plagued Chicago? The Algorithm Knows.*, CHI. TRIB. (May 23, 2019, 10:40 AM), <https://www.chicagotribune.com/2016/05/10/who-will-kill-or-be-killed-in-violence-plagued-chicago-the-algorithm-knows/> [<https://perma.cc/QQ5E-ZYWC>].

⁶³ Brianna Posadas, *How Strategic is Chicago's "Strategic Subjects List"?* *Upturn Investigates.*, MEDIUM (June 22, 2017), <https://medium.com/equal-future/how-strategic-is-chicagos-strategic-subjects-list-upturn-investigates-9e5b4b235a7c> [<https://perma.cc/DCZ2-S96H>].

⁶⁴ Stephanie Kollmann, *An Enormous List of Names Does Nothing to Combat Chicago Crime*, CHI. SUN-TIMES (May 16, 2017, 5:44 PM), <https://chicago.suntimes.com/2017/5/16/18321160/an-enormous-list-of-names-does-nothing-to-combat-chicago-crime> [<https://perma.cc/72E6-PG75>].

⁶⁵ Sharad Goel et al., *Precinct or Prejudice? Understanding Racial Disparities in New York City's Stop-and-Frisk Policy*, 10 ANNALS APPLIED STAT. 365, 384 (2016) [hereinafter Goel et al., *Precinct or Prejudice*]. More specifically, the team found that, comparing a randomly selected weapon-carrier with a randomly selected person who did not have a weapon, the weapon-carrier would have a higher score on the algorithm 83% of the time, a result much higher than chance, which would produce a 50% differentiation rate. *Id.* at 391. See also Sharad Goel et al., *Combating Police Discrimination in the Age of Big Data*, 20 NEW CRIM. L. REV. 181, 211–13 (2017) [hereinafter Goel et al., *Combating Police Discrimination*]. It must be noted that the information in these field identification cards is not entirely trustworthy. There was no check of the officer's categorizations of their reasons for stopping individuals, nor did the officers indicate when they did *not* stop a (likely White?) person who has one of these characteristics. See *id.* at 213–14. These problems can be at least partially addressed through the use of body camera footage and computer analytics, see Farhang Heydari et al., *Putting Police Body-Worn Camera Footage to Work: A Civil Liberties Evaluation of Truleo's AI Analytics Platform*, 46 CARDOZO L. REV. (forthcoming 2025) (I am a co-author of this work) (accessible via https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5030758 [<https://perma.cc/JD5B-SXW4>]).

they were the most robustly predictive items, and those three were assigned points based on their relative predictiveness (with suspicious object assigned three points, and sights and sounds of criminal activity and suspicious bulge assigned one point each).⁶⁶ Goel et al.'s analysis showed that the results produced by this model (which I will call the GSFA, for Goel Short Form Algorithm) were “virtually indistinguishable” from those produced by the five-factor model or an even more complicated model using over a dozen variables identified in the field identification cards plus demographic and other factors.⁶⁷ More specifically, the GSFA correctly differentiated between people with weapons and those without weapons about 80% of the time.⁶⁸

Note, however, that this figure only tells us that the GSFA was much better than chance at identifying who had weapons; it does not give us the hit rate, which tells us how many people who were stopped based on the GSFA were found to have weapons. I asked Goel and his colleagues to calculate that rate for ten different precincts, using the NYPD stop data and the GSFA and its six cutpoints (with five points—three plus one plus one—as the top possible score and zero as the lowest possible score). Results varied significantly between precincts. For instance, in Precinct 32, the one person with a score of five had a gun, roughly 48% of those with a score of four had a weapon, roughly 27% who scored a two or three had a weapon, and 1% of those with one or zero points had a weapon.⁶⁹ In Precinct 23, no five-point scores were produced, while 35% of those with a four, 22% of those with a two or three, and 2% of those with a zero or one had a weapon.⁷⁰ In Precinct 75, the percentages on all six cutpoints fell between 5% and 35%.⁷¹ In Precincts 40 and 101, none of the hit rates for any score rose above 25%.⁷² And so on.

These results illustrate several things about person-based algorithms. First, the algorithms need to be validated on a local population, down to the precinct level; local crime rates, criminal histories, and other variables can vary from precinct to precinct, which may affect hit rates.⁷³ Second, hit rates depend upon cutpoints. A very respectable hit rate can be obtained if the cutpoint authorizing a stop is set high enough (at four or five in the case of the GSFA); the trade-off, of course, is that many fewer weapons will be found

⁶⁶ Goel et al., *Precinct or Prejudice*, *supra* note 65, at 384.

⁶⁷ *Id.* at 386.

⁶⁸ *Id.* at 391.

⁶⁹ Email from Keniel Yao, to author, (Jun. 20, 2021, at 2:06 CT) [hereinafter Goel Data], Precinct 32 file (unpublished data on file with author).

⁷⁰ *Id.*, Precinct 23 file.

⁷¹ *Id.*, Precinct 75 file.

⁷² *Id.*, Precinct 40 & 101 files.

⁷³ John Logan Koepke & David G. Robinson, *Danger Ahead: Risk Assessment and the Future of Bail Reform*, 93 WASH. L. REV. 1725, 1756 (2017) (“Using one jurisdiction’s data to predict outcomes in another is an inherently hazardous exercise . . .”).

because many fewer stops will be made.⁷⁴ For instance, in Precinct 23 roughly 88% of the weapons came from people who scored zero, one, or two on the GSFA;⁷⁵ however, because there were so many of them, the *percentage* of people with those scores who had weapons (the hit rate) was very low (in the 1% range).⁷⁶ A third and related point is that, as the data for Precincts 40 and 101 illustrate, if police lower the cutoff score in an effort to obtain more weapons (to, say, a score of two on the GSFA) they may be hard put to achieve the 20–30% hit rate demanded by proportionality reasoning.⁷⁷

This all adds up to a fourth and final point: Well-constructed algorithms may have better predictive accuracy than seat-of-the-pants assessments by police and thus might significantly reduce the number of unnecessary stops, including, as discussed further below, unnecessary stops of people of color. For instance, the NYPD's hit rate for weapons discovered during the stop and frisk program that was found unconstitutional in *Floyd v. City of New York*⁷⁸ was well below 2%.⁷⁹ Had New York City police limited themselves to stopping only those with scores of four or five on the GSFA, their hit rate would have been much higher (in the 30% to 40% range); at the same time, they would have confronted roughly 80% fewer people, most of whom would not have had weapons on them.⁸⁰ The research by Goel et al. suggests that, if algorithms are validated locally, have good discriminant validity (i.e., an ability to differentiate high- and low-risk individuals or places),⁸¹ and are periodically updated,⁸² they can significantly outperform the qualitative judgments made by the typical cop, presumably because they structure officer decision-making based on statistical analysis.

Quantification of justification standards may strike some as artificial and unresponsive to the reality of policing, which involves consideration of a host of factors that an algorithm cannot capture. Indeed, the Supreme Court has

⁷⁴ Goel et al., *Precinct or Prejudice*, *supra* note 65, at 386–87 (estimating that using the GSFA with a high cut-off police would have discovered only 58% of the weapons the NYPD stop and frisk program discovered).

⁷⁵ Goel Data, *supra* note 69, Precinct 23 file.

