University of Twente & Westfälische Wilhelms-Universität Münster

Faculty of Behavioural, Management & Social Sciences

BSc Public Governance across Borders

Bachelor Thesis

An analysis of the influence of Predictive Policing on the level of police discrimination against ethnic minorities in Europe

Johanna Eyleen Soysal (S2353970)

04.02.2022

Supervisor: Dr. Ringo Ossewaarde

Wordcount: 11695

Abstract

In light of the global protests against racial police discrimination, this thesis examines the extent to which technology ameliorates or entrenches this problem. For this, three European countries are analyzed regarding their adherence to the Ethics Guidelines for Trustworthy AI (EGTAI). This thesis adds to the state of art by focusing on comparing European Predictive Policing projects, which have been neglected to date. The chosen methodology is a content analysis based on critical and postcolonial theories which aim to expose deeper issues that come with Machine Learning, specifically proxy discrimination, and which disproportionately affect marginalized groups such as ethnic minorities. The data consists of NGO and foundation papers, policy papers, guidelines, and scientific publications. The comparative case study approach reveals that none of the projects are fully in line with the EGTAI. However, projects aiming at geographical prediction like PRECOBS in Germany have a higher level of accountability and lower possibilities of discrimination compared to person-based predictions. The comparison allows for a best practice recommendation for Predictive Policing to abandon discriminatory police practices and provide a future of equal police treatment.

Table of Contents

List of abbreviations:

AI- Artificial Intelligence

BAME- Black, Asian, and minority ethnic

CAS- Criminal Anticipation System

EEE- Eastern European Ethnicity

EGTAI- Ethics Guidelines for Trustworthy AI

GM- Gang Matrix

GPP- Geographical Predictive Policing

GVM-Gang Violence Matrix

MOPAC -Metropolitan Police Service Gangs Violence Matrix

ML- Machine Learning

NGO- Non-Governmental Organization

POC- People of Color

PP- Predictive Policing

PPP- Person based Predictive Policing

PRECOBS- Pre-Crime Observation System

1. Introduction

In many countries, the 2020 *Black Lives Matter* movement brought racially motivated misconduct of the criminal system to wide public attention. Initiated after the killing of George Floyd, an unarmed Black man, and the shooting of Breonna Taylor by police officers in her sleep (Oppel, Taylor, & Bogel-Burroughs, 2021), people took the streets to protests the discrimination and violence against Black people.

As the first responders to many crises, police officers have a huge responsibility when it comes to equal treatment of citizens and potential suspects. However, historically speaking, equality has been lacking when it comes to ethnic minorities. Discrimination based on ethnicity in traditional policing has been broadly discussed and proven in the literature. Jefferson (2018) highlights the over-policing of minority communities in cities in the USA, while Baradan (2013) and Schafer et al. (2006) conduct studies that prove that the police arrests Black defendants more frequently for drug crimes and is more likely to detain them for minor traffic misconducts compared to white defendants through decades of colonial mindset found in most Western countries (Mohamed et al., 2020).

However, the current Machine Learning (ML) revolution is influencing the police department to change its methods and rely increasingly on technology. Precisely this cooperation of technology gives both opportunity and vulnerability in crime reduction (Ekblom, 1997), which is why monitoring how technology is used has such a salience for society. The newest emerging ML technology, Predictive Policing, brings hope for more justice to some while raising concerns about more discrimination for others.

This paper focuses on Predictive Policing as an act of using large data sets and Machine Learning to predict where future crimes will happen and who might be suspect. However, the controversy behind these crime-predicting algorithms is high. Stakeholders such as tech companies and police academies, claim benefits like higher efficiency, reducing human bias, increased security, and reduced crime compared to traditional human-based policing. On the other end of the spectrum, there is a substantive group of NGOs such as Amnesty International and research institutes that oppose these claimed benefits and try to raise awareness of the various dangers resulting from Predictive Policing and the problems arising from leaving decisions about the future of an individual to an algorithm. Their reasoning is based on previous studies on projects in the United States for example COMPAS, in which Black people were twice as likely to be labeled incorrectly as high-level crime suspects than white suspects (Zuiderveen Borgesius, 2020). Furthermore, they argue that these systems are untransparent and built on previously biased crime data leading to an entrenchment of current biased police practices.

These are two very opposing views on the potential of using technology to minimize racial bias in the police sector. However, Meijer and Wessel (2019) conclude that most of the aforementioned arguments for or against Predictive Policing in Europe to date are based on anecdotes or predictions in the US and less on empirical evidence. In Europe, PP has scarcely been investigated by the scientific community and there have been no overarching assessments in a political science context thus far. Europe has its own minority groups and legal frameworks to protect them. No literature has attempted to examine the discriminatory effect of Predictive Policing on ethnic minorities in Europe, thus it is crucial to research in a European context instead of relying on information about PP abroad. This research aims to fill the research gaps about the potential and dangers of Predictive Policing in the context of racial discrimination in the police. In other words: Is policing based on algorithms more equal and safer for ethnic minorities in Europe? This paper seeks to provide information on different kinds of Predictive Policing projects and their comparable benefits and shortcomings to establish principles that could guide ML-based policing in Europe.

The research aim is to answer:

> *To what extent are Predictive Policing projects in Europe ensuring the non-discrimination of ethnic minorities?*

In an attempt to answer this, the main question will be split into three parts:

> *Sub question 1: In what ways do European Predictive Policing projects meet the requirements for ethical AI use regarding avoiding bias towards ethnic minorities?*

Because this paper is from a political science perspective, the definition of 'ethical' is derived from the European Union's Ethics Guidelines For Trustworthy AI (EGTAI) as a benchmark for AI systems that are designed to operate equally well for every citizen. The EGTAI aims at closing the gaps in ethical AI regulations and provides potential parties involved in the creation and application of technologies using AI with certain requirements they should meet to be considered ethical, like Stakeholder participation, Equality, and Fairness. Answering this sub-question will allow for a classification of the policing techniques as sufficiently or insufficiently ethical proving whether these projects are established with sufficient acknowledgment of potential biases.

> *Sub question 2: What differences can be found between the projects and how can they be explained?*

This is done by studying the data for stakeholder involvement and influence. Analyzing the parties involved in shaping the Predictive Policing projects and the focus they have, can explain the extent to which different projects manage to create a system without biases against minorities. As a result of this analysis, this paper highlights important stakeholders and the way they mitigate discrimination or fail to do so.

Sub question 3: What are the main shortcomings of Predictive Policing and which solutions are the most viable?

A comparison between the projects will allow for a deeper insight into recurring problems but can also give hints to best practices. Highlighting several examples of these problematic processes will allow for categorizing the biggest issues and give us a deeper understanding of how exactly PP is connected to racial discrimination.

The best-fitting methodology for answering these questions is a content analysis. In contrast to other approaches which aim at developing a new theory, content analysis is used to test and improve already existing theories on racial discrimination through ML. It is ideal for finding meaning and connections in the language used in the data, which in this case is generating an understanding of the specific context of racism in PP.

The importance of addressing this issue now stems from the societal impact ML has and the rapid speed of these technologies, potentially dictating the future of policing and crime detection. Failure to correctly identify and subsequently mitigate existing biases has grave societal consequences. Violations of the EGTAI lead to a biased view of society and disproportional discrimination against ethnic minorities. Thus examining the current Predictive Policing projects and scrutinizing their adherence to the EGTAI allows future companies to build a Predictive Policing system that is fair and effective and fosters trust and legitimacy amongst citizens.

2. Theoretical framework

The following chapter will introduce the theories and main concepts upon which this paper will rely in developing its analysis. For this, it combines literature on racial biases in the police with very recent work on the dangers and opportunities of Machine Learning. To create a better understanding of Predictive Policing, the chapter will start with an elaboration on the mechanisms behind traditional police discrimination, followed by a section on Machine Learning and its potential dangers to minority groups. This knowledge is then used to understand potential Predictive Policing problems such as proxy discrimination and how they produce discrimination. Mohamed et al. (2020) and Prince and Schwartz (2020) work on proxy discrimination is used as a base for hypotheses about discrimination in a European context. Because the inclusion of stakeholders is of vital importance to achieving this equality, the role of the stakeholders will be elaborated.

2.1. Racial police discrimination

Racism in Europe has a long-standing history and as a government institution, the police has a vital role in upkeeping this throughout time. Reports in the UK beginning and middle of the 20th century showed

> "a remarkable degree of consensus about the failings of the police, generally highlighting inactivity in the face of racist violence, a slowness to respond to incidents, a refusal or failure to recognise or accept a racial motivation (or the possibility of one) and hostility to those complaining " (Gordon, 1993).

Similar cases appeared throughout Europe, for example with the Turkish minority in Germany, the Moroccan minority in the Netherlands, and Sinti and Roma in several European states (Björgo & Witte, 1993). The motivation behind racial discrimination has been theorized about plenty, however, for this research, it is not only important how racial police discrimination emerged but also why it is still prevalent in society.

Conflict theory as described by Petrocelli et al. (2019) explains why law enforcement always inherently will be discriminatory against ethnic minorities. They explain why discrimination of ethnic minorities is still ongoing through the concept of the *core-periphery system*, in which a society is made up of different social groups, which strive for dominance to realize their interest. Regarding policing, this means that the dominant class controls the law system, and the law enforcement will act in a way that holds the current majority reigning class in power while suppressing minority groups. The reigning class in the context of Europe is the white majority ethnicity, suppressing the ethnic minorities. Their suppression through law enforcement is paralleled by other disadvantages such as an average lower-income and socioeconomic status due to lack of integration and unequal opportunities among other historical and societal factors. Even more specific, the theory claims that police officers will suspect and arrest ethnic minority individuals more frequently. This leads to a bias in which ethnic minorities and areas in which they live will be overpoliced. Over-policing of an area will then consequently lead to finding more crime and perpetuating the stereotype that a certain ethnic group commits crime more frequently, leading to an endless loop of discrimination, stigmatization, and bias. After establishing how traditional police discrimination is facilitated and carried into our current age, it is important to examine the second component of Predictive Policing, which is modern-day Machine Learning technology.

