

Ethical Concerns of Predictive Policing Softwares

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Ethical Concerns of Predictive Policing Software

Abstract

This literature review attempted to present how predictive policing software and the subsequent ethical concerns of its use are conceptualised by interdisciplinary academics. Three major ethical problems were discussed in this literature view, namely, privacy intrusion, racial discrimination and low police accountability due to low transparency of the predictive softwares. From a jurisprudence perspective, the literatures were certain about the use of predictive policing software would intrude an individual's privacy. The review however showed that claims about predictive policing software *caused* racial profiling and increase the transparency of the softwares. This review also reflected that due to methodological difficulties, it would be difficult to conduct further quantitative empirical studies to improve the situation. It is hoped that this literature review not only give an overview of predictive policing software to the readers, but more importantly to encourage academics and the public to scrutinize the potential ethical problems behind the use of predictive policing software.

Keywords: Predictive Policing, Privacy Intrusion, Racism, Transparency.

Introduction

The benefits of using Big Data to make predictions about the future have attracted a wide range of applications in different fields, for example in biomedical researches and commerce (Richterich, 2018). In western hemisphere, especially in the United States, law enforcement departments were apparently also attracted to adopt predictive tools to enhance their performances and reduce & prevent crimes (Ferguson, 2017a). Using quantitative methods, algorithms allegedly can objectively assess where crimes would occur or identify potential suspects and reduce human biases, as well as increase police efficiency in major metropolis (Ferguson, 2017a, p. 1114; Degeling & Berendt, 2018). However, are predictive policing softwares really as effective and impartial as they seem? What are predictive policing softwares? Is there any potential ethical concern embedded in the use of predictive policing softwares?

To answer these questions, a literature review would be a good choice as it gives an overview about the subject matter. The literature review is composed of five major parts. Part I would be a description of the literatures selected for this review. In that section, it will clearly outline how many literatures were selected and rationale behind choosing these literatures instead of others. Part II will give an overview of two different types of predictive policing software and how they operate. Part III would expand on how predictive policing softwares intruded individual's privacy, particularly the intellectual privacy and the dignity interest of privacy. Part IV would illustrate the debate between scholars on whether there is any racial bias in the predictive algorithms. Part V would show scholars' scepticism towards the transparency of the proclaimed effectiveness of predictive policing software and its subsequent unethical and illiberal consequences. Part VI will be a conclusion of the whole review and made some suggestions about how future studies can enrich our understandings about predictive policing softwares.

I. Data Selection

In this literature review, in total 26 pieces of peer-reviewed literature were selected to discuss the ethical concerns of predictive policing softwares. These literatures were mostly legal and social science academic journals and books that discussed predictive policing softwares adopted in the United States and its subsequent ethical concerns in the past 10 years. These journals were selected based on several criteria. First, the fast paced nature of technological innovation means that a review on older literatures might not be relevant to the ethical problems predictive policing softwares face nowadays. However, as some scholars have suggested too, there are inadequate numbers of literatures discussing the drawbacks of predictive policing softwares (Ferguson, 2017a, Meijer & Wessels, 2019). To strike a balance between relevancy and an in-depth discussion, only literatures published after 2010 were selected in this review. Second, social science journals were selected as topics like racism in law enforcement and keeping the government accountable to the citizens have been long discussed in those disciplines.

As for legal journals, they have shown a more profound discussion on how the use of predictive policing softwares might cause ethical problems compared to social science journals that often briefly touched on the drawbacks without much elaboration. This has made the legal journals a better literature choice in reviewing the ethical concerns of predictive policing, especially concerns about the intrusion of privacy. Third, literatures focusing on predictive policing in United States were selected because United States is the country that has the most extensive use of predictive policing software and most of the available literatures that fulfilled other requirements are written based on the United States' context (Degeling & Berendt, 2018).

It is hoped that by selecting the literatures with these rationales can allow the readers to have a more updated and profound understanding on the ethical concerns of predictive policing software.