⁷⁶ *Id.*

⁷⁷ *See id.*, Precinct 40 & Precinct 101 files.

⁷⁸ *Floyd v. City of New York*, 959 F. Supp. 2d 540, 562 (S.D.N.Y. 2013).

⁷⁹ *Id.* at 559 (“Weapons were seized in 1.0% of the stops of blacks, 1.1% of the stops of Hispanics, and 1.4% of the stops of whites.”).

⁸⁰ *See* Goel et al., *Precinct or Prejudice*, *supra* note 65, at 390–92; Goel et al., *Combatting Police Discrimination*, *supra* note 65, at 219.

⁸¹ For reasons I have explained elsewhere, it is important to have both good discriminant validity (the ability to differentiate high and low risk individuals) and good calibration (the ability to place individuals in specific risk categories). *See* CHRISTOPHER SLOBOGIN, JUST ALGORITHMS: USING SCIENCE TO REDUCE INCARCERATION AND INFORM A JURISPRUDENCE OF RISK 68–71 (2021). Discriminant validity measures, which Goel's group calculated, *see supra* note 65, take into account base rates, while calibration does not. *Id.*

⁸² Goel et al., *Precinct or Prejudice*, *supra* note 65, at 386 (noting that “the model would likely require periodic updating since changes in officers' behavior could affect model performance”).

refused to equate Fourth Amendment justification with any particular numerical probability, instead emphasizing that police and courts should rely on “common sense judgments.”⁸³ But the Court has also lamented the lack of “empirical studies dealing with inferences drawn from suspicious behavior,” acknowledging that “we cannot reasonably demand scientific certainty from judges or law enforcement officers where none exists.”⁸⁴ With the advent of predictive algorithms, empirical studies do exist. And *if* they produce better results than common-sense judgments, the fact that they do not take into account every factor police believe to be important should not count against them. Indeed, given the abysmal hit rates produced by human decision-making (at least in New York City), in the absence of the requisite algorithm-defined threshold for a stop police might be prohibited from detaining an individual unless they have probable cause to arrest, a point that leads directly to the imminence issue.

D. The Imminence Requirement

Even if an algorithm can achieve the proportionality-derived hit rate needed to justify data access and subsequent police actions, a Fourth Amendment seizure cannot be based on a high score alone. Allowing detention in that situation would violate the precept, going back to John Stuart Mill,⁸⁵ and instantiated in the *Terry* line of cases,⁸⁶ that the government should not coercively detain people who have yet to commit a crime unless the risk they pose is imminent. Once shown to have committed a crime, a person’s long-term risk can be a legitimate consideration during sentencing.⁸⁷ But in the policing setting, before arrest and conviction for a crime, the courts—including the Supreme Court in *Terry*—have made clear that preventive deprivations of liberty must be based on *near-term* risk; as the Court noted in a later decision, in every one of its stop cases in this vein “police stopped or seized a person because they suspected he was about to commit a crime, . . . or was committing a crime at the moment of the stop.”⁸⁸

⁸³ See *Illinois v. Gates*, 462 U.S. 213, 235–36 (1983).

⁸⁴ *Illinois v. Wardlow*, 528 U.S. 119, 124–25 (2000).

⁸⁵ JOHN STUART MILL, ON LIBERTY 172 (3rd ed. 1864), <https://archive.org/details/onliberty00inmill/page/n7/mode/2up> [<https://perma.cc/R8VH-LM4C>] (“[T]he preventive function of government . . . is far more liable to be abused, to the prejudice of liberty, than the punitive function; for there is hardly any part of the legitimate freedom of action of a human being which would not admit of being represented, and fairly too, as increasing the facilities for some form or other of delinquency. [However], if a public authority, or even a private person, sees any one evidently preparing to commit a crime, they are not bound to look on inactive . . .”).

⁸⁶ See cases cited *supra* notes 30–44.

⁸⁷ See Christopher Slobogin, *Prevention as the Primary Goal of Sentencing: The Modern Case for Indeterminate Dispositions in Criminal Cases*, 48 SAN DIEGO L. REV. 1127, 1132–34 (2011).

⁸⁸ *United States v. Hensley*, 469 U.S. 221, 227 (1985) (making this statement while holding that police

This limitation also makes good practical sense. Otherwise, an algorithm such as Chicago's SSL, which is based primarily on historical factors such as previous arrests, would authorize the police to stop anyone with a high score anytime they wanted to do so, any day, every day or multiple times a day, even though they find no weapons on any of those occasions.

An example of how failing to abide by the imminence precept can go awry comes from Pasco County, Florida.⁸⁹ In 2020, the Pasco County Sheriff's Department, relying on data from local school records as well as their own records, used profiling techniques to place juveniles in "risk" categories.⁹⁰ Juveniles considered high risk for committing crime—a determination apparently based on their home life, grades, and intelligence, as well as criminal history—were all provided "mentoring" by sheriff's deputies assigned to the juvenile's school.⁹¹ More problematic, deputies also "harassed" high-risk students by going to their homes on a frequent basis.⁹² The proportionality principle would probably prohibit the department's access to school records (which are protected by federal law), given the likelihood that the hit rate associated with the "profile" was extremely low.⁹³ But even if proportionality reasoning were somehow satisfied, the imminence requirement would clearly bar these constant confrontations, absent indicia that antisocial behavior would occur in the near future.

In short, the imminence requirement means that stops and frisks based on predictive algorithms will require what the law has always required (at least in theory): suspicious *conduct* at the time of the stop.⁹⁴ The added value of the algorithm, if any, is that it establishes a baseline before a stop may occur. Because person-based algorithms like the Pasco County program and the SSL rely on static factors (such as arrests or school grades), the imminence limitation is usually very significant, perhaps even preclusive, in such cases. Even with the GSFA, which is based entirely on conduct—specifically, possession of a "suspicious object," the "sights and sounds of criminal

may also stop and question an individual on reasonable suspicion the person has already committed a serious crime).

⁸⁹ Neil Bedi & Kathleen McGrory, *Pasco's Sheriff Uses Grades and Abuse Histories to Label Schoolchildren Potential Criminals.*, TAMPA BAY TIMES (Nov. 19, 2020), <https://projects.tampabay.com/projects/2020/investigations/police-pasco-sheriff-targeted/school-data/> [<https://perma.cc/UE8U-HQ37>].

⁹⁰ *Id.*

⁹¹ *Id.*

⁹² *Id.*

⁹³ See Christopher Slobogin & Kate Weisburd, *Illegitimate Choices: A Minimalist(?) Approach to Consent and Waiver in Criminal Cases*, 101 WASH. U. L. REV. 1913, 1950 (2024), where we argue that even consensual home searches should be barred unless preceded by reasonable suspicion, because—in contrast to other consent contexts—such consents do not provide the consentor with any benefit.