2.2. Machine Learning

Machine learning (ML[1]) is a method of data analysis that has gained immense traction over recent years thanks to the availability of large volumes of data. It is the use of computers to apply algorithms or mathematical formulae to data or information, often in varied forms such as tables, images, audio recordings, and more. While ML brought an increase in efficiency for platforms like Facebook, it also brought a new dimension of discrimination for minorities. Prominent examples are high-paying jobs being advertised via an algorithm to a white male audience, while not appearing to women (Carpenter, 2015). Meanwhile, Google's algorithm produced discriminatory search results and showed heavily sexualized images when a user googled 'Black girl', while the search result for 'white girl' was non-sexualized (Noble, 2018).

This issue has been also titled 'AIs white guy problem' because algorithms reflect the values of their creators as well as the input data (Katyal, 2019). Because algorithms are inherently untransparent, as the mathematical formulae are complex and the data supplied to them may have dozens of dimensions that have effects on each other, the result in links and effects are far more complex than a human mind may comprehend (Coombs et al., 2021). This idea, paired with the fact that historical racism led to biased police data and a lack of ethnic minorities in power positions, consequently, leads to biased output data that reflects the current system of varying privileges and stereotypes.

2.3. Predictive Policing

Predictive policing is the application of Machine Learning to a traditional police system. The current wave of technological advancements in society enables the police to adopt new technologies to navigate its modern environment. One of these new ML-based policing techniques is called *Predictive Policing* and can be understood as an umbrella term for the

[1] For the sake of readability, this paper refers to Machine Learning (ML), Artificial Intelligence (AI) and Algorithm based technology interchangeably due to the fact that ML is a subcategory of AI and thus they share similar characteristics and have large similarities from an ethical standpoint.

> “use of historic crime data to identify individuals or geographic areas with elevated risks for future crimes, in order to target them for increased policing” (Asaro, 2019, p. 41).

In practice, this means that an ML algorithm is fed with collected data on either people or areas as well as data on previous crime occurrences, demographics, and criminal history to calculate criminal patterns. The output of the algorithm is a model that predicts which person or place is likely to be connected to crime in the near future. This impacts the work of the police officers, for example by redirecting their attention away from the whole district which they are observing, onto a smaller area in which the algorithm predicts a high chance of crime to occur.

There are two kinds of Predictive Policing. *Person-based Predictive Policing (PPP)* is designed to predict criminal information regarding individuals. These can be for example how likely someone is a gang member, the likelihood of someone to re-offend, or the probability someone will become involved in criminal activity. However vast the differences between PPP projects, they are connected by the fact that they usually rely on personal data such as individual characteristics like ethnicity, age, and gender (Egbert & Krasmann, 2019). They can also include social networks, based on the theory that a bad social or geographical environment fosters criminal activity (Hung and Yen, 2020). Police forces are then redirected to collect further data on predicted suspects, call them in for interviews or investigate their social networks. The involvement of personal data makes PPP the more controversial method of Predictive Policing.

The second method is geographical Predictive Policing (GPP), which aims at preventing crime in a certain geographical location. This is done by either relying on historical crime data or collecting new data of a given area, such as a city, and then observing where and when areas are targeted by crime. This data will then be used to inform an algorithm based on established police theories such as near-repeat prognostic (Egbert & Krasmann, 2019) to predict in which area a crime such as a burglary is likely to happen. These kinds of systems work with geospatial variations and are always linked to human police officers which have to act upon the predictions.

2.4. Proxy discrimination

Understanding if Predictive Policing discriminates, needs a closer examination of theoretical claims. The opinion of PP is extremely split in the scientific community. The core of the disagreement is the belief or disbelief in the ability of technology to be neutral. Prince and Schwartz (2020) warn of the danger of underestimating the ingrained biases technology holds. As they state,

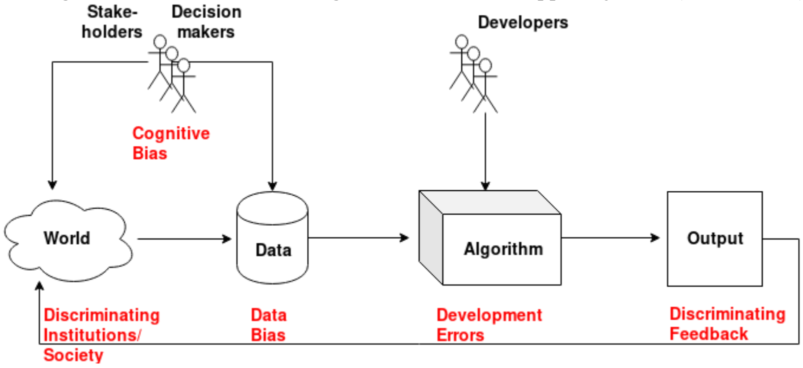
> “one of the most important threats to antidiscrimination regimes posed by this [AI] revolution is largely unexplored or misunderstood in the extant literature. This is the risk that modern algorithms will result in proxy discrimination” (p.1257).

Proxy discrimination describes the process in which a minority group is not discriminated against because of their status as a minority, but rather because of certain characteristics associated with this minority, like their postcode. In the United States, the criminal justice system showed that

> "even where race was not included in the data the algorithm used, the algorithm still learned characteristics in a way that is discriminatory- because other pieces of data it did use correlated with race and led to inadvertent profiling by the algorithm" (Couchman, 2019, p. 5).

In practice, this means that data points such as age, sex, and relations to criminals are put into an algorithm to predict the likelihood of a person to commit a crime. While some argue that this algorithm takes human biases out of the equation and therefore accounts for possible racial discrimination, critical decolonial scholars emphasize that this process enables the presence of proxy discrimination to become present in smart policing techniques.

Figure 1: Discrimination in algorithmic decision support systems (Tolan, 2019)



According to Jefferson (2018), proxy discrimination results from a data collection problem, because "the entire [police] system is built atop data sets compiled by nonscientists operating within a system of racialized policing" (p. 2). Therefore the same discrimination found in traditional policing will be present in Predictive Policing. This makes policing more efficient for the officers but enshrines racial bias in a way that will become even harder to detect and tackle because it is hidden behind an untransparent algorithm. Das and Schuilenburg (2018) warn of this social sorting and self-fulfilling prophecies and call for a reform of the criminal procedure law and the way crime is approached when it is dictated by algorithms. This paper will use their theory on proxy discrimination in trying to analyze the relationship between Predictive Policing and discrimination and examine the assumptions and values that the algorithmic system is based upon.

On the favorable side of Predictive Policing, ACLU (2016), and The Civil Liberties Union for Europe, claim that the AI used in Predictive Policing to detect crime patterns can also be used to examine patterns of misconduct from police officers and can uncover biases and correct them from within the system. Ultimately the claim is that Predictive Policing could be a possible aid to reduce police discrimination. Similarly, Shapiro (2019) brings up another point in favor of Predictive Policing. While acknowledging the potential dangers that come with algorithm usage, he emphasizes that issues like proxy discrimination are already a problem in traditional policing. Therefore PP wouldn't add additional harm but would allow detecting proxy factors for ethnicity which are currently in use and eliminate them. Miró-Llinares (2020) is going as far as claiming that Predictive Policing does not affect crime reduction.

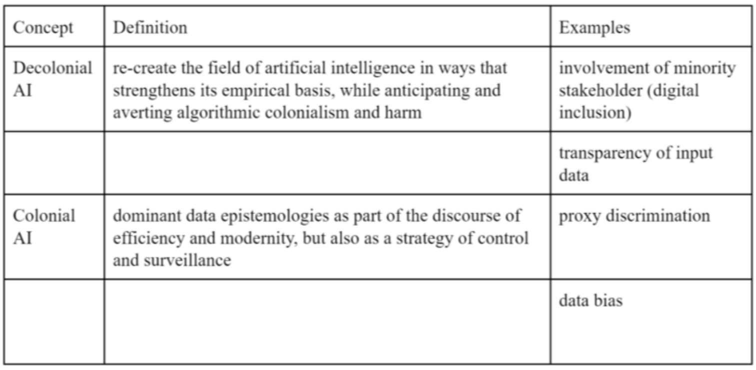
2.5. The role of stakeholders

As an issue that is very new and salient, current stakeholders in Predictive Policing have an important role to fulfill in ensuring a non-discriminatory AI.

> “Stakeholders play a significant role in shaping the future direction and use of advanced technologies such as AI—whether through the establishment of regulatory and ethical frameworks or the promotion of specific algorithmic architectures" (Mohamed, Png & Isaac, 2020, p. 660).

Decolonial scholars Ntousi et al. (2020) and Mohamed et al. (2020) agree that the broad inclusion of stakeholders, especially ones that represent citizens such as NGOs and citizens representatives, are a vital component of creating an ethical algorithm (Figure 2). Furthermore, Cath et al. (2018), argues that ethical AI needs to have an “in-depth plan for linking in a comprehensive socio-political design questions of responsibility of the different stakeholders, of cooperation between them, and of shareable values that underpin our understanding of a ‘good AI society’” (p. 2).

Figure 2: Colonial versus Decolonial AI, based on Mohamed et al. (2020) and Ntousi et al. (2020)



Concept	Definition	Examples
Decolonial AI	re-create the field of artificial intelligence in ways that strengthens its empirical basis, while anticipating and averting algorithmic colonialism and harm	involvement of minority stakeholder (digital inclusion)
		transparency of input data
Colonial AI	dominant data epistemologies as part of the discourse of efficiency and modernity, but also as a strategy of control and surveillance	proxy discrimination
		data bias

While not all stakeholders have equal amounts of power, they all try to influence the development of AI technology to achieve their aims. Thus, looking at the actors involved in Predictive Policing in connection with the extent of discrimination enables a closer look at which stakeholder's involvement grants the best results for the equal treatment of citizens.