II. What are Predictive Policing Softwares?

Predictive policing softwares are widely conceptualised as the use of quantitative technology to predict the probabilities of when and where crimes occur (Degeling & Berendt, 2018; Ferguson, 2017a; Jefferson, 2018). The goals of using predictive policing softwares were to use the calculated probabilities to prevent and reduce crimes from happening (Ferguson, 2017a). These softwares learnt about what factors constituted as a crime classifier via data mining the old crime data and gradually developed an algorithm to predict crimes based on the classifiers it has previously machined learnt as criminal behaviour (Degeling & Berendt, 2018). Different types of predictive policing softwares used different crime classifiers. In western hemisphere, predictive policing softwares were largely characterised into two types. The first type of predictive policing softwares identified where crimes would occur; while the second type identified potential individuals who would commit crimes (Degeling & Berendt, 2018; Ferguson, 2017; Rich, 2016).

To predict potential high crime rate areas, type 1 predictive softwares like Predpol used geo-spatial data as classifiers (Degeling & Berendt, 2018, p. 348; Ferguson, 2017a). The use of geo-spatial data was theoretically supported by what the criminologists had coined as the Near Repeat Effect. Near Repeat Effect referred to the idea that certain kinds of criminal behaviour like burglaries had a tendency to occur repeatedly in an area (Ferguson, 2017a). The algorithm of these softwares was then machine-learned to identify an area as high crime rate by assessing how often a certain kind of criminal behaviour has occurred in a specific location in the past (Kirkpatrick, 2017). Type 1 predictive softwares are usually used for predicting crimes like burglaries and assaults although it can also predict major crimes like gun crimes (Degeling & Berendt, 2018).

To target specific individuals as potential offenders and victims, type 2 predictive softwares, mostly notably the one that built the Chicago heat list, used social network's data of previous criminals and victims as crime classifiers (Degeling & Berendt, 2018; Ferguson, 2012; Ferguson, 2017a; Jefferson, 2018).

The use of social network data was supported by the idea that people who shared the same social network with previous criminals and victims had a higher chance of becoming future criminals and victims respectively (Ferguson, 2017a). The algorithm of such software was then trained to look for specific data like address, phone numbers, neighbourhoods and age of individuals who had relations with prior criminals and victims to identify a list of possible offenders and victims (Ferguson, 2017a, p. 1139). With this heat list, police officers will deliver a “Custom Notification Letter” warning the potential charges these potential offenders might face if they commit a crime (Degeling & Berendt, 2018; Ferguson, 2017a). Degeling & Berendt (2018) also pointed out that very often type 2 predictive policing softwares are used to predict major crimes like feud, drug trades, gang related homicides.

III. Privacy and Predictive Policing

Respect for individuals’ privacy has been long considered as one of the golden rules of data collection ethics (Richerich, 2018). When it comes to collecting and using personal data for predicting crimes, scholars have raised their concerns about how individuals’ privacy might be intruded (Ferguson, 2017; Gray & Citron, 2013; Miller, 2014; Rich, 2016; van Zoonen, 2016).

Before moving forward to the two understands of privacy, we first need to understand some basic legal terminologies that would facilitate our understandings on whether individuals’ privacy had been intruded. The Fourth Amendment in the United States Constitution ensured that any potential intrusion of one’s privacy during investigation required the police to consider all the facts surrounding a suspect and based on all these facts to demonstrate an individual has criminal intention to justify such investigation (Miller, 2014; Rich, 2016). The concepts of considering all the facts and the demonstration of reasonable suspicion of an individual for privacy intrusion are also known as “totality-of-the-circumstances” and “probable cause” in the legal literatures (Miller, 2014; Rich, 2016). As shown in the later paragraphs, it will present scholars worries about how predictive policing softwares failed to conduct the test of totality of circumstance and generate an individualised probable cause that led to an intrusion to privacy. Such concerns stemmed from two understandings of privacy, namely, the dignity interest of privacy and intellectual privacy.

Predicting crimes or disrespecting individuals’ dignity?

From a jurisprudence and methodological perspective, Ferguson (2017a), Miller (2014) and Rich (2016) had offered extensive arguments about how predictive policing softwares infringe an individual’s privacy in terms of the dignity interest of privacy. Miller (2014, p. 127) argued that privacy has a dignity interest, which the sheer action of searching information about an individual can be considered as an offense to privacy. Miller (2014) further argued that the use of predictive policing softwares would go against the dignity interest of privacy as the predictions are made based on searching one’s personal information, especially

type 2 predictive softwares predicting how likely specific individuals are going to commit crimes.

