5 Algorithmic chains of translation

Predictive policing and the need for team-based ethnography

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Introduction

Around the world, police departments use crime prediction software to predict and prevent future offences. Predictive policing is just one of the many ways in which security authorities – and law enforcement agencies in particular – strive to make the future manageable by generating future-related knowledge via socio-technical means. When engaging in predictive policing, police departments do not merely generate anticipatory insights about the future, but actively shape what is to come by intervening in the present. In this chapter, we analyse predictive policing as a socio-technical process of producing and shaping crime-related futures. More precisely, we analyse predictive policing as a "chain of translation" (Latour, 1999: 70). In doing so, we trace the production of crime predictions from algorithmic programming and data input to their execution by police officers: a process that involves many epistemic translations – at different locations but often close in time. We describe predictive policing as an incremental process consisting of different stages, focusing specifically on the German place-based crime prediction software PRECOBS. Approaching this process as a "chain of translation", we show a wide (epistemic) gap that emerges between the beginning of the predictive process and its end. This gap is filled by humans and non-humans alike, in the course of a more or less seamless process, starting at the crime analysis departments of the corresponding police headquarters, and ending on the streets of predicted risk areas. Understanding predictive policing as a chain of translation enables us to analyse it as a productive socio-technical process that proceeds in contingent and, at times, non-linear ways.

This chapter draws on a research project about the implementation and use of crime prediction software that we carried out in Germany and Switzerland between 2017 and 2018. We collected qualitative data from 11 police departments, 4 of them located in Switzerland and 7 in Germany. At the time of data collection, all the departments were either already using predictive policing tools on a regular basis, running field experiments to determine whether to use and/or how to best implement such tools, or developing their own tools. In total, we conducted 62 semi-structured interviews with police officers. These officers worked in a variety of roles, including back-office work,

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managerial work, and patrol work on the street. In addition, we conducted focused ethnographic research with officers to better understand the practical ways in which predictive policing plays out in everyday police work. We were particularly interested in how crime analysts generated and checked crime predictions. Overall, we produced 40 field protocols. Additionally, we drew on a total of 378 documents (e.g., presentation slides, manuals, guidelines) related to the implementation of predictive policing in Germany and Switzerland to complement our ethnography.

Our argument unfolds as follows: first, we characterise predictive policing as a socio-technical process and, ultimately, as a "chain of translation". In the next section, we use the German place-based crime prediction software PRECOBS and its application as an empirical example of such a chain of translation in which we isolate four main stages: crime data, algorithmic analysis, visualisation and dissemination, and patrolling. We close by reflecting on the need for team-based ethnography of predictive systems in policing and beyond.

Predictive policing as a chain of translation

Predictive policing is understood here as the application of algorithmic analysis technologies, which are intended to produce statements about (near-)future crime (cf. Perry *et al.*, 2013: 1f.; Egbert and Leese, 2021: 19). By stressing the analytic work done by algorithms, this understanding of predictive policing highlights the new type of algorithmic agency being introduced to policing through crime prediction software, since older forms of computer software – like text processing or case management software – do not intervene so independently in the knowledge work of police officers. The given understanding of predictive policing implies that we are not dealing with forecasts that convey a long-term view of the (criminal) future, as is the case with crime trends (e.g., Hanslmaier *et al.*, 2015), but with *operational* predictions that can be more or less directly translated into police measures. While crime trends may affect long-term structural changes in police work (such as the overall availability of resources), operational predictions immediately affect how police work is done within existing resource constraints. It is therefore precisely the *acceleration in knowledge generation* achieved through the new technologies of algorithmic data analysis that makes predictive policing possible as a new strategy for police forces (see also Egbert and Leese, 2021: 69–93). Finally, our framing of predictive policing here implies that predictive policing does not only consist of a technical component – the algorithmic creation of crime forecasts – but that the implementation of these forecasts in police measures must always be considered as well, since a perfect crime prediction will not have any preventive effect if the police are not able to act on this prediction in a suitable manner (e.g., because of lacking resources or oversized prediction areas) (Egbert and Leese, 2021: 3f). Predictive policing is, therefore, to be understood as a multi-dimensional, socio-technical process, in the context of which it is not only important to create forecasts that are as accurate as possible, but at least equally significant how these forecasts are brought to the streets. Observing this chain of translation in full can be achieved, as we argue at the end of this chapter, through a multi-sited, team-based ethnography of predictive policing.