2.6. Concluding remarks

This chapter gave an overview of the potential of Predictive Policing to discriminate against ethnic minorities directly or indirectly. A crucial point has been made about the differences between GPP and PPP which shows it is not possible to generalize Predictive Policing. This has been picked up by highlighting the differences between colonial versus decolonial AI which shows that the positive or negative impact is dependent on factors such as stakeholder involvement and transparency. The main expectations derived from critical theories are that there is insufficient protection of minorities, efficiency and cost-benefit are valued over human wellbeing and there is a lack of representation from the people being policed. This is to be weighed against claims of increased fairness and detection and amelioration of existing patterns of discrimination. This crystallizes an important tradeoff inherent in Predictive Policing: the tradeoff between profitability and technological advancement versus protection of the principle of accountability, transparency, and fairness. To answer the research question, three hypotheses based on the theory have been made about the level of racial discrimination in Predictive Policing.

H1: The discrimination in policing technology will vary depending on the stakeholders.

As shown in the colonial versus decolonial debate, it has been argued that a high number of stakeholders will improve non-discrimination. Additionally, it was shown that stakeholders in power of the technologies, like police officers and academies, will prioritize profitability over non-discrimination.

H2: Predictive Policing projects are more likely to discriminate by proxy than by direct discrimination.

While some scholars might argue for the presence of continued direct police discrimination, this hypothesis is in line with Ntousi et al. (2020) in suspecting that racial discrimination through technology is hidden in the black box of algorithms.

H3: Person based Predictive Policing will produce a greater level of discrimination than Geographical Predictive Policing

This hypothesis is formulated to understand whether discrimination is explicitly directed at minority groups, instead of preventing crime in a general area.

3. Methods

This chapter provides an overview of the methods used in this research. The first section will elaborate on the criteria for the selection of the cases of the Gang Matrix, CAS, and PRECOBS. Secondly, the data sources and types as well as their collection is presented. Finally, the choice of a content analysis to answer the research question is justified, the main reason being its ability to distract deeper meaning from the data. Furthermore, this section will provide the coding scheme, as well as an explanation as to what it will uncover.

3.1. Case selection

The three cases were purposefully selected, ensuring the ”selection of information-rich cases related to the phenomenon of interest” (Lawrence et al., 2016). To guarantee enough data and discourse around the project, they needed to be implemented for a minimum of 4 years before this research. Projects were also chosen by the available data. To enable an unbiased view on the projects, they needed to be mentioned in different stakeholder sources, like non-government organizations, the police, and civil society, in languages accessible to the researcher. Secondly, extreme case selection is a good way of highlighting the differences between unusual versus typical cases, thus at least one of the cases needed to be chosen by a substantial amount of racism claims, while at least one needed to have an overwhelming positive coverage in related documents.

3.1.1. Gangs Matrix in the UK

Established in 2014, the *Gang Matrix* (GM) is a “risk-assessment tool to assess and rank London’s suspected gang members according to their ‘propensity for violence’” (Amnesty, 2018, p.2). Disproportionately to the ethnic composition of London, 87 percent of predicted gang members were from Black, Asian, and minority ethnic (BAME) backgrounds. This disproportionality makes the case of the GM exceptional as a research object on potential racial discrimination by an algorithm. The high controversy that resulted among civil organizations upon its launch gives a great insight into potential dangers and the influence of PP on civil society.

Despite the UK not being a member of the EU anymore, all data on the GM has been published before Brexit. Even while still in the EU, the UK always had a special status, reflected in its approach to the AI sector, much like the US governments, due to its special preference for a particular private sector player over other concerns (Cath et al., 2018). In the scope of this research, it will be interesting to see if this special status can be detected in the data when compared to the other two projects.

3.1.2. Crime Anticipation System in the Netherlands

The Crime Anticipation System (CAS) of the Dutch police is a person-based policing project and aims at the detection of potential criminals. In the case of Roermond, the

> "Dutch police collect data on vehicles (...) by using cameras. The collected data is analyzed by an algorithm and allocated a risk score that is supposed to predict whether the driver and passengers of a car are potential pickpockets or shoplifters of Eastern European origin." (Amnesty, 2020, p.11).

The inclusion of ethnicity, (such as skin color and facial features) as a variable related to crime (as seen in Fig 3.) makes the CAS an interesting case in testing direct versus proxy discrimination. Because the CAS "is developed in-house (rather than being a commercially available product, like PredPol), the Dutch police itself is able to shape and tweak the system. In addition, because of the open attitude of the Dutch police and existing transparency laws, researchers are able to request information regarding the types of data that are used and the way in which information is presented" (Oosterloo, & van Schie, 2018, p.2). Access to as much data as possible allows deeper penetration into the project and increases reliability, as the knowledge comes from several sources.

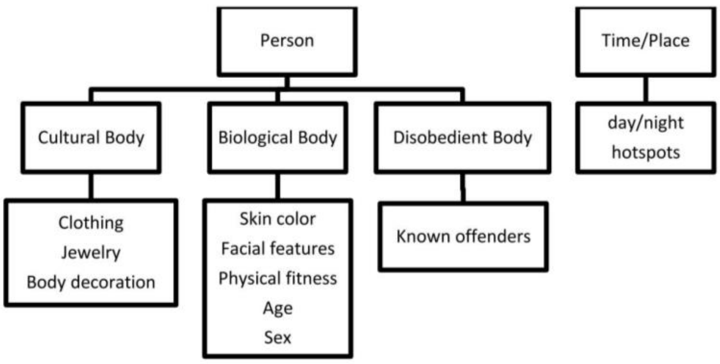


Fig. 3.: Part of the decision-making process of Dutch police officers (Cankaya, 2012, p. 78)

The Netherlands was chosen because of its high level of diversity, with 20 % of the population being immigrants. Furthermore, the country has been under sharp criticism for discrimination and a racist network inside of the police force. In contrast to the high diversity in the population, "the police force in the Netherlands is traditionally a white man's world" (Boogard & Roggeband, 2010, p. 8), where ethnic minorities only make up 6,7 % of the police force.

3.1.3. PRECOBS in Germany

The geographical Pre-Crime Observation System (PRECOBS) in Germany is designed to forecast probabilities of future burglaries in two German states. As a pilot project, PRECOBS has been under scrutiny by the Max Plank Institute as well as the Bertelsmann Stiftung, which will be valuable data to analyze. While Bavaria implemented the system permanently, Baden Württemberg canceled the application based on security concerns, which will allow an insight into the level of discrimination needed to discontinue a project. Besides the Institution reports, official regional government statements will be analyzed as well as official statements by the company which developed PRECOBS and statements by the police departments involved.

3.2. Data collection

The following section will explain which data was chosen for the analysis, how it was collected, and lastly a justification for these choices. Data as such in a qualitative context is not purely numerical but instead refers to words and language. These can take different forms, but the one chosen for this thesis is document analysis. Choosing data from renowned NGOs and research institutes will allow for an unbiased picture of the kinds of proxies enshrined in Predictive Policing and the negative effects they have on ethnic minorities. Key pieces from the NGO sector are two reports by Amnesty International about the Netherlands and the UK. These reports are vital as Amnesty International is a renowned organization that has been accredited for its scientific work, which creates reliability for the data sources compared to smaller, less known, sources. The reports have scientific consistency and rely on citations from state-of-the-art scholars on racial discrimination, and as a publicly accepted organization, they were able to get information from police offers, companies, and the police academies. For the Gang Matrix, in particular, Amnesty International is sitting in the committee of the GM evaluation and can therefore be seen as an extensive and trustworthy source. The fact that they made a report on the Netherlands and the UK enables a great in-depth comparison of these cases on a solid scientific basis. As mentioned throughout this document, Predictive Policing in Europe is a relatively new established process, hence the data collected is less than ten years old. The online search engines Scopus and science of web have been used to find data on the Predictive Policing systems, how they work, and what their potential consequences are. Special attention has been paid to mixing the type of sources to include non-government, police academy, and scientific community as authors to ensure the robustness of data and reduce the probability of skewed results. Some of the data has been collected through key documents, such as the report of the Bertelsmann Stiftung. After initially finding 35 data sources, the sources were analyzed for compatibility with the data scheme as well as balance among the three cases in the volume of information, which led to a final selection of 23 data sources ranging from 10 to 123 pages. The data used totals around 460 pages with information about the process and effects of PRECOBS, GM, and CAS.

3.3. Methods of Data analysis

The research question "*To what extent are Predictive Policing projects in Europe ensuring the non-discrimination of racial minorities?*" requires a methodological approach that can retract deeper meaning from existing documents. A content analysis was chosen because it is suited for the qualitative analysis of textual data is used to gain a detailed understanding and overview of a concept (Given, 2008). Reducing the data to make sense of it is at the core of content analysis and helps the research to derive deeper meaning from the texts. On the one hand, these are conscious messages which can be found by looking at the number of times decolonial criteria such as data bias or transparency are mentioned to understand where the individual project priorities are. On the other hand, a qualitative content analysis enables the identification of unconscious messages communicated by text, which helps to explain what is of most concern to the stakeholders. Because there is proven discrimination in other contexts, this analysis does not need to establish a new theory, but rather fill in the gap of proxy discrimination in European Predictive Policing projects. A content analysis was also chosen because it can analyze vast amounts of qualitative data and it is flexible enough to be applied in varying data sources, such as official documents, reports, and statements to show the individual nature of PP projects.

To conduct the data analysis, a coding scheme based on the literature is established. The literature study showed that discrimination through Predictive Policing is not an active process but a passive one based on the input of proxies linked to ethnic minorities, such as postcode and education. Uncovering if PP tries to mitigate these proxies and prevent discrimination from occurring, requires a suitable coding scheme. The coding will be based on the EGTAI as envisioned by the EU, as this includes the most important criteria needed for ethical AI, in a European Framework.