Indeed, error rates of predictive policing softwares could be huge as later shown in the discussion about transparency and predictive policing. It was argued that false positives cases could have liberty eroding effects. Not only does false positives create financial burdens, more problematically, it was argued this generates increased police surveillance in a certain areas and singling out innocent individuals for investigating crimes they did not have the intention to commit (Degeling & Berendt, 2018; Ferguson, 2017a). The literatures suggested that the dignity interest of privacy has been intruded in false positive cases as individuals' personal information has been searched unnecessary. The intrusion of privacy in false positive cases cannot be justified even the predictive policing softwares managed to produce some correct predictions. It is argued that the jurisprudence behind the 4th Amendment is to guarantee individualised justice but not maximise police efficiency and accuracy (O'Neil; 2016, p. 95; Rich 2016, p. 900). However, false positive cases would imply that the algorithms must have missed out certain facts and these individuals have not been fairly treated with the test of totality-of-circumstances. As Rich (2016) succinctly put it,

“ In other words, the Fourth Amendment would not be satisfied if a police agency conducted ten searches, five on suspects who were almost certainly engaged in criminal activity and five on suspects who almost certainly were not, on the ground that *on average* probable cause existed.” (p. 901)

Therefore, as long as predictive policing softwares failed to provide an individualised test of totality-of-circumstances and customized a probable cause of each investigation, the literatures pointed to the argument that this would have intruded individuals' privacy dignity interest. In the coming section, it will review it is in fact difficult for predictive policing softwares to provide a totality-of-circumstances test for every individual it monitored due to methodological problems.

Predictive crime softwares or Surveillance softwares?

Secondly, the use of predictive policing softwares might intrude the intellectual privacy of individuals. Intellectual privacy can be considered as the privacy of individuals to discuss ideas and beliefs at the time and space they chose under the condition that these discussions did not have any criminal intention (Richards, 2013, p. 1946; Miller, 2014). The right to enjoy intellectual privacy is important for a democratic society for two reasons as Richards (2013) argued. The first reason is that this right represents the fundamental principle a liberal democracy should always uphold- the freedom of choice of an individual to make the decision on what beliefs, thought at the “... time and places of their choosing...”; the second reason is that progressive ideas for a democracy usually were generated by new ideas best kept away from “...the intense scrutiny of public exposure...” (Richards, 2013, p. 1946).

Based on their understandings of intellectual privacy, scholars argued that predictive policing softwares actually cannot conduct the test of totality-of-circumstances solely and establish a sounded probable cause to justify polices' intrusion to one's individual's privacy. Rich (2016) argued that predictive policing softwares failed to provide a holistic assessment of all the facts that made an individual a suspect because predictive softwares could not incorporate facts that they did not machine learn as criminal behaviour and subsequently predict crimes. According to Rich (2016), this problem can not be solved due to technological limitations and the fact that methodologically the data scientists cannot foresee facts that should be considered for a totality-of-circumstances test in future cases but yet to be included in the algorithms and put future facts in the algorithms.

When predictive policing softwares cannot produce individualised probable cause, the literatures argued that these predictive softwares might become surveillance tools monitoring guiltless civilians (Degeling & Berendt, 2018; Miller, 2014; Rich, 2016; Richards, 2013). The harms created by surveillance towards intellectual privacy were paramount and widely discussed in the legal literatures. It is argued that surveillance system would pose psychological pressures to citizens to behave normally in order to avoid being detected by the surveillance system (Miller, 2014, p. 132). Gradually the psychological pressure would make people self-censor any "inappropriate" actions, for example, waving hands in high crime areas as shown in the Philadelphia video or not buying air tickets with cash¹. Consequentially, Miller (2014) argued intellectual privacy would be eroded and people no longer enjoy the freedom to think and discuss ideas but instead act and think uniformly.

When a society loses its intellectual diversity, this would pose a threat to the foundation and progression of a democratic society which intellectual privacy has been considered to play a pivotal roles in them (Richards, 2013). Although predictive policing softwares might cause tremendous harm to intellectual privacy, there were still limited discussions on this issue due to the fact that intellectual privacy was a recently developed idea and the Supreme Court had not ruled out how the predictive policing softwares intruded privacy albeit expressing deep worries in *United v. Jones* (Miller, 2014, p. 135-136). This suggested that the intrusion to intellectual privacy still requires more academic and legal scrutiny.

