How predictive policing entrenches racism under the guise of objectivity

As public trust in the law enforcement system declines and budget cuts continue to plague police departments, more court and police systems have been turning to algorithms to aid administering criminal justice. *(Heaven, 2020)* However, the results of these algorithms have been met with much backlash, with some claiming these “objective” algorithms might not be as impartial as advertised. A Black woman with no criminal history was predicted to have a higher likelihood of committing a future crime than a white man who had already served five years in prison, among other offenses, in Broward County, Florida. *(Mattu, n.d.)* An arrest in high school for a peaceful demonstration-turned-brawl can set a student up for “a lifetime of biased assessment because of that arrest record. *(Heaven, 2020)* Algorithmically-detected crime “hot spots” disproportionately occur in Black and Latino neighborhoods, driving increased racialized policing. *(Jefferson, 2018)* These instances of unfair outcomes related to risk assessment tools — specialized algorithms that help quantify how likely one is to commit another crime or show up at their next hearing — further highlight existing biases within America’s criminal justice system. From this, risk assessment tools used in predictive policing often exacerbate the issues already present in the police system due to the racist roots of law enforcement in the United States and the “dirty data” that results from this structural bias. *(Richardson et al., 2019)* With these historical and algorithmic biases, predictive policing and risk assessment tools related to the court system create, confirm, and further entrench bias into how American police operate and how defendants are treated by the courts, leading to discriminatory consequences that must be addressed before these technologies become even more widespread.

America’s history of policing through technology

Policing in America is rooted in racism, with the concept of the modern police emerging from slave patrols that exploited and fed the racism of poor white people in the South. *(Lally, 2022)* Similar to how police enforce laws through a monopoly on legal violence, slave patrols used terror to stop slave uprisings and return runaway slaves to their own, encouraging compliant, submissive behavior from enslaved people through this threat of violence. Even during the pre-Industrial era, slavery was maintained through policing technologies such as fugitive slave ads, which are seen as precursors to current surveillance technologies. *(Lally, 2022)* However, the history of predictive policing began in the 1960s, where some police departments began using computational models to allocate patrol cars through call forecasting. *(Lally, 2022)* Once Geographic Information Systems (GIS) proliferated, this technology spread to other police departments throughout America, allowing crime analysts to locate crime "hot spots" and target them for increased policing. *(Jefferson, 2018)* In the 1990s, police moved towards more proactive forms of policing such as hotspot mapping, community policing, stop and frisks, and broken windows policing — all of which disproportionately targeted Black and Latino communities of color, among other minority communities. *(Lally, 2022)* As policing became more proactive, officer promotions became increasingly tied to crime statistics, with police officers downplaying the occurrence of "serious crimes" and increasing the number of arrests tied to less serious crimes. *(Lally, 2022)* Two decades later, police departments were faced with distrust due to police violence and widespread corruption, causing some to desire the objectivity of science and data as a way to alleviate officer bias in policing decisions. *(Lally, 2022)*

With this, predictive policing technologies spread through companies like CompStat and PredPol, with optimistic developers and policymakers hailing predictive policing as a way to eliminate the human bias from the law enforcement system. *(DeGeurin, 2018)* Now, algorithm-driven predictive policing is implemented in two ways: place-based predictive policing, which identifies specific areas that are crime hotspots, and person-based predictive policing, which identifies individuals who are at risk of perpetrating or being a victim of a crime. *(Richardson et al., 2019)*

Why risk assessment tools are biased

In recent history, police officers manipulated data to produce annual crime reductions so they could get promotions, carrying out illegal actions such as persuading victims to not file complaints to reduce serious crime statistics and planting drugs on innocent people to meet arrests and summons quotas. *(Richardson et al., 2019)* Despite the close tie between police corruption and police records, the data that informs predictive policing tends to be historical crime records. However, the quality of data inputted into risk assessment tools often goes undisputed due to the presumption that data is "objective." While the companies creating these predictive models claim that they exclude data that reflects biased police practices, there isn't much transparency surrounding what these companies choose to exclude and what types of data they deem as "biased." There is also no standardized method for collecting data from and in police records, making it nearly impossible to isolate dirty data's impact on predictive policing. *(Richardson et al., 2019)* From this, dirty data leads to discriminatory results, exemplified by the case study of Chicago's police department.