⁹⁴ See *Terry v. Ohio*, 392 U.S. 1, 30 (1968) (permitting a stop only "where a police officer observes *unusual conduct* which leads him reasonably to conclude in light of his experience that criminal activity may be afoot") (emphasis added).

activity,” and “a suspicious bulge”—the imminence requirement adds a restriction by ensuring the conduct is occurring *at the time of the stop*.⁹⁵

The imminence requirement’s mandate that suspicious conduct precede an algorithm-based stop addresses a common Fourth Amendment critique of predictive algorithms that—like the GSFA and any other algorithm worth its salt⁹⁶—develop their risk factors by analyzing the histories and conduct of groups of people in an effort to recognize patterns or profiles of criminal activity and criminal actors. In a nutshell, the argument is that their use violates the Supreme Court’s prohibition on stops and arrests based on “unparticularized suspicion” (to use *Terry*’s phrase).⁹⁷ The point is sometimes illustrated by fanciful thought experiments in which it is assumed, say, that based on a study of college student habits, an algorithm can tell us that 60% of the rooms in a college dorm contain contraband.⁹⁸ While the 60% hit rate would exceed the quantified version of probable cause required for search of a residence, permitting a search of every dorm room based solely on that figure, it is argued, would violate the legal requirement that searches must be based on suspicion specific to the individual.⁹⁹

This brand of criticism, which suggests that algorithmic decision-making always violates the Fourth Amendment, is insufficiently nuanced, for two reasons. First, stopping a person who has all the risk factors in an algorithm *is* based on characteristics the person has (e.g., location, arrest history, or pocket bulge). Second, and more importantly, if stops based on nomothetic (group-based) information are impermissible, then all stops are impermissible; even stops purporting to be based on “individualized” suspicion are triggered by assumptions about how people act or should act. For instance, in *Terry v. Ohio*, when Officer McFadden stopped Terry and his companions for walking past and peering into a store several times, he was relying on an “intuitive algorithm,” based on the notion that people who engage in such behavior do not “look right,” to use McFadden’s words.¹⁰⁰

⁹⁵ Goel et al., *Precinct or Prejudice*, *supra* note 65, at 384; Goel et al., *Combating Police Discrimination*, *supra* note 65, at 218–19.

⁹⁶ Some profiles cannot really be called algorithms, because they are not based on any type of scientific or data-driven analysis. For instance, LASER assigned five points each for gang membership, being on probation, prior handgun arrests, and prior arrests for violent crime, and one point for each additional police contact, numbers that were assigned completely arbitrarily with no attempt to discern statistically whether these risk factors were pertinent or how much weight they should be given. *See SMITH*, *supra* note 20, at 6.

⁹⁷ *Terry*, 392 U.S. at 27.

⁹⁸ *See* Orin Kerr, *Why Courts Should Not Quantify Probable Cause*, in *THE POLITICAL HEART OF CRIMINAL PROCEDURE: ESSAYS ON THEMES OF WILLIAM J. STUNTZ* 131, 135–37 (Michael Klarman et al. eds., 2012).

⁹⁹ *See* Kiel Brennan-Marquez, “Plausible Cause”: *Explanatory Standards in the Age of Powerful Machines*, 70 *VAND. L. REV.* 1249, 1252 (2017). Query whether this view would change if the search was for a kidnap victim known to be hidden somewhere in the dorm. *See supra* text accompanying notes 58–60 (discussing how prevention of a serious harm might justify lowering the hit rate requirement).

¹⁰⁰ *Terry*, 392 U.S. at 5.

Predictive judgments about people are often based on past experiences with other people and on stereotypes.¹⁰¹ Frederick Schauer put the point this way: “[O]nce we understand that most of the ordinary differences between general and particular decisionmaking are differences of degree and not differences in kind, we become properly skeptical of a widespread but mistaken view that the particular has some sort of natural epistemological or moral primacy over the general.”¹⁰²

Nonetheless, the intuition that the hypothesized dorm room searches should be prohibited is not off base. As Schauer admits, there can be a “difference[] in degree” between group-based general decision-making and particularized decision-making.¹⁰³ In the profile-driven policing context, that difference is noticeable, for two reasons.

Most important, profile-driven policing that relies solely on statistics derived from static factors, such as number of arrests, demographic features, or neighborhood, violates fundamental notions of autonomy. As Richard Re has contended, stops justified by “population-based statistics” do not afford the innocent target “an opportunity to reduce [the] risk of being searched.”¹⁰⁴ Along the same lines, I have argued that the principle of legality, which has long been the basis for the actus reus requirement in crimes, mandates observation of “risky conduct” before intervention on prevention grounds may occur.¹⁰⁵ In our college dorm room example, since none of the individuals have been observed exercising a choice to engage in wrongdoing or suspicious conduct (such as holding a bag full of a green leafy substance or occupying a room emanating drug-related odors), they should not be subject to state-sanctioned searches or seizures.

A suspicious or risky conduct requirement also protects the innocent, particularly so where profiles are involved. As Jane Bambauer has noted, adherence to the Supreme Court’s notion of individualized suspicion—as operationalized through a suspicious conduct requirement—limits the number of innocent people stopped or “hassled.”¹⁰⁶ In the dorm example, assuming 100 students in 100 rooms, the absence of a conduct requirement would permit searches not only of the sixty students who are committing

¹⁰¹ Barbara D. Underwood, *Law and the Crystal Ball: Predicting Behavior with Statistical Inference and Individualized Judgment*, 88 YALE L.J. 1408, 1427 (1979) (“Although the clinician need not identify in advance the characteristics he will regard as salient, he must nevertheless evaluate the applicant on the basis of a finite number of salient characteristics, and thus, like the statistical decisionmaker, he treats the applicant as a member of a class defined by those characteristics.”).

¹⁰² FREDERICK SCHAUER, *PROFILES, PROBABILITIES, AND STEREOTYPES* 106 (2003).

¹⁰³ *Id.*

¹⁰⁴ Richard M. Re, *Fourth Amendment Fairness*, 116 MICH. L. REV. 1409, 1433 (2018).

¹⁰⁵ CHRISTOPHER SLOBOGIN, *MINDING JUSTICE: LAWS THAT DEPRIVE PEOPLE WITH MENTAL DISABILITY OF LIFE AND LIBERTY* 115–22 (2006).

¹⁰⁶ Jane Bambauer, *Hassle*, 113 MICH. L. REV. 461, 462–65 (2015) (“Hit rates measure suspicion. . . . Hassle rates, by contrast, measure the probability that an innocent person within the relevant population will be stopped or searched under the program.”).

crime, but also of the forty who are not. Compare that outcome to the effect of the intuitive “individualized suspicion” algorithm at work in *Terry*.¹⁰⁷ No one besides Terry and his colleagues met Officer McFadden’s stereotyping judgment.¹⁰⁸ In the dorm case, the hassle rate is 40%; in *Terry*, it was zero.¹⁰⁹

Re and Bambauer make valid points. But in the profile-driven policing setting,¹¹⁰ the requirement that the wrongdoing be imminent addresses both of their concerns. Imminence will not exist unless the target has engaged in conduct that is corroborative of wrongdoing. And although an algorithm might target some innocent people, the requirement that suspicious activity be observed at the time of the stop will both increase the hit rate and minimize the hassle rate.

An added advantage of the risky conduct requirement is that it provides a more palatable explanation for the police intervention than an algorithm based solely on static factors. The procedural justice literature suggests that both the legitimacy of the police and the public’s willingness to assist in their endeavors are significantly undermined when police are opaque about their motives.¹¹¹ If police can explain a stop on the ground that the person possessed a “suspicious item” or manifested the “sights and sounds of criminal activity,” and can back up that conclusion with specific facts, they are likely to be perceived as acting fairly, even if, at bottom, they are working from an algorithm.¹¹² This is a particularly important consequence of the imminence requirement, given the impact of preventive policing on communities of color.