Table 1: coding scheme based on the EGTAI

Principles	**Aim**	**Code words**
Stakeholder participation	Involvement of all **stakeholders** throughout the process ensures trustworthiness	*stakeholder, participation, feedback*
Equality	equality entails that the system's operations cannot generate unfairly **biased** outputs, respect for potentially vulnerable groups	*bias, greater attention for vulnerable people, inclusive and representative data*
Prevention of harm	must be **technically robust** and it should be ensured that they are **not open to malicious use**. Vulnerable persons should receive greater attention. Particular attention must also be paid to situations where AI systems can cause or exacerbate adverse impacts due to **asymmetries of power** or information	*not open to misuse, asymmetry of power, protection of human dignity, safe and secure systems*
Fairness	ensuring an equal and just distribution of both benefits and costs, and ensuring that individuals and groups are free from discrimination and **stigmatization**, the proportionality of means and ends, **ability to contest** and seek effective redress against decisions made by AI systems, and by the humans operating them.	*equal and just contribution of benefits and costs, stigmatization, discrimination, ability to contest,*
Explicability	processes need to be **transparent,** the capabilities and **purpose of AI systems openly communicated,** and decisions – to the extent possible – **explainable t**o those directly and indirectly affected.	*transparent, accountability, explicability, and open communication*

Overall, the EGTAI has seven core principles that should be considered for an automated system to be fair. Due to the limitation and the scope of this thesis, only five principles will be considered (Table 1). The selected criteria were chosen because they entail aspects that are mostly concerned with post-application results and therefore the effects such as discrimination and inclusion of critical civil voices can be measured. After an iterative process of rephrasing the categories, the coding scheme was established true to the language of the document. Staying within the established categories is an important step of deductive coding because a change in categories could distort the original meaning of the theory and decrease the overall reliability of the research. In practice, this means labeling the codes and the criteria according to the EGTAI. To ensure that the categories were comprehensive as well as mutually exclusive (Given, 2008), the document *Automated Discrimination And Mass Surveillance In Predictive Policing In The Netherlands* was analyzed with the initial coding scheme. Checking if all relevant data was included in only one category is important to guarantee the trustworthiness of the analysis and conclusion. The thorough description of the methodology, as well as the exact coding frame in Table 1, are documented for other researchers to be able to duplicate the results of this present study and make it reliable and dependable. The conclusion will be based on the interpretation of the level of adherence to the EGTAI as well as the structural similarities and discrepancies between the projects. Hence, the projects will be examined on their impact on racial discrimination and the frequency of this occurrence.

3.4. Conclusion

In Conclusion, this research aims at uncovering the extent and kind of discrimination in Predictive Policing. As a research method, content analysis is the most adequate to gain in-depth knowledge about the factors that cause discrimination in PP. To facilitate this, a coding scheme has been developed based on five selected principles of the EGTAI. Analyzing to what degree the PP projects comply or stray from compliance to these principles will be the first part of answering the research question. Furthermore, it allows a comparison of the project's stakeholders and outcomes to give an overview of solutions and best practices.

4. Data analysis

By applying the previously elaborated coding scheme, the analysis will study if Predictive Policing produces bias against ethnic minorities or eliminates it. In the first part, the cases are analyzed based on their fulfillment of the five EGTAI criteria. After that, the influence of these criteria on racial discrimination against minorities is analyzed. Uncovering how different projects adhere to ethical AI criteria leads to insight into different problems that can occur, which will connect and inform the theory on Predictive Policing. The analysis will then explore best and worst practices and link these to the goals of the projects as well as the stakeholders associated to get a clearer understanding of which purpose Predictive Policing serves. Combined, the first and the second part collectively generate enough knowledge to answer the sub as well as the main research question: *To what extent are Predictive Policing projects in Europe ensuring the non-discrimination of ethnic minorities?*

4.1. Extent of discrimination

Discrimination can be facilitated through various means. This thesis is relying on the EGTAI (Table 1) to assess to which extent discrimination has been facilitated or actively prevented. Individually to each case, stakeholder participation, equality, non-discrimination and solidarity, prevention of harm, fairness, and explicability will be scrutinized. The criteria can either be positive, not mentioned, or negative. Based on this it is possible to examine similarities and differences.

4.1.1. Stakeholder involvement

The key to preventing harm through the principle of stakeholder participation is insinuating that an AI system is only trustworthy if directly or indirectly involved stakeholders are included in all processes of the projects, for consultation, feedback, and participation.

The Metropolitan Police (MET), and in particular the Trident Gang Command can be identified as the main stakeholder in overseeing the Gang Matrix. Other than primary oversight, local governance is provided by the police and other unspecified authorities in the 32 London boroughs (UK 2). While the project is only managed by a small group of individuals, the stakeholder who will receive information on the criminals is vast. Several documents mentioned the Crown Prosecution Service, local authorities and voluntary sector partner agencies, the National Probation Service, the Community Rehabilitation Companies, the Department of Work and Pension, Children’s Social Care, Youth offending service, police, mental health, probation, and violence against women and children’s specialists and many more having access to documents, as well as having the authority to propose adding individuals to the GM (UK 2). The MET has set up bi-weekly meetings to evaluate compliance of the Matrix with regulations, data protection, and the equality act. These are attended by key stakeholders such as the Trident Independent Advisory Group, the Race Independent Advisory Group, and many voices in the fields of human rights, including Amnesty International. Therefore it can be concluded that there is an awareness of the necessity of ethically focused stakeholder involvement, and the effort to fulfill this criterion. However, it is also to be noted that the people who are affected most, the citizens of London, are not involved in the process of the Gang Matrix at any point of its creation or evaluation. As mentioned in one of the evaluation meetings, the

> “ Section on consideration of public views needed more detail, including further consideration around the kind of public engagement that will need to be pursued to secure public trust and confidence in the model going forward – it was acknowledged that public perception should not, in its own right, be the main determining factor for whether or not the model meets high ethical standards” (UK 28:3).

This means that even though stakeholder participation is there, it is limited and selected and not deemed as a high priority.

The PRECOB (Pre-Crime Observation) system is a geographically based pilot program designed by a cooperation between the Landeskriminalamt Baden-Württemberg and an independent research institute, the Max Plank Institute (MPI), which followed the PRECOBS Program during its initiation phase between 2015-2016. During these two years, the algorithm ran on current crime data and made predictions without it being acted upon and the researchers from the MPI were there to evaluate the project before it was able to be launched. What makes this cooperation so unique is the fact that no other Predictive Policing project has been working with an official unaffiliated institution, as one would expect this would limit the power of the police to implement the system as they see fit. Furthermore, the police force that uses PRECOBS is part of an annual workshop in which scientists, representatives of civil society as well as technical developers come together intersectionality to evaluate the topic of Predictive Policing in Germany (DE 10:3). Thus, there is clear evidence that several stakeholders came together to monitor the system and give input where appropriate.

The CAS is developed in-house (NL 6:1) and is furthermore the exclusive owner of the data and the system used. None of the documents mentioned any other stakeholder being involved and consulted, which is unambiguous evidence for a complete lack thereof. Bas Mali, One of the police sources and head of the police academy even cited that “the police tends to make it exclusively their issue” (NL 17: 3, translated). The only additional actors involved are organizations receiving the information generated by the algorithm, which will be explored in section 4.1.4..

4.1.2. Equality, non-discrimination, and solidarity

The second criterion of the EGTAI is equality, non-discrimination, and solidarity. Through an analysis of the documents regarding their equal respect to all groups of society, this chapter seeks to reveal how far they go to ensure respect and protection of vulnerable groups such as ethnic minorities. Findings of active discrimination will give strength to the arguments of critical decolonial AI scholars such as Mohamed et al. (2020). In case the projects implement measures indicating special attention to minorities, this would reveal that Predictive Policing is implemented as a way to make policing more effective and safer, as argued by Miró-Llinares (2020).

For coding reasons, this was split into the three sub-criteria: greater attention for vulnerable people, such as ethnic minorities who are at risk of exclusion, inclusive and representative data, and bias in output data. Over the 210 pages of documents, bias has been represented the most frequently, with 27 references across the documents, which makes up 24,3 % of the equality criteria. For the UK, 78 % were referenced in terms of critique and only 22 % of the time in a positive context. Examples from the UKs biweekly meeting reports show that the people involved in the ethics section of the policing program have serious concerns, by stating that

> "the language used in the report has the potential to cause unconscious bias. The committee recommends the Lab looks at the language used in the report, including the reference to propensity for certain ethnic minorities to be more likely to commit high-harm offences, given the statistical analysis showed ethnicity was not a reliable predictor" (UK 28: 4).

Furthermore, evaluations from Amnesty International explained that the data on which the predictions are made is old policing data, which as it stands now overpoliced BAME. The data collected on the GM, by government sources like the Royal United Services Institute for Defence and Security Studies shows that even though ethnic minorities make up only a small portion of youth violence, the GM works with a bias targeting the BAME population. The algorithm associates being Black with gang membership and being a gang member gets them framed as criminal and hence overpoliced.

The most distinct finding for Germany was revealed to be in the way PRECOBS implements anti-discrimination measures. The data analysis showed that with 68 % of data referencing anti-discrimination measures it is in stark contrast to the CAS and the GM. Because PRECOBS is a geographical predictive system, none of the criteria used to predict crime are associated with a distinctive group of people. As input data, the system uses burglaries that have been documented in the past, without any mention of perpetrator or victim. Only the criteria: type of crime, successful (yes/no), time of the crime, place of the crime, modus operandi, type of stolen goods, and surroundings are considered (DE 10). Furthermore, all data is anonymized to eliminate conscious bias. Some of the sources voiced the possibility that this ML system improves the equality and fairness of data predictions, compared to the opportunities in traditional policing for police officers to use their authority to profile people that seem suspicious to them without further logical reasoning. In comparison to this, PRECOBS does not offer any room for such discriminatory man-made predictions (DE 33: 7). The term for this can be classified under 'selective forgetting' or 'non-discrimination by design', which is built on the premise that discriminatory input factors such as ethnicity will be purposefully not considered. Nevertheless, there is still potential for proxy discrimination. Because PRECOBS still operates under the current police framework, prior biases about the high crime rates in previously overpoliced neighborhoods still prevail. These areas are usually characterized by low-income and immigrant households.

