Digitizing crime

Waardenburg, L.; Sergeeva, A.; Huysman, Marleen

2018

document version
Publisher's PDF, also known as Version of record

document license
Article 25fa Dutch Copyright Act

citation for published version (APA)
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.

Digitizing crime: How the use of predictive policing influences police work practices

Conference Paper · January 2018

3 authors:

Lauren Waardenburg
Vrije Universiteit Amsterdam

Anastasia Sergeeva
Vrije Universiteit Amsterdam

Marleen Huysman
Vrije Universiteit Amsterdam

EGOS 2018, Sub-theme 02: [SWG] Understanding Organizing in Terms of Digital Media Technology: Histories, Presents, Futures

Title:
Digitizing crime: How the use of predictive policing influences police work practices

Author details:
Lauren Waardenburg
Department of Information, Logistics, and Innovation
Vrije Universiteit Amsterdam
1081 HV Amsterdam
The Netherlands
l.waardenburg@vu.nl

Anastasia Sergeeva
Department of Information, Logistics, and Innovation
Vrije Universiteit Amsterdam
1081 HV Amsterdam
The Netherlands
a.sergeeva@vu.nl

Marleen Huysman
Department of Information, Logistics, and Innovation
Vrije Universiteit Amsterdam
1081 HV Amsterdam
The Netherlands
m.h.huysman@vu.nl

Date:
08 January 2018

ABSTRACT

This research focuses on the consequences of the shift to data-driven work for daily police practices. Our ongoing ethnographic field study of a team of police officers shows that the use of predictive policing algorithms inscribes a specific crime theory-in-use – i.e., the understanding of why crime occurs and how it should be prevented – which influences daily police work. While traditionally having a social-environmental perspective on crime, police officers are shifting attention towards features of the physical environment as explanations for crime occurrence. Our preliminary findings have implications for debates on the consequences of data analytics by showing how the different theory-in-use inscribed in data-driven work influences traditional work practices.

INTRODUCTION

This study examines the phenomenon "predictive policing", i.e., preventing crime by predicting criminal and deviant behavior through large-scale monitoring and data-analysis (Perry, McInnis, Price, Smith, & Hollywood, 2013). Predictive policing includes algorithms used to predict where and when crimes are most likely to occur (Brayne, 2017; Perry et al., 2013) and is part of the shift to data-driven police work – adopted in recent years and growing fast (Brayne, 2017). By the end of 2017, 90 out of 168 Dutch police departments were using predictive policing with the aim to use predictive policing in all Dutch police departments by the end of 2018 (Politie, 2017; NOS, 2017). Another example is the so-called "Smart Policing Initiative" through which federal funds support more than 30 U.S. law enforcement agencies to develop new data-driven practices (Brayne, 2017).

Previous research has looked at how data-driven police work resulted in changes on different levels of the police organization, such as surveillance (Brayne, 2017; Guzik, 2009; Joh, 2016), police culture (Weisburd, Mastrofski, McNally, Greenspan, & Willis, 2003), and criminal procedures (Ferguson, 2015). However, we know little about how the use of predictive policing algorithms influences police work practices. In line with this, we ask the following research question: *what are the consequences of the shift to data-driven work for daily police work?*

Our preliminary findings suggest that the use of algorithms influences police work through inscribing a specific theory-in-use of crime – why crime occurs and how it should be prevented. To provide an interpretation of such inscription, we use insights from criminological perspectives (Arrigo & Williams, 2006; Carrabine, Cox, Lee, Plummer, & South, 2009; Lynch, Stretesky, & Long, 2015). Since criminology is a specific discipline in social sciences that deals with particular issues of social reality – such as the nature of social harm and the fundamentals of crime and crime prevention (Lynch et al., 2015) – definitions of crime are known to be contested and are likely to vary over time (Arrigo & Williams, 2006). We posit in this paper that data-driven approaches to crime may be more susceptible to some criminological explanations of causes and origins of crime than other approaches. Moreover, we emphasize that the use of data-driven technologies by the police are consequential, because they are not simply neutral tools that help to inform police officers. Instead they repurpose the attention to a different explanation of crime through which they might mediate relationships involved in, for example, law enforcement (McLuhan, 1964, 1994; Munro, 2010).

We adopt a practice-based perspective for studying the use of data-driven technology (Orlikowski, 2000; Orlikowski & Scott, 2008) to scrutinize how the shift to data-driven work influences police practices. Considering the developmental stage of our ethnographic research, we present the preliminary findings that will help us answer this question. We zoom in on the daily police practices and focus on comparing the differences between theories-in-use of traditional police work and predictive policing algorithms.