II. ALGORITHMS AND RACE

For years, people of color have wryly joked about the “offenses” of “Driving While Black” and “Walking While Latino.” The tragic fact is that, in practice, these offenses do exist. In part, this is because the ubiquity of our traffic, loitering, and misdemeanor laws, combined with the ease with which they can be violated, give police leeway to do pretty much what they want.¹¹³

¹⁰⁷ See *id.* at 479–80 (citing *Terry v. Ohio*, 392 U.S. 1, 28 (1968)).

¹⁰⁸ See *id.* at 480 (citing *Terry*, 392 U.S. at 6).

¹⁰⁹ See *id.* at 465, 480.

¹¹⁰ If instead the police want to arrest an individual for a *past* crime based on a profile, blameworthy conduct has already occurred and the only issue is whether the requisite suspicion (for an arrest, probable cause) exists.

¹¹¹ Tom R. Tyler, *Can the Police Enhance Their Popular Legitimacy Through Their Conduct?: Using Empirical Research to Inform Law*, U. ILL. L. REV. 1971, 1973, 1998 tbl. 6 (2017).

¹¹² See *id.* at 1995.

¹¹³ See George Yancy, *Walking While Black in the ‘White Gaze’*, N.Y. TIMES (Sept. 1, 2013, 7:00 PM), <https://archive.nytimes.com/opinionator.blogs.nytimes.com/2013/09/01/walking-while-black-in-the-white-gaze/> [<https://perma.cc/GE6W-6447>]; David A. Harris, *Driving While Black and All Other Traffic Offenses: The Supreme Court and Pretextual Traffic Stops*, 87 J. CRIM. L. & CRIMINOLOGY 544, 545 (1997).

More importantly for present purposes, police do not always feel the need to wait until a law has been broken or articulable suspicion has developed before they move in, especially, it seems, when Black people are the target. I show my students tapes of people—all young Black men—stopped for waving to a suspected “drug dealer,” turning a corner “too widely,” or walking away when the police approach them.¹¹⁴ Police have also been known to stop Black people and Latinos simply because they are in “White” neighborhoods, are thought to have an arrest record, or “don’t look right,” to use Officer McFadden’s words.¹¹⁵ And once stopped, detentions can last a long time, accompanied by frisks or full searches.¹¹⁶ Sometimes, as we see so often on nightly news, matters can escalate into the use of deadly force.

The police will say that proactive policing is an important way of keeping a handle on the neighborhood, nipping incipient crime in the bud, discovering people with outstanding warrants, and occasionally serendipitously finding evidence of more serious crime. They are backed up by research suggesting that “aggressive policing” produces higher arrest rates for robbery, decreases various types of thefts and gun crimes, and increases seizures of guns.¹¹⁷ Those affected by these types of police actions instead call them state-sanctioned harassment and assert that traffic and pedestrian laws are often used as pretexts to carry out racist agendas. These assertions are bolstered by studies showing that the hit rates for finding weapons or evidence during street confrontations are in the single digits, and that aggressive patrolling merely displaces crimes to other neighborhoods, is used disproportionately on people of color (as evidenced by lower hit rates for them than for majority groups), and severely damages community attitudes toward the police and government generally.¹¹⁸

In theory, predictive policing algorithms could help resolve the tension between these two perspectives. They could produce better hit rates than traditional policing and, because they are data-driven, could expose in a quantified way the racial disparities associated with traditional street policing. They could also provide concrete information that might help reduce these disparities. As Sendhil Mullainathan has noted, “biased

¹¹⁴ See Ford Sanders, *Judge Rules Former LMPD Officer Violated Teen’s Constitutional Rights During 2018 Traffic Stop*, WHAS11 (Sept. 15, 2022, 4:24 PM), <https://www.whas11.com/article/news/local/tea-ah-lea-louisville-metro-police-violate-4th-amendment-right-judge-rules/417-ce0c7606-9ae7-4107-8a5c-83ac3b3472b4> [<https://perma.cc/LZ8D-MCM2>].

¹¹⁵ *Terry v. Ohio*, 392 U.S. 1, 5 (1968); see MICHAEL K. BROWN, *WORKING THE STREET: POLICE DISCRETION AND THE DILEMMAS OF REFORM* 170–79 (copy. 1981 ed. 1981) (describing the “incongruity,” “prior information,” and “appearance” bases for police detention).

¹¹⁶ See, e.g., BROWN, *supra* note 115, at 171–74.

¹¹⁷ See, e.g., studies in San Diego, Houston, Newark, Kansas City, and Minneapolis reported in Lawrence W. Sherman, *Attacking Crime: Police and Crime Control*, in 15 *CRIME AND JUSTICE: A REVIEW OF RESEARCH* 159, 187 (Michael Tonry ed., 1992).

¹¹⁸ See, e.g., *Floyd v. City of New York*, 959 F. Supp. 2d 540, 573–74 (S.D.N.Y. 2013) (recounting data in New York and its impact).

algorithms are easier to fix than biased people.”¹¹⁹ While police training programs aimed at addressing explicit and implicit bias have had, at best, mixed success,¹²⁰ tools like the GSFA and HunchLab’s algorithm can be mechanistically tweaked (in ways suggested below) to counter whatever racially improper motivations police may have. Because algorithms express in concrete terms the cost of street policing, they could even quantify the grounds for *ending* predictive policing, empirically based *or* traditional.¹²¹

At the same time, if data-driven predictive policing is not ended, or it is not implemented judiciously, it could give police still another reason to stop people on the street, through an algorithm that helps “launder” racially motivated stops by making them appear to be based on neutral numbers.¹²² Consider how this laundering might play out with person-based policing first. It is well documented that, in some cities, Black people are stopped and arrested for minor drug crimes and misdemeanors much more often than other ethnicities, despite similar violation rates.¹²³ This differential treatment may exist for a number of reasons: the greater likelihood that disadvantaged communities lack private spaces and thus commit these offenses where police can more easily observe them; the greater willingness of police to accost Black people than White people for such crimes; the greater concentration of police resources in certain areas of the city; or some

¹¹⁹ Sendhil Mullainathan, *Biased Algorithms Are Easier to Fix Than Biased People*, N.Y. TIMES (Dec. 6, 2019), <https://www.nytimes.com/2019/12/06/business/algorithm-bias-fix.html> [<https://perma.cc/LH8X-FCUA>]; see SLOBOGIN, *supra* note 81, at 90–97, where I develop these points in more detail.

¹²⁰ ROBERT E. WORDEN ET AL., THE IMPACTS OF IMPLICIT BIAS AWARENESS TRAINING IN THE NYPD, 47 (2020), https://www.nyc.gov/assets/nypd/downloads/pdf/analysis_and_planning/impacts-of-implicit-bias-awareness-training-in-%20the-nypd.pdf [<https://perma.cc/D95Q-HMQA>] (finding no meaningful change in behavior in NYPD police after receiving training about implicit bias); Michael Hobbes, *‘Implicit Bias’ Trainings Don’t Actually Change Police Behavior*, HUFFPOST (June 12, 2020, 5:45 AM) (citing similar study), https://www.huffpost.com/entry/implicit-bias-training-doesnt-actually-change-police-behavior_n_5ee28fc3c5b60b32f010ed48 [<https://perma.cc/32NJ-YVHY>].