IV. Racism and Predictive Policing

Racism in policing has long been a problem in United States' law enforcement (Byfield, 2019; Ferguson, 2017b). At the first glance, predictive policing softwares seem to be the panacea to racial policing. Under the United States law,

¹ In a video captured by Philadelphia polices showed that two men were detained simply because they waved hands to each other in a "high crime area" (Miller, 2014, p. 128). Miller (2014, p. 129) also showed Supreme Court has ruled out that it is legitimate to use non-criminal behavior like buying air tickets with cash as classifiers to profile potential narcotic criminals.

it is illegal to put race as a crime prediction classifier and this should help reduce the racial bias in law enforcement (Tonry, 2014). Yet, were algorithms truly racially unbiased? If the answer was no, this would imply that predictive policing softwares would stigmatize a particular racial group and this might cause unethical consequence of treating people in the society unequally (Degeling & Berendt, 2018). Literatures seemed to have mixed findings about whether racial bias truly exists in predictive policing softwares.

Did prediction become more accurate or just more racist?

On one hand, some scholars argued that racial bias did exist in predictive algorithms. From a methodological perspective, many scholars pointed to the fact that many data collected to train the algorithm are racially biased (Ferguson, 2017a, Ferguson, 2017b; Lum & Isaac, 2016). It is true that the predictive algorithms do not contain data about an individual's race and gender as Brantingham, the founder of Predpol, claimed to be, it was argued that data like post code and employment status can be used as proxies of race in major cities (Jefferson, 2018; Kirkpatrick, 2017; O'Neil, 2016). A study from Lum & Isaac (2016) also seems to confirm Jefferson, Kirkpatrick and O'Neil's studies. Lum & Isaac (2016) found that Predpol targeted poor black neighbourhoods more often than white neighbourhoods in combatting drug crimes even though black and white neighbourhoods had equal chance of drug abuse.

When the algorithm data-mined these racially biased data about criminal behaviour, it would also generate racially biased result. When polices followed the bias prediction and sent more police force to arrest Black and Latinx suspects, this generated a new dataset with more Black and Latinx name, addresses and postal code in the dataset (Ferguson, 2017a; O'Neil, 2016). This dataset would then be data-mined and the algorithm machined learnt to predict criminal behaviour with these racially biased data. This process in the long run formed a positive feedback loop that perpetuated a racially biased prediction of crimes (Chan & Bennett Moses, 2016; Ferguson, 2017a; Lum & Isaac, 2016; O'Neil, 2016, p.87).

Although there are no direct empirical studies at the moment showing a racially biased positive feedback loop existed, there were several empirical studies showing a strong correlation of racial bias and predictive policing softwares. Lum & Isaac (2016) showed that Predpol, one of the most popular type 1 predictive softwares, targeted black individuals twice as much as targeting white people when it comes to drug crimes in Oakland. Another study from Jefferson (2018) showed that after the introduction of Chicago heat list, Ethnic minorities like Black, Hispanic and Latinx, accounted for 94% of narcotics arrest; 96% of non-negligent manslaughter and 75% of murder victims in 2010. The same study by Jefferson (2018) also showed that most of the custom notification letters fell in major Black and Latinx districts on the South and Western sides of Chicago. All these empirical studies have shown that instead of removing the racial bias in law enforcement, predictive policing softwares might do the total opposite of its original intention- predicting crimes even more racist.

“Predictive Policing caused racial profiling” - a claim that lacks empirical evidences to support.

On the other hand, some empirical studies showed that racial bias did not exist, or at least it is very difficult to prove a casual relationship between predictive policing and racial profiling. In randomised trial experiments, Brantingham, Valasik & Mohler (2018) have shown that the arrest rates of non-white offenders did not differ when predictive policing softwares are used or not. It was also shown that individuals on the Chicago heat list were not more likely to become homicide victims (Saunders et al, 2016, quoted in Degeling & Berendt, 2018). Indeed, it has been recognized by the some academics that there were inadequate empirical studies to support the claim that there was any cause-and-effect relationship between racial profiling and predictive policing softwares (Degeling & Berendt, 2018; Ferguson, 2017a; Meijer & Wessels, 2019). This further weakened the claim that racial bias exists albeit strong correlation has been shown in several empirical studies.