THE POLICE SETTING

The findings of this study are based on an ongoing ethnographic study at the Dutch Police. We started in January 2016 with following a team of police officers at a specific Dutch police station. Currently, we have conducted about 300 hours of fieldwork in which we observed – next to the daily work at the police station – 70 briefings, 23 team meetings, and 10 interdisciplinary meetings with other public agencies such as the municipality and the Public Prosecution Service. Fieldnotes from the observations of the daily police work and detailed descriptions of numerous informal conversations with the participants comprise the bulk of empirical data that is used for this study. In addition, we have conducted eleven in-depth semi-structured interviews with members of the police station (5 interviews), the data scientist who developed the algorithm (2 interviews), and police members focused on the development of data-driven police work (4 interviews).

We focused on examining the activities of use of the Dutch predictive policing technology: the "Criminal Anticipation System" (CAS), which was introduced to the police station studied in 2014. The CAS uses an algorithm to identify patterns in existing data and develops a heat map that shows where chances of crime are highest.[1] The heat map is used for daily police work, providing directions about where to go at what time to prevent a specific crime. The crimes included are "patterned crimes", such as home burglaries that are repeatedly committed during the holiday season. Due to the calculating capacity of the computer system, every Dutch police station can select between one and four patterned crime themes. For example, the observed police office selected: (1) youth hinder / gun possession, (2) theft / home burglary, (3) robbery, and (4) theft of cars or out of cars (e.g., navigation system, laptop). For this study, we limit our analysis and discussion of crime to these four categories of patterned crimes.

We started our ethnographic study with a broad research question of how work practices of police officers change due to the introduction of predictive policing. During our data collection, we encountered different understandings of crime by the participants: when reflecting on the shifts to data-driven work, they spoke differently about the *causes of crime* or how to *prevent crime*.[2] We present our analysis of these differences below.

FINDINGS

Our preliminary findings suggest that the shift to data-driven police work influences traditional police work because predictive policing inscribes a different theory-in-use. While the traditional understanding of crime is focused on the social environment, using predictive policing turns the attention towards the physical environment. This influences, for example, the crime prevention practices of police officers. Below, we describe this in more detail by comparing the theories-in-use of traditional police work and predictive policing algorithms.

Traditional understanding of crime: social environment as a theory-in-use

Traditionally, to understand and explain why crime occurs, police officers look at a criminal's social environment. One example is family relations, such as the influence of older (criminal) brothers on younger kids. This means that an important part of traditional police work is to connect with the neighborhood families to develop relationships and knowledge of what is happening in their homes. Ronald, one of the police officers, explained why this is important: "When you know people and they trust you, then they start to tell you stuff about what's

[1] In time blocks of four hours and area blocks of 125 by 125 m^2. Currently, about 40% of the home burglaries and 60% of the robberies can be accurately predicted (Willems & Doeleman, 2014).
[2] To systematically analyze these differences across our data, we used three criteria in selective coding. First, we selected all the responses to the question "what is the biggest shift due to predictive policing?". Second, we took all statements where the participants described their use of data. Third, we took all responses to questions about their usual work (without data). We grouped and coded all statements to analyze the differences between the traditional and the data-driven crime theory-in-use.

happening behind these closed doors”. By understanding family dynamics in a neighborhood, the police can intervene and either limit or make use of family influence on a (young) criminal.

Other types of community relations are also assumed to have a high formative effect on criminal behavior. Eva, an intelligence specialist, gave an example of such community influence: “Look, the ones who are now causing youth hinder, you know, they grow. They start with youth stuff and then they talk to big guys because they all group together and, yeah, they just get promoted.” To prevent crime, such influences require police officers to connect with the community to understand the social dynamics in various gangs. For example, a crime prevention strategy is to identify the most central gang members who are expected to have the highest influence on crime occurrence. Traditionally, to understand and prevent crime therefore means to understand the network of people and their roles.

In sum, traditionally, police officers have a crime theory-in-use that understands criminal behavior as arising out of social influence and embedded into a network of relations in which actors have different roles. This echoes the so-called “differential association theory” in criminology that explains that criminal behavior stems from specific affiliation with criminal peers (Burgess & Akers, 1966). Crime prevention strategies following this theory traditionally require in-depth, intimate knowledge of various types of social relations.

Predictive policing: generic data and standard data mining algorithms

The introduction of predictive policing requires police officers to shift their focus to more data-driven work. To understand the implications of this shift for traditional police work, it is important to unpack the characteristics of the predictive policing technology, which together inscribe a specific theory-in-use.