It is this socio-technical as well as iterative-processual character of predictive policing that we aim to highlight in this chapter. More precisely, we propose to understand this process as a "chain of translation". The concept was developed by Bruno Latour (1999: 24ff) in the course of his anthropological study of a soil scientific field expedition in Boa Vista, Brazil, during which he observed the research practice of pedologists, geographers, and botanists, who sought to study whether the savanna was advancing into the forest or the forest was progressing into the savanna. After his ethnographic study of Roger Guillemin's scientific laboratory at the Salk Institute for Biological Studies (Latour and Woolgar, 1979), Latour again paid close attention to day-to-day scientific practices and how scientific facts come about. In doing so, he followed the scientists from Paris to the Amazon rainforest in Brazil, observing the "journey" of the scientific findings from the Brazilian forest to the Parisian laboratory and from there into a journal article. Latour describes this journey as a chain of translation (1999: 27), referring to "the work through which actors modify, displace, and translate their various and contradictory interests" (Latour, 1999: 311). This "chain of transformation" (Latour, 1999: 70) is understood as a cascading, socio-technical process, in the course of which scientific reference is constantly being modified. It is, in the words of Glaser, Pollock, and D'Adderio (2021: 17), "never a simple and clean process."

Drawing on this approach, we argue that the discursive and political circumstances of the introduction and development of crime prediction software are an essential part of predictive policing. This also makes apparent that predictive policing should be recognised first and foremost as a nation-specific phenomenon – depending on the political climate but also on the legal conditions that prevail in each case. With reference to Germany, the introduction of crime prediction software by the PRECOBS manufacturer IfmPt (Institut für musterbasierte Prognoseforschung [Institute for Pattern-Based Prediction Research]) seemed to be market-ready at just the right time: For years, the number of domestic burglaries had steadily increased, leading to an intensifying discussion on the role of police and responsible politicians in the media, turning burglaries into a tangible political problem (Egbert, 2018). In this context, the implementation of predictive policing offered the police the opportunity to indicate an awareness of the burglary problem and to associate themselves with "modernity" and "innovation" as they promised to tackle it (Egbert, 2018, 2022). In this sense, the focus of predictive policing in Germany (and also Switzerland) on domestic burglaries is closely related to political processes around the rising case numbers in this category of offence. However, this type of offence is also quite well suited to predictive policing from an analytical and technical perspective, since professional serial burglars, who are the main focus of crime prediction software (see below), show quite robust spatio-temporal patterns, which lend themselves to predictive policing (Kaufmann, Egbert, and Leese, 2019). In addition, because such a pattern can be analysed without the need to gather a lot of data and, more importantly, without the necessity to analyse person-related data, it is also a rewarding approach from a legal standpoint (cf. Singelnstein and Busch, 2020; Sommerer, 2020).

In the following section, we focus on the generation of the predictions, their dissemination within police organisations, and their implementation on the streets.

The translations of predictive policing

Understanding predictive policing as a chain of translation has two important implications: first, predictive policing is a process consisting of different stages enacted at different locations and at different times. Second, predictive policing does not end with the technical production of predictions, but also *includes* the ways in which the crime predictions are passed along and modified within police departments in order to be implemented on the streets. In this process, many epistemic modifications take place, in the course of which the information carried by the prediction constantly changes. In the following, we describe the different stages of a predictive policing process, as depicted in Figure 5.1: crime data, algorithmic analysis, visualisation and dissemination of patrols, and patrolling in predicted risk areas.

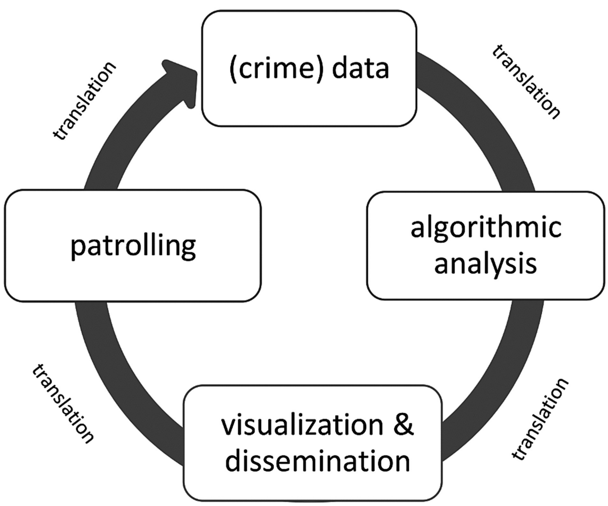

Figure 5.1 Predictive policing as a chain of translation (Egbert and Leese, 2021: 4).