¹²¹ See FERGUSON, *supra* note 1, at 143–166. I have made a proposal that would come close to doing so. Christopher Slobogin, *Equality in the Streets: Using Proportionality Analysis to Regulate Street Policing*, 2 AM. J.L. & EQUAL. 36, 58–62 (2022) (arguing that preventive police confrontations on the street should only occur if police observe conduct that constitutes the actus reus for attempt, as defined under the Model Penal Code).

¹²² Bryan Llenas, *Brave New World of ‘Predictive Policing’ Raises Specter of High-Tech Racial Profiling*, FOX NEWS LATINO (Feb. 25, 2014) (quoting Hanni Fakhoury, staff attorney at the Electronic Frontier Foundation, as saying: “The algorithm is telling you exactly what you programmed it to tell you. ‘Young black kids in the south side of Chicago are more likely to commit crimes,’ and the algorithm lets the police launder this belief. It’s not racism, they can say.”), <http://latino.foxnews.com/latino/news/2014/02/24/brave-new-world-predictive-policing-raises-specter-high-tech-racialprofiling/> [<http://perma.cc/VG5W-WV93>].

¹²³ See Megan Stevenson & Sandra Mayson, *The Scale of Misdemeanor Justice*, 98 B.U. L. REV. 731, 769–70 (2018) (“We find that black people are arrested at more than twice the rate of white people for nine of twelve likely-misdemeanor offenses: vagrancy, prostitution, gambling, drug possession, simple assault, theft, disorderly conduct, vandalism, and ‘other offenses.’”); Ojmarrh Mitchell & Michael S. Caudy, *Examining Racial Disparities in Drug Arrests*, 32 JUST. Q. 288, 309 (2015) (“[R]acial disparity in drug arrests between black and whites cannot be explained by race differences in the *extent* of drug offending, nor the *nature* of drug offending.”)

combination of these and other factors.¹²⁴ Whatever the cause, this differential means that, when they rely on arrest records, even algorithms with well-calibrated and sufficiently high hit rates (i.e., hit rates of 30%) will pinpoint Black individuals much more often than White individuals, with the result that there will be many more Black false positives in absolute terms.

For instance, given racially disparate arrest rates, a Black person with three minor arrests on his record may be no more at risk of carrying a weapon, possessing drugs, or engaging in some other arrestable offense than a White person with one prior arrest.¹²⁵ Yet the Black person will have a much higher threat score on an algorithm that uses number of arrests as a risk factor. It may also be the case that arrests of Black people for minor crimes are less likely to represent solid evidence that the crime was in fact committed;¹²⁶ in that case, the algorithm is doubly misleading if, as it should be, the outcome sought is identifying people who are actually involved in criminal activity.

Based on these types of “dirty data” concerns,¹²⁷ some algorithm developers do not include drug arrests or minor misdemeanors in their inputs.¹²⁸ Just as importantly, developers can specify that the *outcome* variable of the algorithm identify only those prone to violent crime or illegal possession of a gun, and explicitly avoid attempts to predict crimes like possession of contraband or misdemeanors, which are much more likely to be the result of pretextual or biased police actions.¹²⁹ In these ways, the most potent discriminatory impact of racialized policing will likely be avoided.

However, some data indicate that arrests for people of color are inflated even for some types of violent crime.¹³⁰ If so, another potential solution to algorithmic racial bias is to develop algorithms for each race. In effect, that would discount the impact of risk factors such as number of arrests for people of color. For instance, a race-based algorithm might assign a Black person with three arrests a lower relative threat score than a White person with the same arrest history because the comparison group would be other Black

¹²⁴ See P. Jeffery Brantingham, *The Logic of Data Bias and Its Impact on Place-Based Predictive Policing*, 15 OHIO STATE J. CRIM. L. 473, 474–78 (2018) (suggesting these and other possibilities for racial disparities in policing).

¹²⁵ Cf. Sandra G. Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218, 2264 (2019) (noting that, in New Orleans, where she practiced law, a black man with three arrests was not much of a concern—but a white with three arrests was “really bad news!”).

¹²⁶ See Anna Roberts, *Arrests as Guilt*, 70 ALA. L. REV. 987, 993–94 (2019) (detailing the reasons arrests should not be equated with findings of guilt).

¹²⁷ See Rashida Richardson et al., *Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice*, 94 N.Y.U. L. REV. ONLINE 192, 195–96 (2019), <https://www.nyulawreview.org/wp-content/uploads/2019/04/NYULawReview-94-Richardson-Schultz-Crawford.pdf> [<https://perma.cc/8S6Z-RYQB>].

¹²⁸ Andrew Guthrie Ferguson, *Policing Predictive Policing*, 94 WASH. U. L. REV. 1109, 1127 (2017).

¹²⁹ See SLOBOGIN, *supra* note 81, at 49–52 (describing the importance of specifying outcome measures in developing algorithms).

¹³⁰ Ben Grunwald, *Racial Bias in Criminal Records*, 40 J. QUANTITATIVE CRIMINOLOGY 489, 495–96 (2024).

people, not people of all races. Some might object that explicit reliance on race as a discriminating factor violates the Supreme Court’s “anti-classification” approach to the Fourteenth Amendment, which prohibits classifications based on race.¹³¹ Clearly, the Court’s jurisprudence would render impermissible the explicit use of race as a risk factor, as the initial version of the GSFA did.¹³² However, if the developers of a predictive algorithm do not use race as a risk factor but instead, as suggested here, rely on it to define the sample on which the algorithm is validated, an equal protection challenge might be avoided.¹³³

Better yet, as is true with the GSFA, an algorithm could rely solely on suspicious traits. That approach entirely avoids static variables (such as arrests) that could correlate with race and thus might reduce disparate racial impacts. For instance, Goel et al. found that, using GSFA’s model that eschews historical information, only 49% of the 10% of stops associated with a score of four or five were of Black people, compared to 61% of those stopped by police under the NYPD’s actual stop and frisk program.¹³⁴

Use of racially-skewed stops and arrests in algorithms can also have a pernicious impact on place-based policing, because of what Bernard Harcourt has called the ratchet effect.¹³⁵ If arrest data reflects racialized policing, they will tend to identify the same hot spot areas and neighborhoods over and over again, because police will be deployed there and will witness crimes that will then be fed back into the algorithm. In the meantime, neighborhoods with similar crime problems may be ignored because they are never identified by the algorithm. This potential for a vicious cycle of over- and under-enforcement has always afflicted place-based policing, but the quantified nature of algorithms could intensify it.

As with person-based policing, excluding stops and arrests for minor crimes—both as risk factors and as outputs—is one way developers have

¹³¹ Kimberly J. Robinson, *The Constitutional Future of Race-Neutral Efforts to Promote Diversity and Avoid Racial Isolation in Our Elementary and Secondary Schools*, 50 B.C. L. REV. 277, 315 (2009) (“The Court’s current approach to equal protection, which has been labeled an antidiscrimination, anticlassification, or colorblind approach, emphasizes the impropriety of government use of racial classifications.”).