Proving such a cause-and-effect relationship is apparently not an easy task. One of the major problems is that predictive policing softwares developers will not admit any systemic error leading to racism (Degeling & Berendt, 2018; Ferguson, 2017a). There are good reasons why they would not admit such errors. Predictive policing softwares are million-dollar worth business. There is almost no economic incentive for software developers to acknowledge there are systematic errors causing any bias. Admitting any systematic errors related to racism would only make the softwares less competitive on the market and less profitable (Ferguson, 2017a). This might explain why some scholars find little empirical studies on supporting the drawbacks of using predictive algorithms.

Without proving a casual relationship between racial profiling and the predictive algorithm, it remains opaque whether racial profiling is a fact or an unfortunate coincidence. All these literatures have pointed to the fact that it requires more empirical studies to show whether predictive policing softwares *caused* racial profiling. Therefore, it is fair to say that academics remained uncertain whether racial bias exists in predictive policing softwares.

V. Transparency and Predictive Policing

Scholars have also raised their concerns about the transparency of predictive policing. Such concerns come in two folds. First, some scholars argued a more fundamental lack of understanding about the internal validity of predictive policing softwares in predicting and preventing crime. First, some scholars argued there was a lack of transparency about the database. In the following sections, both empirical evidences and methodological issues would show that there is a lack of transparency in both cases and such phenomenon were largely due to methodological and administrative difficulties. A lack of transparency, as argued by social scientists and legal scholars, would pose ethical concerns as it diminished the accountability of the police officers and the government when other ethical worries arise due to the use of these softwares (Berendt, 2012;

Brennan & Oliver, 2013; Chan & Bennett Moses, 2016; Ferguson, 2017a; Leonelli, 2017; Mittelstadt & Floridi, 2015).

“Correlation should not be confused with causation when individual liberties are concerned” Ferguson (2017a, p. 1160)

Internally valid studies refer to studies that can “accurately determine cause-effect relationships”(Ferguson, 2017a, p. 1154). Do predictive policing softwares cause a reduction or prevention of crime? If not, Ferguson (2017a) argued that this would reduce the legitimacy of using the predictive algorithms in the sacrifice of eroding some fundamental liberal rights a democratic society treasure, most notably in this review, the respect of individual’s privacy and racial equality and certainly the accountability of the government and police departments.

Ferguson (2017a) has also pointed to the fact that proving a causation relationship can be difficult from a methodological perspective. Ferguson (2017a, p. 1160) argued that *identifying* a person who might be a criminal is not equivalent to *determining* a person as a criminal. This literature therefore is suggesting that even if predictive policing softwares have a high accuracy in predicting crimes, it would only prove a strong *correlation* between the use of predictive policing softwares and who and where crimes occurred, instead of *causation*.

In order to establish a casual relationship, there are still some fundamental methodological problems academics have to deal with. The first problem, as suggested by Ferguson (2017a), was that successful cases of crimes being prevented or reduced by the predictive softwares are hard to measure. Ferguson (2017a, pp. 1162) has succinctly illustrated a dilemma of measuring successful cases of crimes being prevented and being reduced by predictive policing softwares. Ferguson (2017a) argued that if we considered a prediction successful when it has high accuracy of predicting future crimes and the crime occurred, this meant the prediction failed to reach another objective of preventing crimes because the crimes have already happened. Meanwhile, if successful cases were defined as reducing crimes when more police resources have been sent to prevent it, this would suggest one ought to measure all non-events as successful cases. Without clearly defined cases of successes, most studies were therefore only able to reflect a strong *correlation* between the use of predictive policing softwares and crime-prevention as well as reduction, instead of *causation* (Ferguson, 2017a; Meijer & Wessels, 2019).

Low transparency leads to low accuracy or prediction.

The problem of low transparency is more deep-rooted as it seems. Ferguson (2017a) extensively showed that there are several reasons that hinder scholars to increase the effectiveness and transparency of the dataset. First, it is difficult to get assess of good quality data. This argument was illustrated in three folds. First, real data generated by the algorithms were considered imperfect for testing casual relationship as the same criminal behaviour could be caused by

different factors in different setting of time and space (Ferguson, 2017a, p. 1163). This means system errors that occurred in one specific time and space might not be applicable to another scenario. The second problem largely comes from the software developers' side. As previously discussed in the racial bias section, they have no economic incentive for the software developers to expose their algorithms (Ferguson, 2017a, p. 1151). Without the opportunity to examine the systemic errors that caused low accuracy and effectiveness, it was not possible to solve these errors (Ferguson, 2017). The third problem was that police officers were not professionally trained to understand the predictive algorithms and this meant that even if there was any systemic error, they would not notice it and fixed it (Ferguson, 2017a, p. 1152; Meijer & Wessels, 2019).