First, in our setting predictive policing only deploys generic data that is readily available and easily quantifiable. This means that the analytic tool is not used to mine, visualize, and analyze large amounts of data to identify complex social relations. Instead, the data used is limited to crime reports combined with generic socio-demographics of the neighborhoods and location-specific data provided by the central bureau of statistics (see Table 1 for the specifics of the data included). This set of only generic data is supposed to provide a more comprehensive, objective picture of crime that helps to identify crime patterns previously not (easily) discernible (e.g., the repetitiveness of a specific type of crime within a radius of 250 meters).

Insert Table 1 about here

Second, the analytic techniques used at the police station we studied are developed from standard data mining algorithms that are normally used to construct, for example, customer profiles or personas. Such algorithms are used in marketing campaigns to calculate and prevent turnover intentions. In the case of the police, they are used to calculate crime chances. As Dennis, a data scientist who joined the police to develop (predictive policing) algorithms after extensive experience in marketing, explained: "The idea [of making customer profiles] is of course also useful in the police domain, only here you don't have customers but geographic areas about which you have a lot of data". By using standard data mining algorithms, predictive policing inscribes the implicit understanding that future criminal behavior can be sorted in categories based on past behavior.

Combining generic data and the standard data mining algorithms, a different understanding of what triggers crime is inscribed into predictive policing as compared to the social-environmental perspective that characterizes traditional police work. For example, data scientist Dennis used the case of robbery to explain how plots of certain areas are used to explain where triggering behavior of possible victims may occur:

> Robbery almost always happens in the same district, around the entertainment areas. Of course, that's where the victims are. That's where the drunken tourists stroll around and they don't pay too much attention. (Interviewee 1, data scientist perspective)

Instead of understanding victim behavior based on social-environmental determinants, predictive policing identifies victims by, for example, the number and kind of facilities present in the neighborhood. Another example is the so-called "mobile bandit" crimes, such as theft of cars. From a predictive policing perspective, there is a higher chance of such crimes when there are nearby highway exits, because these provide quick escape routes. Moreover, the distance from the home address of a known burglar is used to estimate the chance of home burglaries. The implicit assumption of predictive policing is that a burglar lives near the crime area, because in this area the burglar will not look like an outlier which gives one the opportunity to act and return unnoticed. The above-mentioned examples give insight into how predictive policing shifts focus to features of the urban structure that define criminal behavior by the tangible network of streets, facilities, and houses, instead of by the intangible network of community relations.

To understand and predict crime, the data-driven theory-in-use is not based on complex analyses of the social environment but on generic data and standard data mining algorithms that point to the physical environment of crime. This echoes the "social disorganization theory" in criminology that posits that physical environment and other macro and aggregated features of neighborhoods and cities are explanatory factors of crime (Shaw & McKay, 1942). Crime prevention strategies following this theory focus on the disruption of general routines and patterns. The identification of such patterns requires a high amount of generic, standardized knowledge of physical features.

The impact of predictive policing on daily police work

Our preliminary findings indicate that the theory-in-use inscribed in predictive policing changes daily police work to focus on the physical environment as used by the algorithm. For example, police officers are now driving through areas predicted to have a high chance of home burglaries to scan whether the front doors have bad locks instead of stopping to talk to the families behind those doors.

Another example is the so-called "dark days offense" in which the amount of late-afternoon and evening surveillance in specific areas is increased a couple of weeks before and after Christmas. "It means that it will get dark early, so people won't be noticed that quickly [when stealing and running away]", explained Ronald. The police officers noticed every year that only specific locations seemed to be the target of home burglaries during this period, but they were unable to identify which locations would be the target at a specific date and time. Due to the use of predictive policing, the police officers are now able to identify which hotspots they need to focus on and the hot times at which they should be available. As a result, the work shifts of the police officers are adapted such that more police officers are scheduled during the "dark days" afternoon and evening shifts to increase the chances of crime prevention. Moreover, their work routes change on such evenings to increase surveillance of hotspots.

As discussed above, the examples from our data indicate that, instead of having a social-environmental perspective on crime, predictive policing inscribes a different theory-in-use that is focused on the physical environment. As a consequence of the shift towards this data-driven work, police officers themselves are now also (implicitly) changing their daily work practices to focus on the physical environment and algorithmic indicators.

CONCLUSION AND IMPLICATIONS

Our preliminary findings present a comparison between two different crime theories-in-use: traditional and data-driven. We have shown that the traditional understanding is more focused on the social explanation of crime, addressing social-environmental determinants of criminal behavior, while the data-driven understanding points at the physical environment for explanations of crime. Our analysis of the two does not claim that one is taken over by the other. Instead, both understandings currently co-exist in the police environment.