The Dutch documents by the Utrecht Data School and the report of the PHRP expert meeting on Predictive Policing, show a high score of negative data on discriminatory data and biased outputs. With a total of 48 mentioned, 45 of them are used in a negative context, which raises high concerns for the general application of the CAS. Resulting from the fact that the system is an in-house technology without further stakeholders involved, the information given about which data is collected is very vague. The given information is based on the facts known about the first CAS project, which derived its prediction among other things on socio-economic factors, criminal history, and demographics (NL 17) as well as what anonymous police officers have declared in various interviews. The general premise is that the system is built on old criminal records as well as data incoming from new sensors which are distributed in Roermond. Included in the second category are personal information like German or Romanian license plates, which are used as a proxy for mobile banditry committed by East Europeans who come to the Netherlands through Germany, or Roma and Sinti coming from Romania (NL 1: 27). Singling out specific nationalities while excluding Dutch nationals indicates that the CAS carries bias and does not treat all citizens equally. An explanation for this can be found in the setup of the projects, because individual police officers have the power to accept or dismiss a suspect prediction, after seeing sensitive data about said driver. However, because there is no official documentation of the process, there is considerable room for individual officers with discriminatory mindsets to protect or discriminate against a certain group of suspects based on factors like their ethnicity, without it being on record. When the police officers only interrogate cars containing Eastern Europeans and Roma and Sinti, this data will be fed back into the algorithm which creates a feedback loop, justifying the over-policing of ethnic minorities.

Data biases have been explicitly mentioned in the academic report reviewing PP in the Netherlands. Several passages highlight that there is potential for unbalanced or otherwise corrupt data sets, measurement errors, and the encoding of human prejudices (NL 18). All of this highlights the concern about biased data in and output in Predictive Policing systems in Roermond and any further project based on the CAS. While much criticism has been put forward against the projects concerning biased data, the police force and academies so far have made no statement on the matter. On the contrary, most police officers vehemently avoid comparisons to problematic projects such as PREDPOL, while glorifying ideas of bias-free and effective policing. One interviewee even claimed that certain biases are justified and should not be adjusted for, revealing no awareness of the causes of differences in crime statistics.

In sum, this section revealed that the PP systems in the Netherlands and the UK were both working with explicit as well as implicit discriminatory mechanisms, such as biased data and specific targeting of minorities by involving ethnicity as a crime predicting factor. These findings are in line with critical scholars like Couchman (2019), warning that PP will not consider ethnic minorities but instead exploit them to keep up their power stance. An exception to this is the GPP system in Germany, which shows signs of active harm prevention, through relying on 'non-discrimination by design', an approach where the human is outside of the loop and the predictions are made for geographical areas instead.

4.1.3. Preventing harm

The third principle, the principle of preventing harm, is focused on the Predictive Policing system itself, in a way that the system shouldn't be abused to discriminate or to create a power asymmetry. Firstly, it scrutinizes if the PP systems are safe and secure or if they could be misused, which would result in harm for anyone who is in the policing system. Secondly, the focus of this criteria is the creation of power asymmetries. According to Ricaurte (2019) and Mohammed (2020), the creation of a power asymmetry is at the core of Predictive Policing systems and should therefore be the most prominent characteristic. If that is not the case, police claims would gain increased credibility.

For the UK, documents released in 2016, show strong complaints about the lack of data protection, which causes harm and potential danger to the people on the GM, among which 86 % are ethnic minorities. However, documents from 2018 forward show some improvements, as the review team states that they are "pleased to see the MPS making steps to make sure the Matrix was compliant with data protection (UK 5: 9)". Additionally, there has been no further mention of problems with the technical robustness of the system, which leads to the conclusion that technically safe systems are provided. The other aspect of this criterion, the protection of human dignity and the power asymmetry does not have notable mentions.

Similar neglect of this principle can be found in the CAS, most of it resulting from a lack of data protection. As an in-house project without further sector involvement, there is no scientific underpinning to the way the system is set up (NL 1). Thus the police collect and use old police data as well as new data without the people under surveillance being aware. With this, they are not just abusing the system, but they are also violating privacy laws and creating an immense power imbalance between themselves and the citizens. This power imbalance is extended through the discretion of the police officers, when and how they want to intervene, and whether they want to record the personal data of the driver and add it to the database or not. Having full discretion on whom to surveil and on which factors abuses the power of the police and neglects the police's duty for non-discriminatory treatment of citizens as well as their explicit protection from harm. The security of the system itself is also under question by the scientific community as well as NGO reports. One source predicts that the PP systems protection is too weak for the vast amount of sensitive data, which is stored in it, which would make it possible for a hacker to access the whole database and harm the people registered with information on their license plates, ANPR data, model and color of the vehicle, its movement patterns, personal information, address and more (NL 18).

In contrast, Germany showed a high level of satisfaction for this criterium. The first reason for this is the extensive monitoring that is happening at all stages of the program and the anonymized data which guarantees a highly secure system. Besides that, the police officers are schooled and have to document as well as monitor everything that is happening, which makes abuse of the system highly unlikely. Before the program was initiated, it needed to be able to predict all the crimes in the area in which it was tested for five years with a 70 % success rate (DE 10:22). The system itself is not highly complex and built on long mathematical formulas, instead, the input factors mentioned in the previous section enable easy understanding and recreation of the ways an area is predicted to be of high risk for a burglary. This is necessary because the project is not operating fully autonomous but has to be used by a schooled and knowledgeable police officer, who double-checks and verifies the results from the system. Concluding, the PRECOB system has been embedded into the existing police structures with enough care that it does not pose any risk to ethnic minorities and shows potential to decrease racial discrimination.

In other words, this section has revealed that there is a lack of security in the PP system of the Netherlands as well as the UK. No measures have been implemented to keep unauthorized actors from accessing the system, which has a dangerous amount of personal data and puts the people in the PP system at risk. The lack of proper security, combined with other factors such as freedom of police officers to police people based on personal values, produces a clear power imbalance in favor of the police force, which is supporting evidence for a critical AI perspective. However, contrasting to the lack of security compliance in the Dutch and British cases, Germany shows excellent data protection and security protocols. They demonstrate constant supervision, data protection protocols, and regular checkups, which means this case is singled out as following a decolonial pattern and does not fit with the assumption of Ricaurte et al. that all predictive policing will be inherently discriminatory.

4.1.4. Fairness

The fourth principle of fairness is split into a substantive and a procedural dimension. The substantive fairness dimension entails a just distribution of benefits and costs without discrimination and stigmatization. The procedural dimension implies that the people who are being policed need to have the ability to contest and seek redress against AI-made decisions. While it is subjective what makes a distribution of costs and benefits fair, there is enough evidence to show that the GM system is disproportionately causing BAME people to carry the cost for the new policing method. The stigmatization lies at the core of the Matrix system. The factors for inclusion in the Matrix are not transparent, and only an accidental leak revealed that a certain area code and listening to rap music and posting ‘gang signs’ on social media are strong crime predictions. However, as advocates for the Black community say, these behaviors are typical characteristics of the Black community and cannot be equated with being a gang member. Therefore the proxies used for the inclusion on the Gang Matrix are discriminatory, as they perpetuate stereotypes about Black people and stigmatize in particular Black men. The ability to contest the inclusion in the GM and the classification as criminal is not given. In contrast, “individuals are not made aware of their inclusion as this could in some circumstances impact on policing operations (GB 5:7)”. Furthermore, the process behind review and retention is equally discretionary and decided on an ad-hoc basis (GB 2:43). As illustrated by this, the BAME minority gets targeted at a much higher rate and is prevented from contesting the resulting discrimination. This aligns with the theory on colonialism in emerging technology, because the ML technology is being used to sustain the power imbalance of the core, represented by the national police force, and the ethnic minorities in the UK, as the periphery.

Discrimination through the PRECOBS doesn't stigmatize people directly but creates a high risk of discrimination by area proxy. As minorities statistically are more likely to be policed and convicted of low-level crimes, this data will show up as a criminal area on the PRECOBS. Going public with this data will attach a stigma to people living in a certain predicted crime area (DE 10:32, 31:8, 32:7). Because no personal information about the potential burglar is available, the general public cannot distinguish between who is criminal and who is not, thus everyone in a predicted crime area will be seen as a potential criminal. The preventative measures at the location of the crime are being made by human police officers, which allows human bias into the decision of whom to suspect. The general presumption of innocence (Momsen and Rennert, 2020) which is required by German law, would lose its meaning because the algorithm produces criminal stereotypes about the majority of people living in high crime areas.

In conclusion, the distribution of the predictions made by PP to other institutions results in the active stigmatization and discrimination of the people involved. In the Gang Matrix system both aspects of fairness are not given and once in the system, police officers, as well as victims, say that it is nearly impossible to get off. While Germany has been an exception so far in previous criteria, they are in line with the Netherlands in failing to provide a fair system. This is the result of stigmatizing minorities by over-policing troubled minority neighborhoods in Germany, and over-policing Roma cars in the Netherlands.

4.1.5. Explicability

The fifth principle of explicability implies that a trustworthy AI system needs to be transparent and explicable. A major concern voiced by critics is that a lack of transparency will be purposefully created by the police to hide their discriminatory practices and aim at extending their power. For the police to provide an ethical PP system, they need to communicate their working process openly, provide as much transparency as possible, and need to be able to offer explanations to anyone directly involved.

The data showed few, but ambiguous results. All of the projects try to create a basic sense of transparency by providing basic information on their projects on official websites, which reveals that the police do not attempt to hide their policing. On the contrary to their general public display of information, the explicability of factors leading to a prediction is incredibly opaque. This hints at superficial transparency that is created for a positive image instead of aiding people who are targeted by Predictive Policing.

Germany shows the most transparent and explicable operational mechanisms, while the Netherlands has the worst result, as they omit any information about the way the CAS works in their official communication. The data support the idea that PRECOBS is designed decolonial to provide security to the people, while the CAS is designed around a colonial power identity. The Gang Matrix underwent an interesting transformation. Early documents show an insufficient level of transparency, with the biggest concern being the

> "opaqueness surrounding the database [which] means that most people will be unaware of the inferences being made about them or being shared with key services. Thus young people have no way to correct inaccurate information or otherwise challenge their inclusion on the matrix (GB 2: 43)".