The Chicago police department was found by the Department of Justice to have both poor and racist data collection practices that disproportionately impacted Black and Latino residents, especially young Black men, from 2011 to 2016. Using the belief of data as "objective," the department decided to implement the Strategic Subject List (SSL) to identify individuals who were at risk of becoming a victim or perpetrator in a shooting or homicide by using data from arrest records. While using arrest records rather than conviction records was already a poor proxy for one's criminal history, as people can be arrested but not convicted of a crime, the list proved to disproportionately include young Black men — the same demographic disproportionately affected by the CPD's biased practices. In addition to this racist overrepresentation of young Black men, the SSL also was not successful in reducing gun violence. *(Richardson et al., 2019)* Instead, it only increased the number of arrests made by the police. *(Richardson et al., 2019)* Similarly, software administered by PredPol was found in a study to leave the racial disparities in arrests unchanged despite increasing arrest rates as a whole in areas marked by the software. *(Lally, 2022)* From this, some argue that predictive policing can create small, "high-crime" areas where police feel that they have to investigate more aggressively, effectively engaging in broken-windows policing in predicted areas and targeting people for offenses based on where they are rather than what they've done.

Furthermore, the lack of interaction and transparency between software developers, police systems, and the algorithm itself further perpetuates issues created by predictive policing. While developers do not code race into their algorithms to emphasize "color blindness," risk assessments aren't race neutral due to the dirty data these algorithms are trained on. *(Schwartzapfel, 2019)* Similarly, while developers have a conceptual understanding of how these predictive systems are meant to be used, a survey of developers showed that most developers don't know how their software is being used and to what extent police officers are actually faithful to the results that these algorithms output. *(Lally, 2022)* At the same time, the modular nature of creating algorithms — splitting a large algorithm into smaller, isolated problems that work together to create the end result — prevents intersectional thinking, ignoring lived experience and diversity as ways to inform policing. In addition to issues surrounding the developer side of predictive policing, police systems are surrounded by a lack of transparency and accountability, making it difficult to investigate whether or not these tools are actually working and how much harm or good these tools are generating. *(Jefferson, 2018)* From this, not only are predictive policing algorithms likely flawed, but the algorithmic guise of objectivity discourages the investigation of these risk assessment tools, leading to questions as to whether or not these technologies should even be used.

Solutions to fix predictive policing

While transparency is an obvious way to enhance accountability for both developers and policing, it should not be the final step towards fixing the consequences of predictive policing. *(Safransky, 2019)* There needs to be greater understanding that algorithmic design and data collection are subjective and involve moral assumptions despite their quantitative qualities. Furthermore, in addition to holding policymakers accountable for their endorsement of these often flawed technologies, we also need to involve the people most affected by the biases present in historical police data when creating and implementing these algorithms. *(Heaven, 2020)*

However, while some might argue that we need to stop using these flawed risk assessment tools until there is a way to guarantee parity, I believe that these algorithms can be helpful in informing policy by using them in context, as racism will still exist in our current policing system whether or not we use algorithms. *(Heilweil, 2020)* Algorithms should be used in policies that are data-informed rather than data-driven, highlighted by the example of Market Value Analysis (MVA) in Detroit. In Detroit, MVA was used to algorithmically redline the city, directing public officials and investors on what neighborhoods should be targeted for investment, development, and public services. MVA took on the perspective of a developer, using criteria that developers would use in evaluating whether or not an area would be profitable. *(Safransky, 2019)* However, MVA claimed objectivity, making deeply political choices under the guise of “apolitical” data analysis. *(Safransky, 2019)* If MVA was used in context, the municipal government could have saved money by using MVA to cut out extraneous external consultancies that prop up developer perspectives and reallocated that money into finding community activists and those impacted by this redlining to share their perspectives and inform policy. Through this, it appears that algorithms that impact urban planning and policing have immense potential to cut costs and increase efficiency. However, overreliance on these algorithms removes humanity, care, and justice from tasks that are inherently human-centered, such as politics and law enforcement. From this, we need to use algorithms as tools that would allow for more time and money to be put into uplifting perspectives of those most impacted by urban policy rather than viewing it as an objective decision-making force.