¹³² See Goel et al., *Combating Police Discrimination*, *supra* note 65, at 215–17.

¹³³ See Aziz Z. Huq, *Constitutional Rights in the Machine-Learning State*, 105 CORNELL L. REV. 1875, 1920 (2020) (“[A]n official’s mere awareness of race raises no constitutional problem. By analogy, it may also be that mere inclusion of race as a feature of training data should not be per se problematic.”). In the sentencing context, it is routine to develop different risk algorithms for men and women, given the lower base rate of offending for females. See Elizabeth E. Wainstein, *The Need for Fairness and Accuracy for Women in Sentencing: Surmounting Challenges to Gender-Specific Statistical Risk Assessment Tools*, 113 J. CRIM. L. & CRIMINOLOGY 31, 34, 47 (2023) (noting that “criminology scholars have introduced . . . different statistical risk assessment tools for men and women,” and that this differentiation increases the accuracy of risk assessments for both groups).

¹³⁴ Goel et al., *Precinct or Prejudice*, *supra* note 65, at 386.

¹³⁵ BERNARD E. HARCOURT, *AGAINST PREDICTION: PROFILING, POLICING, AND PUNISHING IN AN ACTUARIAL AGE* 147 (2007).

tried to minimize this problem. Another alternative is to randomize policing efforts to some extent, as Harcourt and Tracey Meares have suggested.¹³⁶ For instance, at least initially, departments could assign enhanced patrols to half (or some other fraction) of the hot spot areas, while other patrols would be randomly assigned to other parts of the jurisdiction. This approach would mean that some locales known to be associated with above-average crime problems will receive little or no service unless there is a 911 call. Nonetheless, random assignment might be justifiable, at least initially, on the ground that it will generate more reliable, less biased, data.

A final way of avoiding any exacerbation of racialized policing that person-based and place-based predictive algorithms might produce—one that fits nicely with the Defund Police movement’s agenda—is to use the data solely for the purpose of allocating *non*-police resources to people and places. Chicago’s alternative use of its heat list as a means of offering social services to specific individuals is one possibility. Along the same lines, the St. Louis County police department—Officer Keener’s outfit—began sending lists of high-crime areas to a nonprofit called Better Family Life, which deploys social workers and counselors to help connect residents to drug treatment and education programs.¹³⁷ As one report noted, “[i]n theory, HunchLab could provide even more targeted areas for this organization and others to apply their model of what [Better Family Life’s vice president] calls ‘hot-spot resources.’”¹³⁸ This use of algorithmic information, focused on long-term, community-based efforts, may well turn out to be a much more effective preventive mechanism than predictive policing.¹³⁹

III. TRANSPARENCY

Many of the companies involved in the predictive policing industry claim that their algorithms are protected by trade secret law.¹⁴⁰ The advent of more

¹³⁶ Bernard E. Harcourt & Tracey L. Meares, *Randomization and the Fourth Amendment*, 78 U. CHI. L. REV. 809, 866–68 (2011).

¹³⁷ Maurice Chammah, *Policing the Future*, THE MARSHALL PROJECT (Feb. 3, 2016, 7:15 AM), <https://www.themarshallproject.org/2016/02/03/policing-the-future> [<https://perma.cc/6GSJ-7B9T>].

¹³⁸ *Id.*

¹³⁹ See Mayson, *supra* note 125, at 2285–86 (noting that risk algorithms can be used as a “diagnostic tool” that can “identify[] sites and causes of racial disparity in criminal justice” and “help[] to illuminate the causal pathways of crime and arrest risk”). But see Kate Weisburd, *The Carceral Home*, 103 B.U. L. REV. 1879 *passim* (2023) (documenting the various government invasions of the home that occur in the name of rehabilitation).

¹⁴⁰ RALPH CLARK, SOUNDTHINKING, ANNUAL REPORT 2023 23 (2024), <https://ir.soundthinking.com/sec-filings/annual-reports/content/0000950170-24-050011/0000950170-24-050011.pdf> [<https://perma.cc/VX8B-LC6H>]; Conor Friedersdorf, *A Police Department’s Secret Formula for Judging Danger*, THE ATL. (Jan. 13, 2016), <https://www.theatlantic.com/politics/archive/2016/01/a-police-departments-secret-formula-for-judging->

sophisticated versions of artificial intelligence, if applied to policing, will make these types of predictive endeavors even more opaque, because modern AI learns from experience, without explicit programming and in ways that even its developers might not be able to ascertain.¹⁴¹ That is because this type of machine learning can be, in the words of Andrew Selbst and Simon Barocas, both “inscrutable”—impervious to understanding—and “non-intuitive”—meaning that, even if based on an understandable model, it relies on “apparent statistical relationships that defy intuition.”¹⁴² This lack of transparency should be fatal to predictive policing. Open knowledge about the risk factors used and the weights they are assigned is crucial for several reasons.

First, as just explained, algorithms may not use race as a risk factor and probably should not use arrests for minor crimes as an outcome measure. Policymakers and lawyers need to know if these prohibitions are violated by the algorithm. Further, they need to know whether the databases that algorithm developers access (such as gang lists) are accurate, and whether they contain information that should not be accessed (such as bank records). Without transparency, none of these problems can be detected.

Second, transparency is needed to improve algorithms. Hit rate studies should be replicated by an entity independent of the police. In theory, this replication process need only determine whether the algorithm performs as well in the field as with the training data; plumbing the inner workings of the algorithm is not necessary. But improvement is not possible without knowing the relevant variables and their weights. Private companies, driven by a profit motive, should not be trusted to carry out the necessary updating. Rather, periodic audits by independent actors are necessary.¹⁴³

Third, transparency is needed to resolve individual cases fairly. While the determination about whether the algorithm uses appropriate variables and has an acceptable hit rate can be made by a jurisdiction-wide entity (thus avoiding relitigation of such issues in every case), targets and their attorneys should be able to discover whether the algorithm was properly applied in their specific case. In other words, they should be able to get an answer to the question: Did the suspect meet the algorithm’s risk factors? Even if a target turned out to have a weapon or drugs on their person, hindsight bias

danger/423642/ [https://perma.cc/4PUN-C78N]; Michael Kwet, *ShadowDragon: Inside the Social Media Surveillance Software that Can Watch Your Every Move*, THE INTERCEPT (Sept. 21, 2021, 5:03 PM), <https://theintercept.com/2021/09/21/surveillance-social-media-police-microsoft-shadowdragon-kaseware/> [https://perma.cc/FL58-5RQ6].

¹⁴¹ See Sonia K. Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54, 119–20 (2019) (exploring ways of improving algorithmic accountability).

¹⁴² Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORD. L. REV. 1085, 1091 (2018).

¹⁴³ SLOBOGIN, *supra* note 81, at 80 (describing the necessity of periodic independent audits of algorithms).

should not affect whether a stop was legitimate. Stopping someone who does not meet the quantified reasonable suspicion standard associated with the algorithm is just as unconstitutional as a stop based on an unarticulated hunch.