This highlights the idea that ML-based projects are inherently untransparent unless the conscious effort is made to include explanations on how it works to make up for the incomprehensible process. At the same time, there seems to be a conscious effort to increase transparency over the course of its establishment. The Gang Matrix has launched an external public-facing website providing information on the GVM. Information on the website includes

> "what the Gang Violence Matrix (GVM) is, how it works, how names are added and removed, and who uses the GVM. The website also includes some key documents produced relating to the GVM including Data Protection Impact Assessment (DPIA), legal mandate, publication figures showing breakdowns of the GVM as well as the Information Commissioners (ICO) Enforcement Notice and the MOPAC review of the Gang Matrix" (GB 5:4).

The issue of transparency is very ambiguous. While the data showed that no transparency can lead to discrimination (see CAS), too much transparency can also lead to discrimination by violating privacy concerns. Therefore it must be weighed individually how much transparency is needed. In conclusion, it can be said that even though there is an apparent lack of overall transparency, it can be seen that there is an effort to provide explanations as much as possible without risking the efficiency of the project or violating data protection rights.

4.2. Differences in Results

The following section will explore the differences between the Predictive Policing projects in-depth to explain the correlation between the stakeholders of the individual projects and the results. The first hypothesis claimed that the stakeholders involved sis haping the discrimination in Predictive Policing.

Looking at the actors involved, it becomes clear that Germany as the country with the most stakeholders involved also had the best scores for discrimination prevention. The project that had the highest discrimination levels, was the CAS which also had the least number of stakeholders. While the Gang Matrix initially only had stakeholders linked to the police itself, the police force initiated several group meetings in which stakeholders of the civil society were involved. This process aligns with the data, as the reports pre 2018 had a highly negative assessment of the Gang Matrix, while the documents post-2018 had an increase in positive reviews on ethical implications. Thus, all cases provide evidence in line with H1.

Another crucial point to consider is the role of proxy discrimination which the second Hypotheses focused on. As examples for proxy discrimination in person-based Predictive Policing, the CAS and GM both focus on variables connected to a certain type of ethnic group. In the case of the UK, proxy discrimination is facilitated by classifying certain 'Black' behavior as gang behavior. This is problematic because young Black men who publicly spend time with other Black men and listen to rap music will be classified as gang members according to GM guidelines. This stigmatization is furthered by sharing the classification as predicted criminal to other stakeholders such as housing associations and job centers. Therefore a young Black man is not directly profiled for being Black, but over the proxy of associating within a group of other Black men.

The operation over proxy discrimination is evident in a comparable manner in the Netherlands. While they directly discriminate against Eastern Europeans and Roma and Sinti, they also indirectly discriminate over their license plate policy. Firstly, as admitted by a Dutch police officer, having a German or Romanian license plate is a factor associated with a high-risk crime factor. Romanian license plates are proxies for Roma and Sinti and German license plates, especially in combination with a bigger group or family in the car, are associated with mobile banditry groups from East Europe, which reach the Netherlands by driving through Germany. The direct discrimination found in the CAS was an unexpected finding, which is not fully in line with theories on proxy discrimination that claim a shift from direct discrimination in traditional policing to proxy discrimination in Predictive Policing. However, as proxy discrimination was found more frequently than direct discrimination, the finding of direct discrimination could just symbolize the gradual shift from the old to a new system.

Lastly, a highly interesting finding is that while the differences among the projects were vast, all projects were ultimately evaluated as non-effective in reducing crime. Besides the theoretical benefits of Predictive Policing by the police academies and offices, none of the evaluation reports or scientific papers could find a connection between implementing Predictive Policing and decreased rates of crime.

Knowing that there is no direct benefit when it comes to upholding the law or protecting citizens, the question arises why these algorithmic projects are still in use and which purpose they serve. Looking deeper into the motivations behind the implementation and performing a stakeholder analysis is too much for the scope of this paper but would be a valuable research topic for future research in this area.

4.3. Concluding remarks

This section revealed that there is a clear difference between person-based Predictive Policing and geographical Predictive Policing, where the former scored a lot worse in the compliance of non-discriminatory practices. This supports the third hypothesis of this research and is in line with scholars that are critical about using personal data points to predict crime (Hung & Yen, 2020; Coombs et al., 2021). Furthermore, it revealed that the Netherlands' understanding of Predictive Policing is closest to the US American one and thus shows the most troubling results. The lack of attention to ethnic discrimination, transparency, and civil society participation results in a system designed to maintain the power position of the police at the expense of criminalizing citizens based on their Eastern European or Roma identity. The UK also has a problematic relation towards ethnic minorities in the GM, exemplified by the over-policing of BAME people who represent over 80 percent of predicted suspects. Interesting in the case of the UK is that after the backlash of civil society organizations due to the massive racial discrimination, the police has opened the system up to various stakeholders and scrutiny and produced a better record in the following years. The German Predictive Policing system produced by far the best results, in all accounts which can be explained by the level of preparation and examination it had to undergo before being able to be used in real life.

5. Conclusion

Analyzing the cases of Predictive Policing (PP) in the Netherlands, the UK and Germany gave important insights into the extent of discrimination facilitated through PP in Europe. Above all, the analysis concludes that none of the projects satisfy all criteria for a fully ethical AI. Furthermore, it became evident that there was a pattern to which criteria were considered and which were neglected. In total, the best scores were made on safe and secure systems, while discrimination and biased input data, as well as power imbalance, showed the least satisfactory results. The analysis also showed a connection between the number of stakeholders involved and the compliance with ethical anti-discrimination measures. This implies that the police deploy Predictive Policing to secure their role as power holders in society and not to ensure equal protection of citizens, as has been claimed by Schwarz & Prince (2020). The second part of the analysis revealed that there is a clear distinction in the effect of person-based or geographically based policing. The former yields unsatisfactory results and triggers discrimination, stigmatization, and bias against individuals. The latter functions anonymized and therefore has no potential for direct discrimination, however even geographical Predictive Policing can create stigmatization due to over-policing of certain 'troubled' neighborhoods which stigmatizes all inhabitants as potential criminals.

A major ambiguity is the role of transparency. While some level of transparency would aid this process of eliminating bias, there is a trade-off between efficiency, privacy, and transparency, where it is impossible to satisfy all three criteria.

Concerning views on the potential and effectiveness of Predictive Policing, the stakeholders are highly divided. Generally, actors close to the police using the system have expressed highly favorable opinions towards Predictive Policing, while mostly not even recognizing the potential for harmful impacts of the policing mechanisms. On the other hand of the spectrum, every civil society organization expresses high concern not just about the current discrimination but also explicitly warns of the harmful consequences that would result from a spread of Predictive Policing. A possible explanation for this could be found in Petrocelli's Core-Periphery system, which would explain why the police documents spoke highly of the PP projects to sustain their power as the main stakeholder.

Due to its deviating nature, it is mentionable that the case of the PRECOBS in Germany had some noticeable differences from the findings, while the Netherlands and Great Britain followed a similar pattern in their lack of compliance with the EGTAI. An example of this is that the Bund Deutscher Kriminalbeamter, which is the association of German police officers, showed clear awareness of the potential of discrimination through Predictive Policing. A possible explanation for the good scores concerning nondiscrimination in the PRECOB system is the awareness that the police demonstrated about the potential dangers of PP, and the attempt to mitigate those by including various stakeholders in all stages, anonymized the data, and performing regular inspections for compliance with ethical guidelines. Finding meaningful differences in the projects also supports the idea that Predictive Policing algorithms are highly individualistic and context-dependent. The results of non-compliance with the EGTAI were in line with Petrocelli (2020) and Ntousi (2020) in so far as it provides evidence that the police as the main power holder behind PP creates discriminatory consequences for ethnic minorities. In contrast, where the power is shared among several stakeholders, including marginalized communities, such as the Ethical Board, or the racial focus group in the UK, there is a clear improvement on the extent of the discriminatory impact on ethnic minorities. In conclusion, this research provided evidence that Predictive Policing in Europe suffers from the same shortcomings as discussed in international cases and can be linked to the active and passive discrimination of ethnic minorities.

After scrutinizing the similarities and differences, it was possible to identify best practices and give direct recommendations for future ML policing technologies, based on literature and research findings. Among the solutions, the most promising one is to increase stakeholder involvement with a clear focus on civil society stakeholders with the power to assess and evaluate the program. To create a decolonized policing system, the inclusion of stakeholders representing disadvantaged groups such as ethnic minorities is crucial to avoid the replication and entrenchment of harmful power dynamics between the police and civil society. This process can be facilitated by having separate ethnic minority or ethic committees, involving non-governmental organizations or an independent examination board with full access to the Predictive Policing system.

One of the most stressed points by civil society organizations as well as research institutes was an increase in the evaluation of data protection. As clearly demonstrated in the bad-practice case of the GM, whenever a suspect was added to the Gang Matrix, their information was freely shared with a broad array of actors ranging from housing companies to job recruiters. This person will then be stigmatized in important aspects of life which has grave consequences for their future. Thus, a reduction of actors receiving this sensitive data, as well as limiting the sensitive data that can be recorded would help destigmatize people that are sought out by Predictive Policing.

In connection to this, it is vital to make the mechanisms of PP as well as the input data more transparent. The way the systems currently operate, stigmatizes everyone who is added to the Predictive Policing system as a criminal. In most cases, this is not true, as the Gang Matrix proved that people were added because their social media profiles showed glorification of ‘gang music’ and in Germany, entire neighborhoods are declared as inhabiting criminals. However, this includes many people that are marginalized and cannot afford to move out of criminal neighborhoods. Therefore, the grounds on which people are selected needs to be made public and it needs to be ensured that an entry into the system does not equate to being a criminal in any means.

This research managed to provide substantial research for closing the research gap on Predictive Policing in Germany. However, it also had some limitations, like the lack of information due to police transparency as well as the reliance on qualitative data. For the future, research that is based on interviews or focus groups with people Police insiders could provide substantial information on the importance of anti-discrimination measures in the police. Furthermore, a long-time in-depth study of individual Predictive Policing projects is recommended.