Crime data

To follow the crime prediction, our journey starts before a prediction exists. One of the main epistemic components of crime predictions is the police's crime data. The police mobilise external data as well as their own data in order to generate predictions. For example, the police of North Rhine-Westphalia bought data – inter alia, concerning the socio-economic composition of residential neighbourhoods – from the geo-marketing agency Nexiga[1] for their prediction system SKALA (System zur Kriminalitätsauswertung und Lageantizipation [System for Crime Evaluation and Situation Anticipation]) (LKA NRW, 2018: 24). However, the most important source of information for the production of crime predictions in Germany is the crime data gathered by the police themselves (this is also true for Switzerland). Notably, no arrest data are used, which is important when it comes to the question of bias and feedback loop (see below), as arrest data reflect the biased control and detention practices of police officers (Lum and Isaac 2016; Egbert and Mann, 2021).

In Germany, this data refers principally to the times and places of residential burglaries, which is the main offence predicted in Germany. In most cases, no other police data are used for prediction (Egbert and Krasmann, 2019). This is directly related to the dominant theory used for predictive pattern recognition in Germany, the near-repeat theory (see below). This theory requires only a few data points, usually only concerning the type of offence that is of interest, in this case, domestic burglary. For example, this applies to the crime prediction software PRECOBS (Pre Crime Observation System), which is the only commercial crime prediction software in German-speaking countries and the model for most non-commercial crime prediction software used by police in these countries (Egbert and Leese, 2021: 7). As depicted at the bottom of Figure 5.2, which shows the PRECOBS" "operator view", the software only uses the times and locations of past burglaries, the modus operandi (how the offender gets into the residence), and information about the goods that were stolen.

However, if the underlying data are not reliable, the algorithmically generated results will not be, either. This is known in computer science as "garbage in, garbage out" and poses a huge challenge for police departments using crime prediction software, as the crime data gathered by the police is inherently biased – due to racial profiling, to name only the most obvious problem (Richardson, Schultz, and Crawford, 2019; Egbert and Mann, 2021). Nevertheless, for current predictive policing applications in Germany, bias is less of a problem because domestic burglaries are reported by victims and their reporting behaviour does not correlate with offenders' ethnic background – as it is generally not known to them. Reporting behaviour in general, however, is correlated to the socio-demographic status of the victims, with individuals from marginalised groups being less likely to report crimes to the police. This is partially because low-income households do not have relevant insurance

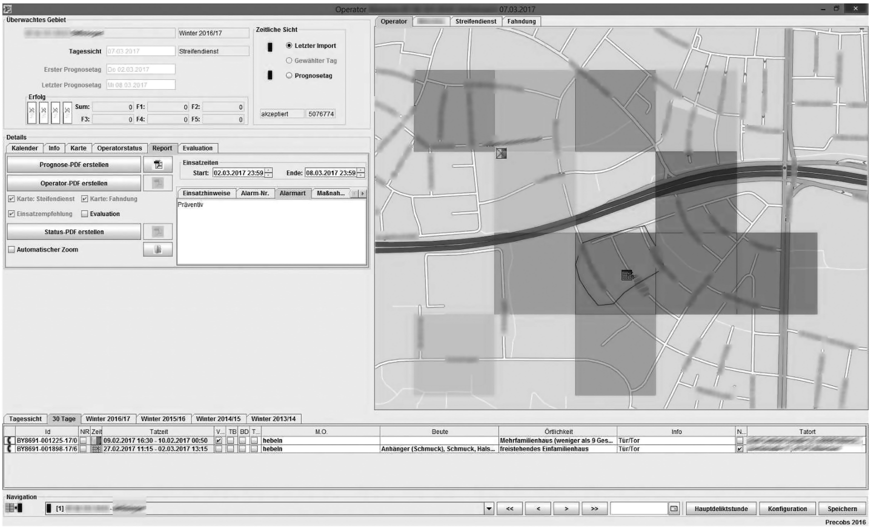

Figure 5.2 PRECOBS "operator view". The map on the right is given to patrol officers. Light to dark shades of gray refer to tiles coloured blue, green, yellow, or red depending on predicted levels of risk. The table at the bottom contains the data PRECOBS analyses to estimate whether a newly registered domestic burglary was executed by a professional burglar based on place and time of offence as well as modus operandi ("M.O.") and haul ("Beute"). Source: Screenshot by authors.