Because transparency is so important, it is unfortunate that the law dealing with the subject of algorithmic transparency is in a fledgling state. The case most on point is from a state court and addresses *sentencing* algorithms.¹⁴⁴ In *State v. Loomis*, the Wisconsin Supreme Court held that the Due Process Clause is not violated by a sentence based on a risk assessment tool protected by trade secret law.¹⁴⁵ The court pointed out that, while the company that developed the algorithm refused to disclose its inner workings, Loomis was given a list of twenty-one questions and answers used by the evaluator in calculating the offender's risk score.¹⁴⁶ Thus, the court said, Loomis had "the opportunity to verify that the questions and answers listed on the [algorithm] report were accurate."¹⁴⁷ However, Loomis did not know if the answers to those questions comprised all the information that went into the algorithm, whether (conversely) only some of the answers influenced the evaluation, or what weight was assigned to any answers that were used.¹⁴⁸ For instance, the fact that Loomis was able to verify that the evaluators using the algorithm correctly calculated how many times he had been arrested (one of the algorithm's risk factors) elucidated nothing about how that information affected his sentence, thus leaving unclear whether the judge should have been foreclosed from considering his record independent of his algorithmic score.¹⁴⁹ Neither did it tell him whether, if he could elaborate on his answers (by, for instance, noting that many of the previous arrests had been for misdemeanors), the risk score would change.¹⁵⁰ The relevance of all of this to profile-driven policing should be clear.

In making his argument that more transparency was required, Loomis relied on *Gardner v. Florida*,¹⁵¹ a United States Supreme Court case holding that, in a capital sentencing proceeding, "[a] defendant has a constitutionally protected due process right to be sentenced upon accurate information."¹⁵² But, as the Wisconsin Supreme Court pointed out, that case could be construed to mean only that the defendant must have the opportunity to "refute, supplement or explain" facts relied upon by the judge to impose

¹⁴⁴ See generally *State v. Loomis*, 881 N.W.2d 749 (Wis. 2016).

¹⁴⁵ *Id.* at 753.

¹⁴⁶ *Id.* at 761–62.

¹⁴⁷ *Id.* at 761.

¹⁴⁸ See *id.* at 761–62.

¹⁴⁹ See *id.*

¹⁵⁰ See *id.*

¹⁵¹ *Id.* at 760–62 (citing *Gardner v. Florida*, 430 U.S. 349, 362 (1977)).

¹⁵² *Id.* at 760 (quoting *State v. Travis*, 832 N.W.2d 491, 496 (Wis. 2013)).

sentence.¹⁵³ Further, *Gardner* could be distinguished on the ground that it involved sentencing in a capital case, where accuracy concerns have always been paramount.¹⁵⁴

More relevant to the policing context is *Roviaro v. United States*, involving a simple drug case, where the Supreme Court held that the identity of a confidential informant must be revealed to the defendant when the informant possesses facts that are relevant to the defense.¹⁵⁵ The Court was unimpressed with the argument that the officers who “ran” the informant could describe to the court what the informant said and did with Roviaro; questioning of the officers “was hardly a substitute for an opportunity to examine the man who had been nearest to [Roviaro] and took part in the transaction.”¹⁵⁶ Analogously, questioning the developers of the algorithm or the police who used it about the information they inputted is not a substitute for questioning the algorithm itself. Although *Loomis*, *Gardner*, and *Roviaro* were all based on the Due Process Clause, the better constitutional hook is the Sixth Amendment’s Confrontation Clause, which guarantees the right to confront one’s accusers.¹⁵⁷ As Andrea Roth has observed in discussing government use of technology in the criminal justice system more generally, “[t]he state’s use of accusatory machine conveyances to prove a defendant’s guilt seems to implicate many of the same dignitary and accuracy concerns underlying the framers’ preoccupation [in drafting the Confrontation Clause] with in-the-shadows accusations and ex parte affidavits.”¹⁵⁸

Roviaro establishes that even strong claims of a need for secrecy—the confidentiality of informants is considered sacrosanct in policing circles¹⁵⁹—should not prevail when the information is crucial to the case. While *Roviaro* has been given short shrift in more recent lower court decisions, its central rationale has not been abandoned.¹⁶⁰ Some lower courts have followed its logic in requiring that defendants be given the facts and opinions underlying

¹⁵³ *Id.* at 760–61.

¹⁵⁴ *Sawyer v. Whitley*, 505 U.S. 333, 366 (1992) (Blackmun, J., concurring) (“Nowhere is the need for accuracy greater than when the State exercises its ultimate authority and takes the life of one of its citizens.”).

¹⁵⁵ *Roviaro v. United States*, 353 U.S. 53, 65 (1957).

¹⁵⁶ *Id.* at 64. Although *Rovario* only requires cross-examination at trial, its logic should apply to any proceeding at which an “informant” is key to the state’s case. Further, since the informant at issue here—a place-based or person-based algorithm developed for police use—would be used repeatedly, the need for a reliability determination is much greater than in the human informant cases.

¹⁵⁷ See generally U.S. CONST. amend VI.

¹⁵⁸ Andrea Roth, *Machine Testimony*, 126 YALE L.J. 1972, 2042 (2017).

¹⁵⁹ See RICHARD VAN DUIZEND ET AL., THE SEARCH WARRANT PROCESS: PRECONCEPTIONS, PERCEPTIONS, AND PRACTICES 26 (1985) (“[L]aw enforcement officers and prosecutors apparently prefer to forgo the possibility of a conviction rather than to jeopardize the well-being of informants by divulging their identities.”).

¹⁶⁰ See Zathrina Zasell Gutierrez Perez, *Piercing the Veil of Informant Confidentiality: The Role of In Camera Hearings in the Roviaro Determination*, 46 AM. CRIM. L. REV. 179, 202–13 (2009) (describing federal appellate courts’ approaches to *Roviaro*).

their proposed sentences.¹⁶¹ Analogously, in the profile-driven policing setting, independent entities should have the ability to retest privately developed algorithms, and attorneys for targeted individuals ought to be informed if their client is on a hot list and the reasons why, so that misinformation can be corrected and the application of the algorithm double-checked.

IV. A PRELIMINARY ASSESSMENT OF PREDICTIVE POLICING

Whether predictive algorithms can improve policing, or instead are simply a fancy cover for racially skewed and ultimately ineffective police tactics, remains to be seen. Given its potential for preventing crime in a relatively unbiased manner and for identifying, *ex ante*, the factors justifying stops in a way that minimizes *ex post* rationalizations, predictive policing cannot be summarily dismissed. But if the foregoing limitations arising from proportionality analysis were to apply, the fate of predictive algorithms would be in serious doubt.

This is especially so with respect to algorithms aimed at identifying hot people rather than hot spots. First, a person-based algorithm should only use risk factors that rely on data that is already in the public record, unless its hit rate justifies accessing nonpublic information or steps are taken to anonymize that information from the government. Second, the algorithm's hit rates would also have to justify whatever action the police claim it justifies; if that action is a stop, for instance, it might need to generate hit rates of approximately 30%, barring a serious imminent threat. Third, even then, the algorithm should not be used as a basis for a stop unless, immediately prior to the stop, the police observe or obtain through witnesses evidence of suspicious conduct. Fourth, the algorithm should take into account and correct for the effects of racially disparate policing, which might require the exclusion of arrests for less serious crimes as risk factors and a focus on violent crime as an outcome measure. Fifth, independent experts, preferably from a university or research institute setting, should initially and periodically thereafter have access to the inner workings of the algorithm to assess whether it meets these requirements. And sixth, defense attorneys must be able to find out how the algorithm was applied in their specific cases. Ideally, all of these concerns would be identified by statute and fleshed out in departmental or judicial policies, with courts applying constitutional finetuning if necessary.¹⁶²

¹⁶¹ See, e.g., *United States v. Millán-Isaac*, 749 F.3d 57, 70 (1st Cir. 2014); *Smith v. Woods*, 505 F. App'x 560, 568 (6th Cir. 2012); *United States v. Hayes*, 171 F.3d 389, 394 (6th Cir. 1999).