The lack of transparency can be reflected with the low accuracy rate of prediction. Previous empirical studies have demonstrated predictive policing softwares often were not so accurate and effective in predicting or preventing crimes, as very often there are false positive cases as discussed in the racial bias section. Degeling & Berendt (2018) have shown that Predpol only have 35% accuracy in terms of predicting where crimes occurred. Although another study have shown that Predpol had a higher accuracy in predicting crimes, that particular study has been criticised for cherry picking the data and this further weakened the claim of high accuracy (Ferguson, 2017a). Only one of the literatures have shown that Predpol was 10 times more efficient than random patrolling and 2 times more accurate compared to police intelligence in Kent, Britain (O'Neil, 2016).

For type two predictive policing softwares that target specific individuals, literatures suggested that it is even more difficult to establish a causal relationship between predictive policing softwares and reducing or preventing crimes. Nine predictive policing softwares that identified specific individuals have limited accuracy due to technological limitations (Yang, Wong & Coid, 2010). In one of the rare cases which the Chicago heat list has successfully predicted 78% of gunshot victims who died during the Memorial weekend in 2016, the prediction failed to reach its goal of reducing crimes when Chicago has witnessed the highest number of manslaughter cases in August that year (Ferguson, 2017a). All these empirical studies have shown that there is a low accuracy problem when it comes to crime-prevention and even in a rare case that indicates a high accuracy, it failed to reach another goal of predictive policing softwares, preventing them from happening in the beginning.

All these literatures also pointed to the fact that currently both academics and police forces had little knowledge about how predictive policing softwares actually operate. Attempts to improve the situations by increasing the transparency of our understanding of these softwares are expected to be difficult due to methodological hurdles and economic interests of the software developers.

VI. Conclusion

This literature review attempted to explore what are predictive policing softwares and some ethical concerns of using these algorithms. The literature reviews have shown that academics were quite certain that the use of predictive algorithms would pose threat to an individuals' intellectual privacy and dignity interest. Even worse, scholars worried that predictive policing softwares might turn to surveillance tool when they did not abide to the constitutional constrains. However, the literatures have shown that it remains open questions whether predictive policing softwares have *caused* racial profiling and crime reduction or prevention. They also pointed out that proving the two casual relationships would be difficult tasks due to methodological, commercial and administrative reasons.

Generally speaking, literatures from different disciplines have reflected a severe inadequacy of empirical studies or Supreme Court cases that could facilitate a better understanding about the ethical concerns of using predictive policing softwares and predictive policing software itself. As one might tell, this problem also troubled this literature review as it relied on several key journals to demonstrate the ethical concerns of predictive policing softwares. To sum up, it would be fair to claim that ethical concerns about predictive policing softwares are topics yet to be explored and deserved more efforts and scrutiny, concerning the liberty-eroding and unethical consequences they might possibly bring to our society.

Reference

Berendt, B. (2012). More than modelling and hiding: towards a comprehensive view of Web mining and privacy. *Data Mining and Knowledge Discovery*, 24(3), 697-737. 10.1007/s10618-012-0254-1

Brennan, T. and Oliver, W. (2013). The emergence of machine learning techniques in criminology. *Criminology & Public Policy*, 12(3), 551- 562. 10.1111/1745-9133.12055

Brantingham, P.J, (2018). The logic of data bias and its impact on place-based predictive policing. *Ohio State Journal of Criminal Law*, 15(2), 473- 486. <http://hdl.handle.net/1811/85819>

Brantingham, P.J., Valasik, M. and Mohler, G. (2018). Does predictive policing lead to biased arrests? Results from a randomized controlled trial. *Statistics and Public Policy*, 5(1) 1-6. 10.1080/2330443X.2018.1438940

Byfield, N. (2019). Race science and surveillance: police as the new race scientists. *Social Identities*, 25(1), 91-106. 10.1080/13504630.2017.1418599