(e.g., KKV NRW, 2006). The relative completeness of data on burglaries is a consequence of insurance companies making compensation for damages conditional on providing a police report. Only when police activities directly shape the number of reported offences does racial profiling have an immediate impact on the predictions (Egbert and Mann, 2021).

Our ethnographic research of predictive policing practices shows that data quality as well as data input speed poses a challenge for police departments. The case processing systems of German police departments do not align well with the needs of crime prediction tools, which call for reliable and frequently updated data. As we will see in the next section, the near-repeat prediction pattern is an ephemeral one, demanding fast prediction work and quick patrol reaction. However, this poses a particular challenge, as the data input of police reports is less reliable the more recent it is, since some information is not available when the data are initially entered, or they are simply entered incorrectly (Egbert and Leese, 2021: 69–93). In fact, the police in Hamburg cancelled the pilot project of crime prediction software because they found that generally, their police officers were not sufficiently aware of the need for proper and fast data input, making it impossible to implement crime prediction software in a functioning manner (Hauber, Jarchow, and Rabitz-Suhr, 2019: 317ff.).

The important role of different data sources, their quality, and accessibility suggests that an ethnography of predictive policing should attend to the wider organisational processes through which input data gets assembled. These processes do not start with the software itself, but earlier, with the data entry. Our research thus points to the importance of attending to police practices *creating* the data entries that ultimately form the basis on which the crime prediction software functions. We will return to this further below and first consider the functioning of the software itself.

Algorithmic analysis

Like in the case of (crime) data, the algorithmic part of crime prediction is also relevant before a crime prediction even exists. Besides the (crime) data, the underlying prediction pattern that is "baked into" the algorithm is the second major epistemic component of predictive policing – without a pattern, there is no prediction (Kaufmann, Egbert, and Leese, 2019). To be manageable, the pattern must have a spatio-temporal context, which can be integrated into the police's day-to-day practices (see below).

As already noted, in Germany, the near-repeat prediction pattern is by far the most dominant theory informing the pattern recognition algorithms of crime prediction software (Egbert and Krasmann, 2019: 27ff.). Its main hypothesis comes from the assumption that previous victimisation is a good predictor for renewed victimisation. It follows the model of a professional serial burglar as "homo oeconomicus", acting as an "optimal forager" (Sidebottom and Wortley, 2016: 168). Rationally calculating the potential risks and earnings of a raid, professional burglars are assumed to strike again shortly after a successful burglary and in its vicinity. These follow-up offences, called near-repeats, are the target variable of most of the crime prediction software used in Germany, including PRECOBS. Ultimately, it is their aim to predict the follow-up offences for a defined spatio-temporal context (e.g., a radius of 500 m and a time span of seven days).

To accomplish this, PRECOBS uses so-called trigger and anti-trigger criteria for assessing the level of professionalism of a newly reported domestic burglary (Schweer, 2015; Balogh, 2016). In fact, the work of PRECOBS comes down to assessing whether the burglary in question was carried out by a professional or not. The near-repeat theory provides that a heightened risk can only be assumed when a professional offender was at work. More specifically, PRECOBS and similar crime prediction software are tasked with identifying burglaries that were carried out by non-professionals because non-professionals are assumed not to return according to near-repeat theory. Hence, sending patrols to the corresponding areas would be useless, or, perhaps more importantly, would be seen from an organisational viewpoint as a waste of resources.