The findings offer implications for research on data analytics at work. First, recent debates indicate the controversial nature of "datification" which might result in, for example, discrimination (Newell & Marabelli, 2015). However, there is limited empirical work considering this. Our study provides an empirical example of what this controversy may entail by showing that predictive policing inscribes a different theory-in-use. We show that beyond simply being a helpful tool, algorithms have a more profound, but less obvious influence on police work: they repurpose attention to a different explanation for crime occurrence, which may, for example, eventually mediate relations involved in law enforcement (McLuhan, 1964, 1994; Munro, 2010).

Second, previous research has indicated that the fast spread of predictive policing transforms the work practices of police officers (Brayne, 2017). However, current studies do not focus on the influence of the theories-in-use inscribed in the algorithm. We show that daily police work shifts attention to the data-driven theory-in-use by focusing on indicators available in the physical environment. Especially considering the high-stake, ethically charged contexts of police work, it is of critical importance to be aware of such consequences of shifting to data-driven work and to carefully study this.

REFERENCES

Arrigo, B. A., & Williams, C. R. (2006). ***Philosophy, crime, and criminology.*** Chicago: University of Illinois Press.

Brayne, S. (2017). Big Data Surveillance: The Case of Policing. ***American Sociological Review***, 82: 977–1008.

Burgess, R. L., & Akers, R. L. (1966). A differential association-reinforcement theory of criminal behavior. ***Social Problems,*** 14: 128–147.

Carrabine, E., Cox, P., Lee, M., Plummer, K., & South, N. (2009). ***Criminology: A sociological introduction***. New York: Routledge.

Ferguson, A. G. (2015). Big data and predictive reasonable suspicion. ***University of Pennsylvania Law Review,*** 63: 327–410.

Guzik, K. (2009). Discrimination by design: Predictive data mining as security practice in the United States' 'War on Terrorism'. ***Surveillance and Society,*** 7:1–17.

Joh, E. E. (2016). The New Surveillance Discretion: Automated Suspicion, Big Data, and Policing. ***Harvard Law and Policy Review,*** 10: 15–42.

Lynch, M. J., Stretesky, P. B., & Long, M. A. (2015). ***Defining Crime.*** New York: Palgrave Macmillan.

McLuhan, M. (1964, 1994). ***Understanding media: The extensions of man.*** Cambridge, MA.: The MIT Press.

Munro, I. (2010). Defending the network organization: An analysis of information warfare with reference to Heidegger. ***Organization,*** 17: 199–222.

Newell, S., & Marabelli, M. (2015). Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of "datification." ***Journal of Strategic Information Systems***, 24: 3–14.

NOS (2017). ***Politie gaat misdaad voorspellen met nieuw systeem.*** Retrieved January 03, 2018, from https://nos.nl/artikel/2173288-politie-gaat-misdaad-voorspellen-met-nieuw-systeem.html

Orlikowski, W. J. (2000). Using technology and constituting structures: A practice lens for studying technology in organizations. ***Organization Science,*** 11: 404–428.

Orlikowski, W. J., & Scott, S. V. (2008). Sociomateriality: Challenging the Separation of Technology, Work and Organization. ***The Academy of Management Annals***, 2: 433–474.

Perry, W. L., McInnis, C. C., Price, S., Smith, S., & Hollywood, J. S. (2013). ***Predictive policing. The role of crime forecasting in law enforcement operations.*** Santa Monica: RAND Corporation.

Politie (2017). ***Criminaliteits Anticipatie Systeem verder uitgerold bij Nationale Politie.*** Retrieved January 03, 2018, from https://www.politie.nl/nieuws/2017/mei/15/05-cas.html

Shaw, C. R., & McKay, H. D. (1942). ***Juvenile delinquency and urban areas.*** Chicago: University of Chicago Press.

Weisburd, D., Mastrofski, S. D., McNally, A. M., Greenspan, R., & Willis, J. J. (2003). Reforming to preserve: COMPSTAT and strategic problem-solving in American policing. ***Criminology and Public Policy,*** 2: 421–456.

Willems, D., & Doeleman, R. (2014). Predictive policing – wens of werkelijkheid? ***Tijdschrift voor de Politie,*** 76(4/5): 39–42.

TABLES

TABLE 1

Overview of the data included in the predictive policing algorithm

Type of data included	Input variables of the algorithm
Crime reports	· Number of times the crime occurred · Specific location of the crime · Specific time of the day · Season
Socio-demographics and location-specific data	· Number and kind of companies present in the neighborhood (e.g., bars, coffee shops, banks) · Distance to closest known offender (e.g., mugger, robber, burglar) · Mean distance to 10 closest known offenders · Distance to nearest highway exit · Number of burglaries, robberies, etcetera, in several different time periods (relative to the reference moment)