Chan, J. and Bennett Moses, L. (2016). Is big data challenging criminology?. *Theoretical Criminology*, 20(1), 21-39. 10.1177/1362480615586614

Degeling, M. and Berendt, B. (2018). What is wrong about robocops as

consultants? A technological-centric critique of predictive policing. *AI & Society*, 33, 347- 256. <https://doi.org/10.1007/s00146-017-0730-7>

Ferguson, A. G. (2012). Predictive policing and reasonable suspicion. *Emory Law Journal*, 62(2), 259-326. <https://ssrn.com/abstract=2050001>

Ferguson, A. G. (2017a). Policing predictive policing. *Washington University Law Review*, 94(5), 1109-1190.
https://openscholarship.wustl.edu/law_lawreview/vol94/iss5/5

Ferguson, A.G. (2017b). *The rise of big data policing: Surveillance, race, and the future of law enforcement*. New York: New York University Press.

Gray, D. and Citron, D. (2013) The right to quantitative privacy. *Minnesota Law Review*, 98, 62-144. <https://ssrn.com/abstract=2228919>

Jefferson, B.J. (2018). Predictable policing: Predictive crime mapping and geographies of policing and race. *Annals of the American Association of Geographers*, 108 (1), 1-16. <https://doi.org/10.1080/24694452.2017.1293500>

Kirkpatrick, K. (2017). It's not the algorithm, it's the data. *Communications of the ACM*, 60 (2), 21-23. <https://doi.org/10.1145/3022181>

Leonelli, S. (2016). Locating ethics in data science: responsibility and accountability in global and distributed knowledge production systems. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 374 (2083), <https://doi.org/10.1098/rsta.2016.0122>

Lum, K. and Isaac, W. (2016) To predict or to serve? *Significance*, 13, 14-19.
<https://doi.org/10.1111/j.1740-9713.2016.00960.x>

Meijer, A. and Wessels, M. (2019). Predictive policing: Review of benefits and drawbacks. *International Journal of Public Administration*, 42(12), 1031-1039.
<https://doi.org/10.1080/01900692.2019.1575664>

Miller, K. (2014). Total surveillance, big data, and predictive crime technology: privacy perfect storm. *Journal of Technology Law Policy*, 19(1), 105-146.
<https://heinonline.org/HOL/P?h=hein.journals/jt19&i=111>.

Mittelstadt, B. and Floridi, L. (2015). The ethics of big data: current and foreseeable Issues in Biomedical Contexts. *Science and Engineering Ethics*. 10.1007/s11948-015-9652-2.

O'Neil, C. (2016). *Weapons of math destruction. How big data increases inequality and threatens democracy*. United Kingdom: Penguin Books.

- Rich, M. L. (2016). Machine Learning, automated suspicion algorithms, and the fourth amendment. *University of Pennsylvania Law Review*, 164(4), 871-930. <https://ssrn.com/abstract=2593795>
- Richards, N. (2013). The dangers of surveillance. *Harvard Law Review*, 126(7), 1934-1965. <https://heinonline.org/HOL/P?h=hein.journals/hlr126&i=1964>.
- Richterich, A. (2018). *The Big Data Agenda: Data Ethics and Critical Data Studies*. London: University of Westminster Press. doi:10.2307/j.ctv5vddsw
- Saunders, J., Hunt, P. and Hollywood, J. (2016). Predictions put into practice: a quasi-experimental evaluation of Chicago's predictive policing pilot. *Journal of Experimental Criminology*, 12, 347- 371. <https://doi.org/10.1007/s11292-016-9272-0>.
- Tonry, M. (2014). Legal and ethical issues in the prediction of recidivism. *Federal Sentencing Reporter*, 26(3), 167-176. 10.1525/fsr.2014.26.3.167
- van Zoonen, L. (2016). Privacy concerns in smart cities. *Government Information Quarterly*, 33(3), 472-480. <https://doi.org/10.1016/j.giq.2016.06.004>
- Yang, M., Wong, S. C. and Coid, J. (2010). The efficacy of violence prediction: a meta-analytic comparison of nine risk assessment tools. *Psychological Bulletin*, 136 (5), 740- 767. [10.1037/a0020473](https://doi.org/10.1037/a0020473)