PRECOBS uses so-called trigger and anti-trigger criteria, which indicate professional (trigger criteria) and non-professional (anti-trigger criteria) offender behaviour. As depicted at the bottom of Figure 5.2, the modus operandi ("M.O.") is assessed in order to determine (non-)professional proceedings. The possible ways of gaining unauthorised access to a flat or a house are categorised as professional and non-professional methods for this purpose. For example, drilling a window or a door to be able to open it without a key is assumed to be an expert skill, pointing to a professional offender. In contrast to this, if the police report states that a window or door was smashed with a stone, this is considered non-professional conduct, as it is noisy, something a professional offender would try to avoid. Besides the modus operandi, the stolen goods ("Beute") are also categorised as indicators for (non-)professional offender behaviour. While small and costly goods are assumed to indicate professional offenders, goods which are difficult to transport and/or are hard to resell point to relationship crimes such as the theft of personal belongings or stealing to take revenge and, hence, non-professional offenders (Schweer, 2015; Balogh, 2016).

Two things become clear when looking at the prediction process of PRECOBS and similar crime prediction software. First, we note the relatively low technical sophistication, which is a long way from public and media images of artificial intelligence. Second, we find that crime prediction software in Germany is loaded with socially mediated criminological theories (like rational-choice theory) and expert knowledge (e.g., definition of trigger/anti-trigger), which signals the general contingency of the corresponding predictions. In our research project, we reacted to this finding by complementing our observations of the prediction process at police stations with interviews with the developers of such software – be it from external firms or in-house developers.

Visualisation and dissemination

On our journey following a crime prediction, we are still in the police headquarters, observing the crime prediction production at the desk of the software operator. Once the software has determined whether a newly reported domestic burglary was carried out by a professional offender or not, the operator needs to decide whether this is a "meaningful decision" and whether the prediction should be sent to the responsible police station. PRECOBS and similar crime prediction software in Germany follow a semi-automated prediction process (Egbert and Leese, 2021: 98f). One reason a prediction might be declined could be that the operator knows that a serial burglar has recently been taken into custody – information the software cannot have – making the operator doubt that a near-repeat follow-up burglary could take place (Egbert and Leese, 2021: 99). In the course of the manual assessment of the prediction's reliability, and against the backdrop of the ethnically-coded narratives in police departments in Germany and Switzerland (see below), it is not unlikely that stereotypical knowledge – be it referring to burglars or to areas – will also play a role in the decision taken in the headquarters. Although our empirical data do not directly confirm this conjecture, the ethnographic study of the Dutch crime prediction software CAS (Crime Anticipation System) by Waardenburg, Huysman, and Sergeeva (2021: 10) shows that in the informational enrichment of place-based crime predictions of domestic burglaries, stereotypical knowledge of the area in question – namely referring to drug consumers ("junkies") – is used.

When it comes to the dissemination of predictions from the operator to the local police forces, it is of paramount importance to consider their visual character. The map excerpt depicted on the right in Figure 5.2 is also the visual extract given to the local police officers. The main idea is that police officers use the colour-coded map to decide where to patrol more intensively (Schweer, 2015). Following existing work on scientific representations in Science and Technology Studies (e.g., Coopmans *et al.*, 2014; Latour, 1990), the epistemic intervention of visual knowledge tools, as well as the hard and extensive work invested in the creation of corresponding images, can be considered. Like scientists, the police need to produce tables, graphs, diagrams, illustrations, and images in order to make insights from algorithmic risk calculations tangible and intelligible, in order to establish credibility for the calculated risk scores and corresponding patrol activities, and, last but not least, share insights among different specialised divisions (Egbert and Leese, 2021: 116ff). Several transformations take place in the process of making anticipated crime visible on a map. This process includes the collection and processing of burglary data from the last five years to assess the burglary intensity in an area. Only those areas where burglaries have happened often are analysed by PRECOBS (so-called "near-repeat affine areas"). These areas are more closely assessed in terms of the concrete distribution of near-repeat burglaries in the past, which is then translated into the colour-coded tiles Figure 5.2. Making use of colour perceptions deeply rooted in our culture, the red tiles demonstrate high-risk areas, which allegedly require a particularly high level of attention.

In our ethnographic research, we paid particular attention to the translations that representations of risk undergo as they are being circulated among different police divisions with specific functions and needs. Our analysis showed that as a visual risk representation began to circulate through a police organisation, it was gradually simplified and stripped of contextual information until, when it came to street-level policing, it had been transformed in such a way that police officers perceived it as a self-evident indicator for the fact that crime will happen unless it is prevented.