6. References

Asaro, P. M. (2019). AI Ethics in Predictive Policing: From Models of Threat to an Ethics of Care. *IEEE Technology and Society Magazine*, *38*(2), 40–53.https://doi.org/10.1109/mts.2019.2915154

Baradaran-Baughman, S. (2012). Race, Prediction & Discretion . 81 George Washington Law Review 157 (2013), Available at SSRN: https://ssrn.com/abstract=2035064

Björgo, T., & Witte, R. (1993). *Racist Violence in Europe*. Palgrave Macmillanhttps://doi.org/10.1007/978-1-349-23034-1

Boogaard, B., & Roggeband, C. (2010). Paradoxes of Intersectionality: Theorizing Inequality in the Dutch Police Force through Structure and Agency. *Organization*, *17*(1), 53–75. https://doi.org/10.1177/1350508409350042

Çankaya, S.(2012): De controle van marsmannetjes en ander schorriemorrie. Het beslissingsprocess tijdens proactief politiewerk. Boom Lemma, Amsterdam

Carpenter, J. (2015, July 6). Google's algorithm shows prestigious job ads to men, but not to women. Here's why that should worry you. *The Washington Post*. https://www.washingtonpost.com/news/the-intersect/wp/2015/07/06/googles-algorithm-shows-prestigious-job-ads-to-men-but-not-to-women-heres-why-that-should-worry-you/

Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., & Floridi, L. (2018). Artificial Intelligence and the 'Good Society': the US, EU, and UK approach. *Science and Engineering Ethics*, *24*, 505–528. https://doi.org/10.1007/s11948-017-9901-7

Coombs, C., Stacey, P., Kawalek, P., Simeonova, B., Becker, J., Bergener, K., Carvalho, J. L., Fantinato, M., Garmann-Johnsen, N. F., Grimme, C., Stein, A., & Trautmann, H. (2021). What is it about humanity that we can't give away to intelligent machines? A European perspective. *International Journal of Information Management*, *58*, 1–13. https://doi.org/10.1016/j.ijinfomgt.2021.102311

Couchman, H. (2019, February). *Policing by machine. Predictive policing and the threat to our rights*. Liberty. https://www.libertyhumanrights.org.uk/issue/policing-by-machine/

Djeffal, C. (2018, December). *Künstliche intelligenz in der öffentlichen verwaltung* (No. 3). Nationalen E-Government Kompetenzzentrum e. V. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3289109

Ekblom, P. (1997). Gearing up against crime: A dynamic framework to help designers keep up with the adaptive criminal in a changing world. *International Journal of Risk, Security and Crime Prevention*, *2*(4), 249–265.https://www.researchgate.net/profile/PaulEkblom/publication/291456106_Gearing_up_against_crime_A_dynamic_framework_to_help_designers_keep_up_with_the_adaptive_criminal_in_a_changing_world/links/56b4b1ab08ae83713174a339/Gearing-up-against-crime-A-dynamic-framework-to-help-designers-keep-up-with-the-adaptive-criminal-in-a-changing-world.pdf

Given, L. M. (2008). *The SAGE Encyclopedia of Qualitative Research Methods* (1st ed.). SAGE Publications, Inc.

European Union Agency for Fundamental Rights. (2018). #BigData: Discrimination in data-supported decision making. Publications Office of the European Union. https://fra.europa.eu/en/publication/2018/bigdata-discrimination-data-supported-decision-making

Gordon P. (1993) The Police and Racist Violence in Britain. In: Björgo T., Witte R. (eds) Racist Violence in Europe. Palgrave Macmillan, London. https://doi.org/10.1007/978-1-349-23034-1_12

Hung, T. W., & Yen, C. P. (2020). On the person-based predictive policing of AI. *Ethics and Information Technology*, *23*(3), 165–176. https://doi.org/10.1007/s10676-020-09539-x

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

Katyal, S. K. (2019). Private accountability in the age of artificial intelligence. UCLA Law Review, 66(1), 54-141. Retrieved from https://escholarship.org/uc/item/18n256z1

Lawrence A. Palinkas, Sarah M. Horwitz, Carla A. Green, Jennifer P. Wisdom, Naihua Duan, Kimberly Hoagwood. (2016): Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Adm Policy Ment Health.* Author manuscript; available in PMC 2016 Sep 1. Published in final edited form as: Adm Policy Ment Health. 2015 Sep; 42(5): 533–544. DOI: 10.1007/s10488-013-0528-y PMCID: PMC4012002

Meijer, A., & 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

Miró-Llinares, F. (2020). *Predictive policing: Utopia or dystopia? On attitudes towards the use of big data algorithms for law enforcement* [Preprint]. Miguel Hernandez University of Elche. https://10.31235/osf.io/a7juk

Mohamed, S., Png, M. T., & Isaac, W. (2020). Decolonial AI: Decolonial theory as sociotechnical foresight in artificial intelligence. *Philosophy & Technology*, *33*(4),659–684. https://doi.org/10.1007/s13347-020-00405-8

Momsen, C., & Rennert, C. (2020). Big Data-Based Predictive Policing and the Changing Nature of Criminal Justice – Consequences of the extended Use of Big Data, Algorithms and AI in the Area of Criminal Law Enforcement –. KriminalPolizei Zeitung, 3, 160–172. https://www.jura.fuberlin.de/fachbereich/einrichtungen/strafrecht/lehrende/momsenc/mitarbeiter/momsen_carsten/momsen-rennert-big-data-based-predictive-policing-and-the-changing-nature-of-criminal-justice.pdf

Noble, S. U. (2018). *Algorithms of Oppression: How Search Engines Reinforce Racism*. New York, USA: New York University Press. https://doi.org/10.18574/9781479833641

Ntoutsi, E., Fafalios, P., Gadiraju, U., Iosifidis, V., Nejdl, W., Vidal, M., Ruggieri, S., Turini, F., Papadopoulos, S., Krasanakis, E., Kompatsiaris, I., Kinder-Kurlanda, K., Wagner, C., Karimi, F., Fernandez, M., Alani, H., Berendt, B., Kruegel, T., Heinze, C., . . .Staab, S. (2020). Bias in data-driven artificial intelligence systems—An introductory survey. *WIREs Data Mining and Knowledge Discovery*, *10*(3). https://doi.org/10.1002/widm.1356

Oosterloo, S., & van Schie, G. (2018, March). The politics and biases of the “Crime anticipation system” of the dutch police. In J. Bates, P. D. Clough, R. Jäschke, & J. Jahna (Eds.), *Proceedings of the International Workshop on Bias in Information, Algorithms, and Systems* (pp. 30–41). CEUR.

Oppel, R. A., Jr, Taylor, D. B., & Bogel-Burroughs, N. (2021, April 26). What to Know About Breonna Taylor’s Death. The New York Times. https://www.nytimes.com/article/breonna-taylor-police.html

Petrocelli, M., Piquero, A. R., & Smith, M. R. (2003). Conflict theory and racial profiling: An empirical analysis of police traffic stop data. *Journal of Criminal Justice*, *31*(1), 1–11. https://doi.org/10.1016/s0047-2352(02)00195-2

Ricaurte, P. (2019). Data Epistemologies, The Coloniality of Power, and Resistance. *Television & New Media*, *20*(4), 350–365. https://doi.org/10.1177/1527476419831640

Schwarcz, D., & Prince, A. E. R. (2020). Proxy discrimination in the age of artificial intelligence and big data. *Iowa Law Review*, *105*, 1257–1318. https://scholarship.law.umn.edu/faculty_articles/682

Shapiro, A. (2019). Predictive Policing for Reform? Indeterminacy and Intervention in Big Data Policing. *Surveillance & Society*, *17*(3/4), 456–472. https://doi.org/10.24908/ss.v17i3/4.10410

Schafer, J., Carter, D. & Wells, W. (2006). Decision Making in Traffic Stop Encounters: A Multivariate Analysis of Police Behavior. Police Quarterly. 9. 184-209. 10.1177/1098611104264990.

Tolan, S. (2019, September 18). HUMAINT at PHRP Expert Meeting on Predictive Policing [European Unions Science and Knowledge blog post]. JRC Science Hub Communities - European Commission. https://ec.europa.eu/jrc/communities/en/community/humaint/article/humaint-phrp-expert-meeting-predictive-policing

Zuiderveen Borgesius, F. J. (2020). Strengthening legal protection against discrimination by algorithms and artificial intelligence. *The International Journal of Human Rights*, *24*(10), 1572–1593. https://doi.org/10.1080/13642987.2020.1743976

7. Appendix

Appendix A: Ethical framework for AI use: 5 Principles to prevent harm:

1. Stakeholder Participation. In order to develop AI systems that are trustworthy, it is advisable to consult stakeholders who may directly or indirectly be affected by the system throughout its life cycle. It is beneficial to solicit regular feedback even after deployment and set up longer term mechanisms for stakeholder participation, for example by ensuring workers information, consultation and participation throughout the whole process of implementing AI systems at organisations.
2. Equality, non-discrimination and solidarity - including the rights of persons at risk of exclusion. Equal respect for the moral worth and dignity of all human beings must be ensured. This goes beyond non-discrimination, which tolerates the drawing of distinctions between dissimilar situations based on objective justifications. In an AI context, equality entails that the system's operations cannot generate unfairly biased outputs (e.g. the data used to train AI systems should be as inclusive as possible, representing different population groups). This also requires adequate respect for potentially vulnerable persons and groups, 21 such as workers, women, persons with disabilities, ethnic minorities, children, consumers or others at risk of exclusion
3. The principle of prevention of harm AI systems should neither cause nor exacerbate harm or otherwise adversely affect human beings. This entails the protection of human dignity as well as mental and physical integrity. AI systems and the environments in which they operate must be safe and secure. They must be technically robust and it should be ensured that they are not open to malicious use. Vulnerable persons should receive greater attention and be included in the development, deployment and use of AI systems. Particular attention must also be paid to situations where AI systems can cause or exacerbate adverse impacts due to asymmetries of power or information, such as between employers and employees, businesses and consumers or governments and citizens. Preventing harm also entails consideration of the natural environment and all living beings.
4. The principle of fairness The development, deployment and use of AI systems must be fair. While we acknowledge that there are many different interpretations of fairness, we believe that fairness has both a substantive and a procedural dimension. The substantive dimension implies a commitment to: ensuring equal and just distribution of both benefits and costs, and ensuring that individuals and groups are free from unfair bias, discrimination and stigmatisation. If unfair biases can be avoided, AI systems could even increase societal fairness. Equal opportunity in terms of access to education, goods, services and technology should also be fostered. Moreover, the use of AI systems should never lead to people being deceived or unjustifiably impaired in their freedom of choice. Additionally, fairness implies that AI practitioners should respect the principle of proportionality between means and ends, and consider carefully how to balance competing interests and objectives. The procedural dimension of fairness entails the ability to contest and seek effective redress against decisions made by AI systems and by the humans operating them.32 In order to do so, the entity accountable for the decision must be identifiable, and the decision-making processes should be explicable
5. The principle of explicability Explicability is crucial for building and maintaining users' trust in AI systems. This means that processes need to be transparent, the capabilities and purpose of AI systems openly communicated, and decisions – to the extent possible – explainable to those directly and indirectly affected. Without such information, a decision cannot be duly contested. An explanation as to why a model has generated a particular output or decision (and what combination of input factors contributed to that) is not always possible. These cases are referred to as 'black box' algorithms and require special attention. In those circumstances, other explicability measures (e.g. traceability, auditability and transparent communication on system capabilities) may be required, provided that the system as a whole respects fundamental rights. The degree to which explicability is needed is highly dependent on the context and the severity of the consequences if that output is erroneous or otherwise inaccurate.

Appendix B: Documents for Analysis

Germany

Bund Deutscher Kriminalbeamter. (2020, August). Predictive Policing – Vorausschauende Polizeiarbeit [Comment on the article "Positionspapier des Bund Deutscher Kriminalbeamter e.V. "]. *Bund Deutscher Kriminalbeamter*. https://www.bdk.de/der-bdk/wer-wir-sind/positionen/2020-11-12-positionspapier-predictive-policing.pdf

Egbert, S. (2017, August 4). *Siegeszug der Algorithmen? Predictive Policing im deutschsprachigen Raum | APuZ*. bpb.de. Retrieved October 14, 2021, from https://www.bpb.de/apuz/253603/siegeszug-der-algorithmen-predictive-policing-im-deutschsprachigen-raum

Fair Trials. (2021, November). AUTOMATING INJUSTICE: THE USE OF ARTIFICIAL INTELLIGENCE & AUTOMATED DECISION-MAKING SYSTEMS IN CRIMINAL JUSTICE IN EUROPE. https://www.fairtrials.org/app/uploads/2021/11/Automating_Injustice.pdf

Institut Für Musterbasierte Prognosetechnik GmbH. (2017, September 6). Max-Planck-Institut in Freiburg veröffentlicht Evaluationsbericht [Comment on the article "Predictive Policing – eine Evaluationsstudie zu vorhersagebasierter Polizeiarbeit"]. *Institut Für Musterbasierte Prognosetechnik GmbH*. https://www.mpg.de/14268002/mpicc_jb_2019

Knobloch, T. (2018, August). *VOR DIE LAGE KOMMEN: PREDICTIVE POLICING IN DEUTSCHLAND Chancen und Gefahren datenanalytischer Prognosetechnik und Empfehlungen für den Einsatz in der Polizeiarbeit*. Bertelsmann Stiftung. https://www.bertelsmann-stiftung.de/fileadmin/files/BSt/Publikationen/GrauePublikationen/predictive.policing.pdf

Max-Planck-Institut für ausländisches und internationales Strafrecht Freiburg im Breisgau. (2017). *PREDICTIVE POLICING ALS INSTRUMENT ZUR PRÄVENTION VON WOHNUNGSEINBRUCHDIEBSTAHL* (No. 50). Hans-Jörg Albrecht, Albin Eser und Ulrich Sieber. https://www.researchgate.net/publication/320451111_Predictive_Policing_als_Instrument_zur_Prevention_von_Wohnungseinbruchdiebstahl_Evaluationsergebnisse_zum_Baden-Wurttembergischen_Pilotprojekt_P4

Richter, S., & Kind, S. (2016, May). *Predicitve Policing* (No. 9). BÜRO FÜR TECHNIKFOLGEN-ABSCHÄTZUNG BEIM DEUTSCHEN BUNDESTAG. https://www.tab-beim-bundestag.de/de/pdf/publikationen/themenprofile/Themenkurzprofil-009.pdf

Seidensticker, K., Bode, K., & Stoffel, F. (2018). *Predictive Policing in Germany*. Konstanzer Online Publikations System. http://nbn-resolving.de/urn:nbn:de:bsz:352–2-14sbvox1ik0z06

Thurn, R., & Egbert, S. (2019, March). *Predic-tive Policing: Die Algorith-mi-sie-rung der Polizei als Risiko für die Bürger-rechte?* (No. 227). Humanistische Union. https://www.humanistische-union.de/publikationen/vorgaenge/227/publikation/predictive-policing-die-algorithmisierung-der-polizei-als-risiko-fuer-die-buergerrechte-1/

The Netherlands

Amnesty International. (2021, June 1). Netherlands: We sense trouble: Automated discrimination and mass surveillance in predictive policing in the Netherlands. Retrieved April 2021, from https://www.amnesty.org/en/documents/eur35/2971/2020/en/

Dechesne, F., Dignum, V., Zardiashvili, L., & Bieger, J. (2019, March). AI & Ethics at the Police: Towards Responsible use of Artificial Intelligence in the Dutch Police (1.2.). University of Leiden. https://www.universiteitleiden.nl/binaries/content/assets/rechtsgeleerdheid/instituut-voor-metajuridica/artificiele-intelligentie-en-ethiek-bij-de-politie/ai-and-ethics-at-the-police-towards-responsible-use-of-artificial-intelligence-at-the-dutch-police-2019..pdf

Fair Trials. (2021, November). AUTOMATING INJUSTICE: THE USE OF ARTIFICIAL INTELLIGENCE & AUTOMATED DECISION-MAKING SYSTEMS IN CRIMINAL JUSTICE IN EUROPE. https://www.fairtrials.org/app/uploads/2021/11/Automating_Injustice.pdf

Predictive policing: Niet alleen een zaak van de politie. Politieacademie.Nl. Retrieved August 12, 2021, from https://www.politieacademie.nl/kennisenonderzoek/kennis/mediatheek/PDF/93870.PDF

Mali, B.-, Bronkhorst-Giesen, C., & den Hengst, M. (2017, February). Predictive policing: lessen voor de toekomst Een evaluatie van de landelijke pilot. Politieacademie. https://www.politieacademie.nl/kennisenonderzoek/kennis/mediatheek/PDF/93263.PDF

Oosterloo, S., & van Schie, G. (2018, March). The politics and biases of the "Crime anticipation system" of the dutch police. In J. Bates, P. D. Clough, R. Jäschke, & J. Jahna (Eds.), *Proceedings of the International Workshop on Bias in Information, Algorithms, and Systems* (pp. 30–41). CEUR.

Police and Human Right Programme (PHRP) of Amnesty International Netherlands. (2019, May). PHRP EXPERT MEETING ON PREDICTIVE POLICING. expert meeting on predictive policing, Netherlands.

Waardenburg, L., Sergeeva, A., & Huysman, M. (2018). Digitizing crime: How the use of predictive policing influences police work practices. Paper presented at 34th European Group for Organizational Studies (EGOS) Colloquium, Tallinn, Estonia.

Willems, D. (2014). CAS: Crime Anticipation System Predictive Policing in Amsterdam [Slides]. Event.Cwi.Nl. https://event.cwi.nl/mtw2014/media/files/Willems,%20Dick%20-%20CAS%20Crime%20anticipation%20system%20_%20predicting%20policing%20in%20Amsterdam.pdf

Willems, D., & Doeleman, R. (2014, May). Predictive Policing – wens of werkelijkheid? Het Tijdschrift Voor de Politie. https://www.politieacademie.nl/kennisenonderzoek/kennis/mediatheek/pdf/89539.pdf

The UK

Couchman, H. (2019, February). *Policing by machine. Predictive policing and the threat to our rights*. Liberty. https://www.libertyhumanrights.org.uk/issue/policing-by-machine/

Amnesty International. (2018, May). TRAPPED IN THE MATRIX Secrecy, stigma, and bias in the Met's Gangs Database. Amnesty International UK The Human Rights Action Centre. https://www.amnesty.org.uk/files/reports/Trapped%20in%20the%20Matrix%20Amnesty%20report.pdf

Babuta, A., & Oswald, M. (2019, September). Data Analytics and Algorithmic Bias in Policing. Royal United Services Institute for Defence and Security Studies. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/831750/RUSI_Report_-_Algorithms_and_Bias_in_Policing.pdf

Fair Trials. (2021, November). AUTOMATING INJUSTICE: THE USE OF ARTIFICIAL INTELLIGENCE & AUTOMATED DECISION-MAKING SYSTEMS IN CRIMINAL JUSTICE IN EUROPE. https://www.fairtrials.org/app/uploads/2021/11/Automating_Injustice.pdf

House of Lords: Artificial Intelligence Committee. (2017, April). AI in the UK: ready, willing and able? (No. 2017–19). UK parliament. https://publications.parliament.uk/pa/ld201719/ldselect/ldai/100/10002.htm

Mott, J. (2018, November). EQUALITY IMPACT ASSESSMENT. In Metropolitan Police (Ed.), Form 6119A. https://www.met.police.uk/SysSiteAssets/media/downloads/force-content/met/about-us/gangs-violence-matrix/equality-impact-assessment-relating-to-gangs-violence-matrix.pdf?__cf_chl_captcha_tk__=Wghuo22oHfXDRhEm1DbSOiRfymMcZgy7O4RUgwhtGtU-1642822224-0-gaNycGzNCKU