¹⁶² See generally PRINCIPLES OF THE L., POLICING § 1.06 (AM. L. INST. 2023) (requiring written policies); *id.* § 2.06 (requiring transparency and explanation of factors for algorithms and profiles).

Because the GSFA generates good hit rates (from a proportionality perspective) at scores of four and five, is based entirely on recent suspicious conduct (and thus does not rely on any historical information that might misleadingly correlate with race), and is statistically transparent, it might meet all of these limitations. But Chicago's heat list and the Beware algorithm, if used to justify stops or frisks, almost certainly do not. And even the GSFA can be faulted for relying on relatively vague types of triggering conduct.

Place-based profiling is not off the hook either. Good hot spot algorithms might help deploy the police in an efficient way, which in turn might enhance deterrence through timely police presence. But physically detaining an individual—even one found in a very hot spot—should still require suspicious conduct. Recall the traffic stop made by Officer Keener, described at the beginning of this Article.¹⁶³ The hot spot report that Keener says influenced his actions predicted a heightened risk of assault for individuals in the area.¹⁶⁴ But conduct signaling that the young man he stopped was contemplating an assault was entirely lacking.¹⁶⁵ To the extent a place-based profile is proffered as a reason for such stops, it should be given no weight at all. The Supreme Court agrees, stating in *Illinois v. Wardlow* that “[a]n individual’s presence in an area of expected criminal activity, standing alone, is not enough to support a reasonable, particularized suspicion that the person is committing a crime.”¹⁶⁶

The nature of profile-driven data-based policing is likely to change as technology advances. For instance, in the not-too-distant future, surveillance camera systems may come equipped with “anomaly” detection capacity that uses machine learning to alert to behavioral patterns, emotions, or appearances that are “abnormal,” such as walking back and forth or in circles, looking angry, or wearing unusual clothing.¹⁶⁷ The likelihood is significant that this type of system, left unregulated, would result in increased hassle of individuals, chilling of innocent activity, and racially biased interventions. Imagine, for instance, how an anomaly detector might react to a person walking up and down the street for exercise, yelling at a driver for cutting him off and then following the driver, or entering a neighborhood populated mostly by people of a different race.

¹⁶³ See *supra* text accompanying note 1.

¹⁶⁴ FERGUSON, *supra* note 1, at 64.

¹⁶⁵ See *id.*

¹⁶⁶ *Illinois v. Wardlow*, 528 U.S. 119, 124 (2000) (citing *Brown v. Texas*, 443 U.S. 47 (1979)).

¹⁶⁷ JAY STANLEY, AM. CIV. LIBERTIES UNION, THE DAWN OF ROBOTIC SURVEILLANCE: AI, VIDEO ANALYTICS, AND PRIVACY 15–17 (2019), <https://www.aclu.org/report/dawn-robot-surveillance#> [<https://perma.cc/G4W5-UB2D>]. For a nascent version of this technology, see Digit. Just., *Digitensory Technologies Avista Smart Sensors*, YOUTUBE (Sept. 14, 2012), <https://www.youtube.com/watch?v=JamGobiS5wg> [<https://perma.cc/VCG5-G57F>].

Police using these detectors can often point to conduct by the target, and the fact that the conduct is identified as an “anomaly” might, in at least some cases, make it suspicious not only in the eyes of the police but also of the courts, especially if the “anomaly” is based on a pattern highly correlated with criminal activity (e.g., an individual repeatedly taking money from another person, going back into their apartment, and returning with a small package that is handed over). Even then, however, an anomaly, by itself, might not produce the hit rate for full-blown stops demanded by proportionality analysis. If not, at most, proportionality reasoning would permit surveillance of people who trigger the device, unless further suspicion develops.

Consider also the Department of Homeland Security’s (DHS) Future Attribute Screening Technology (FAST), a biometric-based algorithm that is meant to detect terrorists by measuring body and eye movements, eye blink rate and pupil variation, body heat changes, breathing patterns, voice pitch changes, alternations in vocal rhythm, and changes in intonations of speech.¹⁶⁸ Depending on whether it is deployed remotely or through “contact,” the DHS claims FAST has a hit rate of 70–81%, well above what is needed to justify a detention for questioning on proportionality grounds, especially since the threat to be prevented is serious.¹⁶⁹ Assuming DHS’s hit rate claim can be replicated in the real world and that it only targets terrorists and other potentially violent actors (very significant assumptions), proportionality reasoning might lead to the conclusion that, at the least, a short detention of any person who triggers the algorithm for the purpose of questioning and checking terrorist watchlists is justifiable. At the same time, the biometric information collected by FAST is difficult to classify as conduct, and thus may be an insufficient ground, by itself, for meeting the imminence requirement. Further, the device is likely to produce a noticeable hassle rate given the number of nervous people at airports.

It can be anticipated that science will continue to raise difficult legal questions about when predictive seizures and searches can justifiably lead to long-term surveillance and physical confrontations. Proportionality analysis, together with the imminence requirement, provides a framework for answering those questions. This framework, when supplemented by algorithmic information, would also force courts to face difficult normative decisions that they can easily gloss over when concepts like reasonable suspicion are not quantified. It requires judges to answer questions such as:

¹⁶⁸ Dep’t of Homeland Sec., *Future Attribute Screening Technology*, DHS SCI. & TECH. DIRECTORATE (Nov. 18, 2024), <https://www.dhs.gov/sites/default/files/publications/Future%20Attribute%20Screening%20Technology-FAST.pdf> [https://perma.cc/X6CR-3RY4].

¹⁶⁹ *Id.*

Should the Fourth Amendment permit prolonged stops based on a 25% chance the person stopped has a gun?

Finally, while this framework or something like it is essential in determining whether profile-driven policing is legally permissible, it is meant to answer *only* the constitutional questions. Even if all of its requirements are met, the ultimate decision about profile-driven policing should be based on whether it brings more benefits than costs, not only as measured by scientists but as assessed by the affected community.¹⁷⁰ In the street context, for instance, even if profile-driven policing reduces crime, its reliance on “numbers” and predictive analytics could exacerbate already high police-citizen tensions, and the money spent on developing algorithms might be better spent on social services and other crime reduction efforts. This Article does not purport to address these types of issues.

¹⁷⁰ Cf. Ngozi Okidegbe, *To Democratize Algorithms*, 69 UCLA L. REV. 1688, 1698 (2023) (arguing for “short-term strategies . . . that endow oppressed groups with the power to determine if and how a public sector decisionmaking process is automated or informed by algorithmic use,” and recommending “the creation of a new commission subjected to negotiated rulemaking that would be tasked with determining current and future algorithmic use”).