Patrolling

On our journey following the crime prediction through the police department, we have now arrived at our destination: the streets of the predicted risk area. As previously indicated, predictive policing is not only about producing crime predictions. A crime prediction itself has no value for the police. Rather, to have any preventive value, the forecasts must be implemented. That is, police officers have to use the predictions on the streets; otherwise, they have no effect.

In general, there are two strategies for using the predictions generated by PRECOBS and similar crime prediction software: first, a repressive approach can be applied, in the course of which surveillance forces are sent into the predicted risk areas. Dressed in civilian clothes, they can monitor the risk area and catch the perpetrator(s) in the act of committing the crime. Second, uniformed patrol forces can be deployed to patrol the predicted risk areas and deter inclined offenders through their visible presence ("focused deterrence", Ferguson, 2017: 35ff.). Since predictive policing is mainly used for cost-saving – the aim is to "do more with less" (Beck and McCue, 2009) – the second type of intervention is implemented almost exclusively. The observation of (complete) risk areas is much too resource-intensive (Egbert and Leese, 2012: 194; Pett and Gluba, 2017).

Understanding predictive policing as a chain of translation makes it mandatory to analyse closely the (mostly) preventively orientated control practices of patrol officers in the predicted risk areas. In fact, it is an open question whether risk areas are patrolled more intensively at all. In some cases, the human resources to follow up on forecasts are simply not available. This was a problem for the Saxonian police in the course of their trial of PRECOBS, leading to the decision not to adopt this software for regular operation (Fengler, 2020). Another reason for local officers not to implement a prediction can be conflicting operations in the affected areas (about which the operators of the crime prediction software have no knowledge), for example, an observation mission, which would be disturbed by (increased) police presence.

Although we were not able to participate in patrol missions in the predicted risk areas, the numerous interviews we conducted showed quite clearly that the predictions change the way the police control the affected areas and the people who are present there. The police officers who are supposed to increase patrols in a predicted risk area usually only have information about the location and size of the area to be patrolled. Their only task is to show their presence there, to dissuade potential perpetrators from their plans, who – as the assumption goes – are not willing to take the risk of arrest or conviction (Pett and Gluba, 2017). However, these patrols are also regularly used to look for suspicious incidents and, if indicated, to check people and cars. In this respect, the question of who or what is considered suspicious becomes virulent. In a way, people who happen to be in the risk area at the time the police are patrolling there tend to become the object of "ecological contamination" (Smith, 1986: 316) – the spatial risk passes on to them (Egbert, 2020; Egbert and Mann, 2021). This is in fact an ecological fallacy, as the risk attached to the area does not allow for a connection to the risk level of the people present in this area. The problem gets worse when focusing on the group of people the police regularly target in the risk areas. Police officers in the risk areas mostly look for cars and people coming from Eastern Europe (Egbert and Mann, 2021: 34; Egbert and Leese, 2021: 194) because of narratives that the expansion of the European Union to the East is a major reason for the increase in burglaries in Central Europe (see e.g., Winter, 2015) – racial profiling par excellence.

Team-based ethnography of crime prediction software

In proposing to understand predictive policing as a chain of translation, we have highlighted our understanding of predictive policing as a socio-technical and processual practice. Predictive policing consists not only of technical practices around precise and reliable predictions but also of the predictions' dissemination in police departments and their implementation by patrol officers. Understanding predictive policing as a chain of translation enables us to focus specifically on the epistemic transformations inherent in this algorithmically mediated practice and highlight its locally dispersed character. As we have shown, an analysis of predictive policing as a chain of translation is missing important parts if it does not account for the actual practices of patrol officers in the streets, implementing the predictions and making predictive policing potentially effective in the first place. Among other things, analysing control practices in risk areas shows that an understanding of predictive policing from a purely technical perspective does not capture the whole translation picture – especially when it comes to the question of discrimination and bias. In the context of place-based predictions that we have described, no personal data is used for creating the predictions. Proponents of place-based predictions therefore often claim that this form of prediction cannot be discriminatory in itself. However, our look into the concrete implementation practices makes clear that people can nevertheless (unjustifiably) become the focus of the police in the context of predictive policing.

When examining the data generated by the patrol of predicted risk areas, the chain of translation of predictive policing becomes a circle. This implies that the control practices in the risk areas have an effect on how crime numbers develop, which in turn changes the data to be processed by the predictive algorithms. From the police's point of view, that is not necessarily a bad thing because changing the data by reducing the number of domestic burglaries in the predicted areas is a key aim of predictive policing. However, this proactive policing character of predictive policing has the potential to generate self-fulfilling prophecies, more specifically a self-escalating feedback loop (O'Neil, 2016: 87; Egbert and Mann, 2021: 35f). By sending police officers into risk areas, who then – by stopping people and reporting crimes there, etc. – generate more data about this very area, predictive policing increases the possibility of future predictions in the same area. This problem does not (yet) exist in Germany, as the crime prediction software only uses data coming from the police investigation reports filed at the initiative of burglary victims.

And the likelihood of reporting a domestic burglary to the police does not correlate positively with the presence of police patrols – as the regulations of the insurance companies are influential here (see above). Therefore, as the intensified patrols do not generate a higher probability of more burglaries being reported in these areas, the probability of future predictions in affected areas will not be increased by current crime predictions. Ethnography, we argue, is especially well suited to a thorough analysis of the full chain of translation constituting the practice of predictive policing. This is even more true when approaching predictive policing as a team: a real-time, multi-sited ethnography of predictive policing allows for following a specific forecast "live" as it travels through the various stations.

We would frame this approach as a *team-based ethnography of algorithmic systems*.

For several years now, there has been a lively discussion on the role of the internet and digital technologies in ethnographic research. Initially, the focus of the debate was more on the role of the internet and its possibilities of communicating and (virtually) interacting, referred to as "virtual ethnography" (Hine, 2000), "webnography" (Strübing, 2006; translation by the authors), or "netnography" (Kozinets, 2010), but recently digital ethnographic approaches have become more prominent (e.g., Pink *et al.*, 2016). These approaches have broadened the scope of ethnographic research by not exclusively focusing on the internet, but on digital practices in general, especially smartphone use. However, what is missing in most of these accounts is a focus on the algorithmic work behind it, including the developers' interests and values written into the algorithms, as well as the effects of algorithmic affordances on users. This approach – which, following Seaver (2017) and Christin (2020) – could be called the "ethnography of algorithmic systems", is interested, on the one hand, in the work that goes into the creation and maintenance of algorithms; on the other hand, it interrogates the social consequences of algorithms on their surroundings. Seaver (2017: 1), for example, writes about tactics of an "ethnography of algorithmic systems" by focusing on algorithms as "heterogeneous and diffuse sociotechnical systems" and thus understanding them not as rigid, fixed formulas, but, following Mol's (2002) praxiography, as "part of broad patterns of meaning and practice that can be engaged with empirically" (see also Glaser, Pollock, and D'Adderio, 2021). Algorithms are not to be understood merely as cultural components, therefore, but as culture itself, which is produced situationally through culturally conditioned practices (Seaver, 2017: 4f). Against this background, following Seaver, ethnography offers itself aptly as a methodological approach because "(e)thnography is also good for seeing algorithms *as*, rather than *in* culture – for apprehending the everyday practices that constitute them and keep them working and changing" (2017: 6; emphasis in original). Additionally, Kitchin (2017: 24–26), in his overview of (critical) algorithm research, focuses on a total of six methodological approaches, two of which are explicitly ethnographically orientated: participant observation of programming teams to reconstruct the story behind the creation of an algorithm, and the study of people's practices with algorithmic systems and their effects, e.g., on organisations and how they perform and (re)structure their endeavours. Likewise, Christin (2020) highlights the suitability of ethnographic approaches for the study of algorithms given the black box character of most algorithmic systems in contemporary society – for example, due to their proprietary nature or their complex architecture (see also Pasquale, 2015; Burrell, 2016). In her words: "(E)thnographic approaches shed light on the complex intermingling of social, cultural, and technological aspects of computational systems in our daily lives. They provide rich and fine-grained data on how algorithms are built and used" (Christin, 2020: 903). In addition, she proposes making use of the sociology of enrolments, especially by following Callon (1986), thus understanding algorithms as embedded in complex and dynamic networks of human and non-human actants (Christin, 2020: 904f). Combining both approaches, Christin (2020: 906) proposes reducing the problem of algorithmic opacity by "decentering the analysis" of algorithms. That is, to focus not on the algorithmic system alone but to study the corresponding collective of human and non-human actants as a whole (see also Glaser, Pollock, and D'Adderio, 2021). In a similar vein, Lange, Lenglet, and Seyfert (2019: 606f), with reference to high-frequency trading algorithms, propose reacting to the character of algorithms as "quasi-objects" – following Serres' (1982) – since they are not collectable in a material sense, to make use of multi-sited ethnographic approaches, so enabling "different modes of interpretation of algorithms".

Building on these ethnographic accounts of algorithms, a team-based ethnography – near real-time and multi-sited – of algorithmic systems seems to be well-suited to observing the different stages of predictive policing's chain of translation. Such an ethnography of predictive policing would need to be a multi-sited ethnography (Marcus, 1995), as the crime predictions travel. And it would need to be a team-based ethnography (e.g., Jarzabkowski, Bednarek, and Cabantous, 2015), since predictions travel in (near) real time, making it impossible for a single researcher to follow a particular crime prediction from its generation in the department onto the streets, where it is implemented by patrol officers. For the implementation of predictive policing discussed in this chapter, this would mean that one ethnographer shadows the operator of the crime prediction software, closely observing the generation and assessment of the prediction. Another ethnographer attends the decision-making of local police authorities concerning the (non-)application of predictions. Yet another ethnographer attends the patrol situation in the risk area, enabling them to observe the arrival of the prediction at its final destination. This also allows for close attention to the possible feedback loop associated with crime predictions. That is the question of how police presence in the predicted risk area generates new data, which flow back into the department and affect future predictive work. This necessitates close observation of what data are entered into the police databanks, for example, by the patrol officers, and how these data are then further used for new crime predictions. In this context, the benefit of a team-based ethnography of predictive policing emerges, by allowing not only the analysis of a predictive policing chain at different locations but also the analysis of a predictive policing chain in (near) real time, as multiple ethnographers study the process in parallel.

While we focus here on the concrete implementation of crime predictions in police departments, the chain of translation constituting predictive policing can also be defined more broadly, as we have already indicated above, for example, by integrating the political and discursive contexts of such algorithms, including their role in the programming of the software. In fact, with reference to the extensive scientific work behind image-processing algorithms, Jaton (2021) illustrates the importance of starting an (ethnographic) analysis by studying the programming of the algorithms themselves – well before they are implemented on a daily basis “in the wild”. However, in many cases, algorithmic chains of translation will likely contain too many sites, actors, and/or actants to be analysable in their entirety, making it necessary to focus on particular segments of the chain.

Finally, the advantages of such an approach should be contrasted with some of its disadvantages. Gaining field access is a challenging part of ethnographic research. This holds particularly true for settings like the police, where “formal secrecy” (Costas and Grey, 2014: 1424) plays an important role. In a multi-sited ethnography, researchers need to negotiate access at more than one site. A clear disadvantage is that negotiating field access for multiple sites of formal secrecy can take a very long time and bears a substantial risk of failure. Failure can occur even after having gained access, for example, when researchers get caught up in micro-political struggles between involved organisations. For example, we learnt from our previous research that oftentimes predictive policing systems are maintained by a state-level police department. This state-level department creates predictions and delivers them to municipal-level police departments. State-level departments are interested in whether municipal-level departments use the predictions or not. However, they often refrain from establishing formal evaluation procedures. We see the risk that state-level organisations try to enrol ethnographers as informants on the activities of municipal departments. In turn, municipal departments might become sceptical of the researchers, suspecting them to be informants for the state-organisation. Even in a situation of formal access, getting caught up in such a dynamic might hamper the success of the ethnographic endeavour.

Conclusion

Drawing on ethnographic fieldwork in Germany and Switzerland, we analysed predictive policing as a chain of translation (Latour, 1999). In doing so, we followed the implementation of crime prediction software within a police department to the destinations targeted by the software, highlighting both the processual and socio-technical character of this approach. In the course of our research, we placed special emphasis on the epistemic transformations, which involve examples such as the visualisation of a crime prediction for the sake of its convenient manageability by patrol officers. Based on our account of predictive policing, we ultimately proposed that the ethnographic study of predictive policing as a socially embedded chain of translation calls for a team-based approach following the multi-sited and (near-)real-time journey of crime predictions.

Note

1 https://www.nexiga.com/ (last accessed: 16.11.2021).

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